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

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Nonpoint-source water pollution remains a major issue despite decades of research and sizable conservation programs. We suggest that by taking advantage of contemporary modeling and optimization approaches, good approximations to physical relationships can be constructed so that even in the presence of unobservable field emissions and nonlinear fate and transport relationships, standard economic tools of command-and-control requirements, performance standards, and trading can be implemented. The Boone River Watershed in the U.S. state of Iowa is used for empirical demonstration. Although the approach can be used to construct voluntary conservation policies, the described policies involve imposing requirements on agricultural polluters rather than relying on voluntary actions alone.

Key words: agricultural conservation practices, agricultural nonpoint-source pollution, conservation policy, cost-effective policy design, evolutionary algorithms, multi-objective optimization, performance standards, water quality trading.

JEL codes: C63, Q2, Q28, Q53.

The emission of nutrients and sediment from agricultural fields remains a significant pollution problem across a substantial portion of the United States. Recent data from the National Summary of Assessed Waters Report by the US Environmental Protection Agency (US EPA) indicates that 53% of the assessed rivers and streams, and over 65% of the assessed lakes are water quality impaired, and that progress over the past decade has been largely nonexistent (figure 1).[1] In these assessments, agriculture is identified as the leading source of river and stream impairments, and is the third-largest source of lake, pond, and reservoir impairments. Emphasizing the role of agriculture in this problem, Ribaudo, Heimlich, and Peters (2005) note that in two-thirds of the 700 nitrogen-impaired watersheds across the United States, completely eliminating point sources would reduce nitrogen contributions by only 10% or less. Thus, if progress is to be made in reducing water quality impairments, significant reductions in nutrient inputs from agriculture are necessary.

The Clean Water Act passed in 1972 remains the primary federal legislation for addressing water quality problems from both point and nonpoint sources (Shabman and Stephenson 2007). The legislation placed the property rights with respect to emissions from point sources in the hands of the public: point sources of water pollution are

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[1] http://www.epa.gov/waters/ir/index.html

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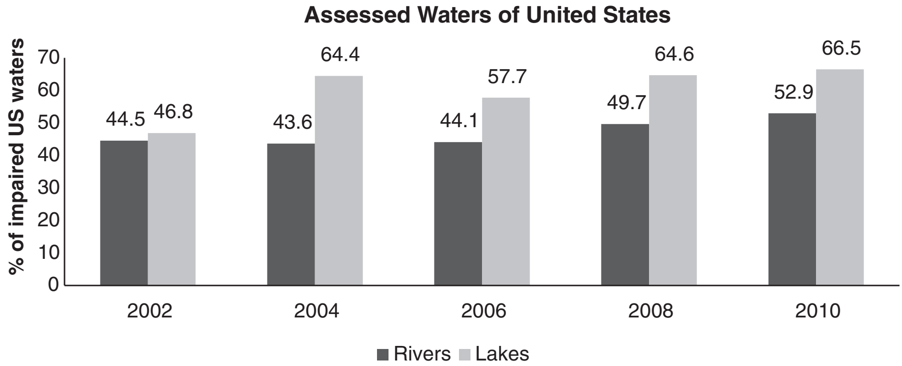

Figure 1. U.S. waters assessed as impaired, percentage

Source: EPA National Summary of Assessed Waters Report 2002, 2004, 2006, 2008, and 2010.

legally required to hold permits to cover any release into the nation's waterways, and face penalties for noncompliance. Implementing approaches to reduce emissions from nonpoint sources are largely under the purview of states via the Total Maximum Daily Load (TMDL) program. Under this program, states are tasked with identifying the sources of urban and agricultural nonpoint source emissions that lead to waterway impairments, and also with implementing approaches to reduce those impairments. In most cases, states have chosen to adopt voluntary approaches that depend on moral suasion or conservation payments to induce farmers to adopt conservation practices. This effectively assigns farmers the property rights to pollute.

However, there are cases where states have opted to reverse this property right. A notable example is in Florida, where as part of the Everglades Forever Act, passed in 1996, the South Florida Agricultural Management District has established mandatory nonpoint source control to lower the phosphorus levels in the Everglades Agricultural Area (EAA) by implementing a best management permitting program. The program includes performance metrics for each best management practice, on-site verification, and monitoring to ensure that the conservation practices are implemented consistently, and recommends adjustments if the water quality goals are not achieved. The program also has a research component that continually revises and improves the recommended best management practices.[2] Each landowner in the EAA must hold a permit that includes: (*a*) an approval for a best management practice for each crop or land use (designated in terms of "points" of conservation credit) and; (*b*) an approval for a discharge monitoring plan.[3] Over the 17-year history of the program, measureable reductions in ambient pollution from these sources have averaged over 55% (Daroub et al. 2011; Smith 2012).

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 and Dunn 1986; Shortle and Horan 2001). Two recent comprehensive surveys provide excellent reviews of the policy instruments for water quality pollution, with particular attention paid to the instruments for nonpoint source pollution (Shortle and Horan 2013) and drinking water (Olmstead 2010). Much of the NPS work has focused on the design of these programs in the context of the existing regulatory structure and the associated focus on the voluntary adoption of abatement actions from agriculture (Ribaudo et al. 2008; Braden et al. 1989; Wu and Babcock 1996; Carpentier, Bosch, and Batie 1998; Khanna et al. 2003). Russell and Clark (2006) call for the public to assert its control over NPS pollution, especially in developing countries where subsidies may be infeasible. Starting in the 1980s, and following their success in addressing air pollution, market mechanisms for water quality attracted

[2] http://www.sfwmd.gov/portal/page/portal/xweb%20protecting%20and%20restoring/best%20mangement%20practices.

[3] http://www.sfwmd.gov/portal/page/portal/xweb%20-%20release%202/everglades%20wod%20permits.

the attention of economists and policy makers, with a large body of literature emerging as a result. For example, Fisher-Vanden and Olmstead (2013) and Shortle (2013) assess the current status of the water quality programs in the United States and worldwide, respectively. These authors provide useful insights about lessons learned so far, as well about the research needs for improving the efficiency of the trading markets for water quality.

In this article we consider the design of policies to address NPS pollution after the current property rights have been (or can be) reversed. Specifically, we examine the efficient design of agricultural water pollution control when the state or local regulator has the option of imposing regulations or standards (either tradable or otherwise) on agricultural nonpoint sources. We do not suggest that such policies are likely to be adopted broadly in the near term, and recognize the important political economy issues associated with a change from historical property rights. However, the Florida case and examples elsewhere (e.g., Maryland has recently imposed stricter nutrient management plan requirements on farmers, including a ban on winter fertilizer applications and a requirement for crop setbacks near waterways) suggests that serious analysis of these options is timely, particularly given the significant water quality problems remaining in agricultural watersheds.[4,5]

In considering the design of programs to reduce agricultural nonpoint source emissions we focus on several difficult issues that have challenged regulators in policy design, regardless of the property rights assignment.[6] First, producers have a variety of conservation practices from which to choose, many of which impose both direct and implicit costs (lost yield, additional risk, etc.) that are likely to vary by farm characteristics, climate, and other idiosyncratic farm features. Thus, individual producers are quite likely to have better information about their true cost of adopting conservation practices than regulators. From the regulators' perspective, this means that it will generally be difficult to identify *ex ante* the least-cost allocation of emission reductions efficiently across sources: it follows that market-based instruments have the potential to improve efficiency (Shortle 1990; Malik, Letson, and Crutchfield 1993).

A second difficulty relates to observing and monitoring the pollution impacts of farming activities on water quality. Although it may be technically possible in some cases to measure nutrients that leave a field (e.g., by monitoring tile drains for nitrogen concentrations), the cost is likely to be prohibitive and monitoring is often not viable. Thus, focusing on observable abatement actions and/or observable inputs has been suggested (Griffin and Bromley 1982; Shortle and Dunn 1986). As previous researchers have noted, this approach can come at a high efficiency cost if practice or input-based approaches do not allow targeting conservation actions to fields where they are most cost-effective.

Third, issues of characterizing pollution do not stop at the field scale. 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 many theoretical papers often postulate that the fate and transport process is linear and separable between emissions from various fields, water quality researchers note that this process is actually likely to be highly nonlinear and nonseparable, which introduces the problem of endogeneity in the impact of an individual farmer's actions (Braden et al. 1989; Lintner and Weersink 1999; Khanna et al. 2003). Taken together, these issues preclude any simple policy from achieving first-best outcomes, even when the inherent stochasticity of nonpoint source pollution processes is ignored or coped with by assuming known distributions of stochastic components and focusing on specified moments (e.g., mean) of the pollution or economic damage outcomes.

We refer to the watershed-level pollution process as a "water quality production function," also sometimes referred to as a "fate and transport" function (Shortle and Horan 2013). For our simple conceptual exposition, we will assume that this function is differentiable, although the state of practice in environmental sciences is to employ biophysical simulation models to capture the

[4] Internationally, the Lake Taupo trading program in New Zealand serves as an example of a trading program imposed solely on NPS polluters (Shortle and Horan 2013).

[5] http://mda.maryland.gov/resource_conservation/counties/Read%20the%20Revised%20Regs.pdf

[6] The approaches considered in this article can be modified to apply to cases where farmers have property rights as well. We focus on the hypothetical reversal of property rights for reasons of brevity, but also because without such reversals, limited public funds are unlikely to be sufficient to reduce NPS problems to levels consistent with the Clean Water Act objectives.

key nonlinearities and interactions between individual emissions as they contribute to watershed-level indicators of water quality.[7] Our results apply regardless of whether the function can be written down in a compact mathematical form or is represented by a computer model.

With these three challenges in mind, we propose and evaluate a range of simple and practical policy approaches for regulating emissions from nonpoint agricultural sources that are focused on abatement actions at the farm scale, and which utilize the full state-of-the-art environmental process models. We start by characterizing the first-best (cost-efficient) solution and argue that first-best is not possible due to the combination of the nonlinear, nonseparable feature of realistic water quality production functions and the regulators' incomplete cost information. Next, we turn to second-best incentive-based approaches that address both issues. Three types of second-best policies are addressed. First, a command and control (CAC) policy is evaluated where regulators use their imperfect cost estimates for each abatement action implemented in different locations in conjunction with the realistic water quality production function to assign practices. In this case, the most accurate water quality production function will be used, but, under imperfect cost information, inefficient allocations of abatement actions to specific field locations are likely. Second, a trading program is evaluated where the regulator develops a linear and separable approximation to the complex water quality production function, which is then used to define trading ratios in a water quality trading program. Since trading is allowed, this approach overcomes the issue of information asymmetry in costs of abatement actions, but since trades will be based on the linear approximation to the underlying production function, the ambient water quality target may not be met. The third approach is a performance standard (PS) at the field scale and is a mixture of the other two approaches. As in the CAC case, the regulator identifies the least cost solution using her (imperfect) cost of abatement and the complex water quality production function, and sets a field-level standard at each location based on the chosen abatement action. However, in this case the farmer can choose a different abatement action as long it achieves the same edge-of-field emission reduction. In this way the farmer can take advantage of cost differences that are known to be true, but that the regulator is not aware of.

After fleshing out the properties of these three policies, we evaluate them in a real watershed context, where we anticipate the potential tradeoff between cost-efficiency and effectiveness of a program (where the specified water quality target may not be met due to the simplification of the complex water quality production function).[8] Using simulation-optimization tools, which use the unmodified water quality production function, we approximate the first-best solutions, then provide an empirical assessment of (*a*) inefficiencies in terms of pollution target attainment due to approximations needed to implement PS and trading, and (*b*) the inefficiencies in terms of minimization of cost in the presence of cost heterogeneity and cost information asymmetry. We then present an empirical correction that adjusts for inefficiency in the pollution process approximation used for a trading approach, which appears to be robust to the quality of regulators' cost information.

Conceptual Model

We now consider a simple model of pollution where water quality in a watershed is impaired by runoff from agricultural fields (e.g., nitrogen or phosphorus). There are N farms in the watershed, and they 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 watershed. Let r_i be the ith farm's actual reduction in pollution (which could potentially be measured) at the edge of the field (i.e., farm-level pollution abatement): $r_i = r_i(\mathbf{x_i}, \gamma_i, \xi) \quad \forall i = 1, \ldots, N$, where $\mathbf{x_i}$ represents the $J \times 1$ vector of abatement actions implemented by farm i,

[7] As Xepapadeas (2011) points out, "Another way [to regulate NPS pollution] is to acquire information about individual emissions and in this way to transform the NPS pollution problem into a PS problem so that conventional environmental policy instruments can be applied." We follow this logic, and extend it to the context of not only acquiring information about individual emissions based on observable conservation actions but also to the context of acquiring better information on the impact of individual emissions on ambient pollution outcomes.

[8] 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 approach could be applied to any other summary statistic of the distribution.

γ_i represents the farm's physical characteristics, and ξ represents the random factor related to the weather and/or other stochastic influences.[9] Abatement costs are defined as the difference between baseline profits and the profits associated with adopting a conservation practice on a given field. 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 price takers in both output and input markets. The baseline edge-of-field emissions are the result of profit maximization behavior absent any regulations regarding pollution or conservation practices.

The resulting ambient water quality is given by an expected water quality production function, $W(\mathbf{r}(\mathbf{x}))$, which is a function of the vector of each farm's individual edge-of-field emission reductions, and the expectation is taken with respect to the (assumed known) distribution of ξ, that is, $W(\mathbf{r}) = E_\xi W(\mathbf{r}(\xi), \xi)$. The ambient pollution level will depend on the edge-of-field emissions, as well as the location of those fields within the watershed. The water quality production function reflects the complexity of the hydrological and biochemical 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 exactly known, though the modeling science is rapidly improving and there are a number of watershed-based water quality models that accurately approximate these hydrological and biophysical processes, for example the Soil and Water Assessment Tool (SWAT), and the Water Erosion Prediction Project (WEPP) (Daniel et al. 2011).

The ambient water quality at the watershed outlet can be rewritten as $W(\mathbf{r}) = W^0 - A(\mathbf{r})$, where W^0 is the expected level of water quality in the absence of regulation, and $A(\mathbf{r})$ is the expected ambient pollution reduction associated with $\mathbf{r}$ vector of emission reductions—or more simply the abatement function. Expected ambient water quality associated with any given set of abatement actions emission reductions can be expressed as the difference between the expected no-control (baseline) ambient water quality level and the expected in-stream abatement.

In the following subsections, we identify the first-best (least-cost) solution to the problem of meeting an ambient water quality target, and contrast it to the solutions that are feasible under asymmetric information on costs. We also consider when the relationship between in-field conservation actions and edge-of-field abatement is imperfectly measured and the regulator instead relies on edge-of-field models of pollution abatement.[10] Next we consider three policies, command-and-control (CAC), an on-farm performance standard (PS), and a watershed-level trading program, each of which imply different levels of farmer flexibility and levels of information and optimization burdens for the regulator. We consider the need for simple approximations to the pollution process for incentive policy implementation and subsequently evaluate the quality of needed approximations empirically. We suggest the use of a points-based system as a simple approach for implementing both a performance standard or trading program, and provide the empirical assessment of the approach under simulated cost information asymmetry.

First-best Scenario

Suppose we seek to achieve a particular level of expected total ambient emissions reduction, $\bar{A}$, and the regulator knows the form of edge-of-field abatement function $r_i(\boldsymbol{x}_i)$ and the ambient abatement function $\mathrm{A}(r(\mathbf{x}))$ (and, as we assume throughout, can form an unbiased expectation with respect to ξ).[11,12] The cost minimization problem for

[9] We use the term "abatement action" broadly to refer to a single conservation practice or to a combination of practices that are simultaneously beneficial. We also include retiring land from production in this set.

[10] Examples exist where regulation is based on theoretical models. According to Millock et al. (2002), the French Agence de l'Eau imposes effluent charges based on model estimates. However, firms can lower their effluent bill if they can install monitoring equipment and show that their emissions are lower than model estimates. In our case, if farmers wanted to do that they could do so, and their monitored emissions would be multiplied by the estimated delivery coefficient to convert emissions reductions to points.

[11] The distribution of ξ is assumed known for simplicity, and in practice could perhaps be taken to be the historical distribution of stochastic weather. However, ongoing climate change introduces an additional uncertainty over the form of the distribution itself. Practical solutions may include using climate-model derived distributions, with the possibility of using model ensembles to address model uncertainty. Interestingly, the same considerations apply to $\mathrm{A}(\mathbf{r})$ function itself, meaning that the issue of model uncertainty and performance looms in the background, and water quality estimates could also be formed using model ensembles. We do not take up these potentially important practical considerations in this work. The issues of cost information asymmetry or the fact that practical incentive-based policies would likely require a simplification of modeled outcomes to be promulgated to the farmers still seem to apply.

[12] The assumption that we know the form of $r_i(x_i)$ is not identical to the assumption that the regulator is able to monitor

a regulator seeking to minimize the overall abatement costs and meet the ambient emission reduction can be written as:[13]

$$(1) \qquad \min_{x_i} \Sigma_i C_i(\mathbf{x}_i) \text{ s.t. } \mathrm{A}(r(\mathbf{x})) \geq \bar{A}.$$

Assume for the sake of demonstration that $\mathrm{A}(r(\mathbf{x}))$ is twice differentiable (although in the empirical work $\mathrm{A}(r(\mathbf{x}))$ will be represented by a process model), and that it is nonlinear and nonseparable:

$$(2) \qquad \frac{\partial A(r(\mathbf{x}))}{\partial x_{ij}} = \frac{\partial \mathrm{A}(r_{-i}(\mathbf{x}); r_i(\mathbf{x}))}{\partial r_i} \frac{\partial r_i(\mathbf{x}_i)}{\partial x_{ij}}$$

where the $r_{-i}(\mathbf{x})$ notation refers to the potential importance of abatement actions on farms other than i, as argued for in Braden et al. (1989), Lintner and Weersink (1999), Randhir et al. (2000), and Khanna et al. (2003). Nonseparability refers to the dependence of the marginal impact of conservation action on other conservation actions (e.g., on other farms in the flowpath of nutrients). Randhir et al. (2000) provide a visual illustration of nonseparability of actions in a watershed, while nonlinearity refers to the marginal impact being nonconstant in x_{ij} (Shortle and Horan 2013).[14] The solution vector $\mathbf{x}^*$ specifies the least-cost abatement action for each field. Clearly, under nonseparability and nonlinearity, each element of the optimal solution vector depends on optimal abatement actions on other farms via the optimality conditions for solving equation (1):

$$(3) \qquad \frac{\partial C_i\left(\mathbf{x}_i^*\right)}{\partial x_{ij}} - \lambda^* \frac{\partial \mathrm{A}\left(r_{-i}\left(\mathbf{x}^*\right); r_i\left(\mathbf{x}^*\right)\right)}{\partial r_i} \frac{\partial r_i\left(\mathbf{x}_i^*\right)}{\partial x_{ij}} \geq 0$$

and the associated complementary slackness conditions.[15]

If the regulator has perfect information on costs of abatement actions, the technical ability to solve equation (1), and the property rights assignment allowed for direct regulation, then a CAC policy directing farmers to implement $\mathbf{x}^*$ would achieve the first-best solution. Obviously, we do not expect this to be the case. Alternatively, if the regulator does not know the abatement costs at individual farms, but the ambient water quality function is linear and separable, then incentive-based polices can overcome this information asymmetry, effectively putting the optimization burden on private actors to achieve a first-best solution. To be precise, when the expected pollution abatement is linear and separable both at the edge of field and at the watershed outlet, $A(r(\mathbf{x})) = \sum_i^N d_i r_i(\boldsymbol{x}_\mathbf{i}) = \sum_i^N \sum_{j=1}^J d_i w_{ij} x_{ij}$, a trading program in expected edge-of-field emissions reductions $r_i(\boldsymbol{x}_\mathbf{i}) = \sum_{j=1}^J w_{ij} x_{ij}$ using the ratios of "delivery coefficients" d_i as the trading ratio will achieve a first-best solution, as demonstrated in Montgomery (1972). This is familiar theoretical territory, and was recently reviewed, for example, by Olmstead (2010).[16]

However, if the water quality production function is not linear and separable and the costs of abatement actions at the individual field scale are not known to the regulator, it will not be possible to achieve a first-best solution using standard policy tools. We thus turn to second-best options.

Second-best Approaches

In considering the second best approaches, we assume that while the regulator does not know the true costs of abatement actions at the field scale, he does have an accurate mean estimate of the cost of adopting each abatement action averaged across farm types and locations within the watershed. Data of this sort is available and routinely used in a variety of conservation program cost share

edge-of-field emissions. We assume that only ambient (watershed outlet) water quality is monitored. Should monitoring at the edge-of-field become more common, better farm-level approximations could be provided to farmers, who need to quickly compute the impact of their (counterfactual) actions, and farmers are unlikely to be equipped to run edge-of-field simulation models.

[13] Shortle and Horan (2013) identify the conditions under which the cost-efficient solution would be second-best on the grounds of full economic efficiency, when damages are monetized. While their argument is likely to apply, we point out that even this (potentially second-best) target may be difficult to achieve.

[14] As a simple example, $f(x, y) = xy$ is nonseparable in the sense that $f_x = y$, but linear in x because $f_{xx} = 0$.

[15] For ease of exposition, we omit the farm-level constraints for each abatement action ($0 \leq x_{ij} \leq FarmSize$), but those constraints are imposed in the empirical part of the article.

[16] In practice, of course, the presence of multiple trading ratios may hinder the program performance by introducing additional complexity in farmers' decision-making. We acknowledge that these issues are likely to apply, but we wish to focus on the scenario where private trading outcomes match the theoretically predicted ones.

programs, so it seems a reasonable assumption. Further, we assume that the regulator has access to a relatively accurate watershed model that represents the complex fate and transport properties of the watershed for the pollutants of interest.[17] An important second-best question arises: What are the consequences of using a linear approximation to nonlinear and nonseparable $A(r(\mathbf{x}))$ when watershed trading or edge-of-field trading (performance standard) is allowed? The consequence can only be in terms of abatement *ex post* because once a Montgomery-type trading linear trading system is implemented, whatever abatement level is achieved is theoretically expected to be cost-efficient. The performance of the second-best trading approach will then depend on the quality of linear approximation.[18]

CAC Approach

A CAC approach involves direct prescription of the vector of abatement actions across farms. If the regulator has no information on the cost of abatement actions, the best he can do is to employ a *satisficing* approach: that is, to prescribe $\{\mathbf{x}_{CAC}^{Sat} \mid A(r(\mathbf{x}_{CAC}^{Sat})) = \bar{A}\}$. Here, the vector of abatement actions chosen might simply be to require that all fields in all locations adopt the same conservation practice (or bundle) that achieves the ambient target. This corresponds to a very simplistic form of CAC and is unlikely to be even approximately cost-effective.

However, the environmental agency is likely to have some limited information on the distribution of costs. Assume, for example, that the agency knows the vector of average costs, $\bar{\boldsymbol{\theta}}$, but not the cost at each individual location. A second CAC approach, which we call optimizing CAC, involves the use of this information to solve:

$$(4) \qquad \min_{x_i} \Sigma_i C_i(\boldsymbol{x}_\mathbf{i}, \bar{\boldsymbol{\theta}}) \text{ s.t. } \mathrm{A}(r(\mathbf{x})) \geq \bar{A}$$

where $\bar{\boldsymbol{\theta}}$ represents a vector of the regulator's best estimates of costs. The solution to this problem will generally differ from that obtained in solving equation (1), and the assignment of abatement practices, $\mathbf{x}_{CAC}^{Opt}(\bar{\boldsymbol{\theta}})$, will not necessarily coincide with the least-cost solution, $\mathbf{x}^*(\boldsymbol{\theta})$, where we make explicit its dependence on the $NJ \times 1$ vector of true costs, $\boldsymbol{\theta}$. In general, we expect this approach to perform better as the quality of the regulator's cost information improves.

Performance Standard

Using PS, the regulator allows the farmer to choose the lowest-cost combination of abatement to satisfy the imposed performance standard. The on-farm performance standard is chosen by the regulator under the best possible accounting for complexity in the form of $A(\mathbf{r})$, and the set of performance requirements $\hat{\mathbf{r}}$ could satisfy $A(\hat{\mathbf{r}}) = \bar{A}$ exactly. Again, the performance standard vector could be selected without any cost information under a satisficing approach: $A(\hat{\mathbf{r}}_{PS}^{Sat}) = \bar{A}$, or the regulator could rely on her best set of cost estimates $\bar{\boldsymbol{\theta}}$ to obtain an optimizing set of performance requirements $\{\hat{\mathbf{r}}_{PS}^{Opt}(\bar{\boldsymbol{\theta}}) \mid A(\hat{\mathbf{r}}_{PS}^{Opt}(\bar{\boldsymbol{\theta}})) = \bar{A}\}$. Since farmers know their true costs, they may be able to meet the performance standard allocated to them less expensively. If faced with a performance standard (either of satisficing or optimizing form), farmers could solve the following optimization problem:

$$(5) \qquad \min_{x_i} C_i(\boldsymbol{x_i}, \boldsymbol{\theta}_i) \text{ s.t. } r_i(\boldsymbol{x_i}) \geq \hat{r}_i(\bar{\boldsymbol{\theta}})$$

where they use their true vector of conservation practice costs, $\boldsymbol{\theta_i}$, to solve the problem. Note that if the PS policy took this form, the farmers could either be using the true monitored edge-of-field reductions or the "true" (best available) $r_i(\boldsymbol{x_i})$ function (model) used by the regulator. In these circumstances,

[17] The water quality production function will in reality have approximation errors relating to calibration, parameter uncertainty, etc. While important, these errors are beyond the scope of our work. Issues of nonseparability and nonlinearity also arise in, for example, conservation biology (where spatial configuration of protected areas determines the conservation benefit). Framing the problem in terms of a spatial externality (which may be a productive way to think about the nonseparability issue), authors like Parkhurst and Shogren (2007) have proposed incentive-based policies that attempt to approximate the desirable spatial outcome (contiguous protection). The standing challenge in that area as well is to provide workable incentive-based policies that could produce desirable environmental outcomes under asymmetric information and nonseparability of individual conservation actions.

[18] An underlying question for second-best policy is thus: What is more important to account for: accurately modeling the complex consequences of abatement actions or cost heterogeneity? In an application to groundwater extraction, Kuwayama and Brozovic (2013) find (under a linearly additive abatement function) that ignoring abatement action complexity may generate most of the cost savings for low abatement targets, but that accounting for spatial heterogeneity in the effect of abatement actions becomes more important as abatement goals are increased.

the water quality goal would be met exactly. However, as monitoring is costly and all farmers likely lack the capacity to run the edge-of-field models embodied by $r_i(\mathbf{x_i})$, a simplification of $r_i(\boldsymbol{x_i})$ could greatly reduce the burden placed on farmers. Specifically, we can approximate $r_i(\boldsymbol{x_i}) \cong \sum_{j=1}^{J} w_{ij}x_{ij}$. In this case, farmers solving equation (5) would result in a solution vector, $\mathbf{x}_{PS}^{k}(\mathbf{w})$, which could fail to meet the water quality goal due to the approximation error associated with using linear weights, $\mathbf{w}$.[19] The sign of edge-of-field approximation error depends on whether $r_i(\boldsymbol{x_i})$ is convex (underestimates abatement effectiveness) or concave (overestimates abatement effectiveness) in $\boldsymbol{x_i}$.[20]

In terms of cost-efficiency, to the extent that a regulator's cost information is able to capture cost heterogeneity across abatement actions and locations, we expect that an optimizing PS policy, resulting in $\mathbf{x}_{PS}^{Opt}(\mathbf{w})$, will be more cost-efficient than a satisficing PS policy, resulting in $\mathbf{x}_{PS}^{Sat}(\mathbf{w})$. However, to the extent that the satisficing approach might result in the selection of higher-cost abatement actions, and if cost and effectiveness of abatement actions are positively correlated, we may expect that, for an *ex ante* situation given $\bar{A}$, $\mathrm{A}(\mathbf{x}_{PS}^{Sat}(\mathbf{w})) \geq \mathrm{A}(\mathbf{x}_{PS}^{Opt}(\mathbf{w}))$.

Trading under Nonseparability and Nonlinearity of Individual Abatement Actions

The alternative that in principle can lead to cost-efficiency without a need for any cost information by the regulator is trading in water quality improvement credits, which relies on private optimizing behavior to minimize the cost. At the crux of the market design 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, Montgomery (1972) demonstrated that 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.[21]

However, under a nonlinear and nonseparable water quality production function, the ability to set the right trading ratio and the effective trading system cap (constraint) is not assured. To demonstrate, the second-order Taylor series expansion around some initial vector of on-farm pollution reductions (e.g., baseline) can be written as:

$$\begin{aligned} A(\mathbf{r}) &\cong A(\mathbf{r^0}) + \nabla_A(\mathbf{r^0})\mathbf{r} + \mathbf{r}'\nabla_A^2(\mathbf{r^0})\mathbf{r} \\ &= 0 + \mathbf{d}_A(\mathbf{r^0})\mathbf{r} + \mathbf{r}'\nabla_A^2(\mathbf{r^0})\mathbf{r}. \end{aligned} \tag{6}$$

In this case, the vector of marginal impacts of edge-of-field abatement on ambient water quality, $\mathbf{d}_A(\mathbf{r^0})$, can potentially serve as the vector of delivery coefficients and provide the basis for forming the trading ratios, but two things need to be observed. First, under nonseparability, the "delivery coefficient" vector is a function of the abatement activities of other farms (equation 2), and if a trading system is to be set up, some initial vector of abatement actions needs to be used. The approximation presented above may be quite accurate in the vicinity of the initial abatement action vector (that is, around the baseline), but may be quite poor at the post-trading vector of on-farm abatements. Second, under nonlinearity, the linear approximation will under- (over)estimate ambient abatement if the water quality production function is convex (concave) in abatement. This may lead to non-attainment (even on average) of the water quality goal, and may require the linearization based on fixed-delivery coefficients, $\mathbf{d}_A(\mathbf{r^0})\mathbf{r}$, to be empirically adjusted upward or downward for the convex and concave $A(\mathbf{r})$, respectively. This adjustment leads to a tighter cap on emissions (a larger abatement credit target) for the concave function, with a less stringent cap (a smaller abatement credit target) in the

[19] The definition of x_i can include all feasible interactions of "atomic" abatement actions feasible at the field scale. For k atomic abatement actions for example, Conservation Tillage, Grassed Waterways, Nutrient management, x_i could be defined as the feasible subset of all the abatement action combinations (power set with 2^k elements), and the resulting linearization in x_i can capture more of the potential nonlinearity and interdependence than a linearization utilizing k individual abatement actions.

[20] Consider a 2nd-order Taylor series expansion of the edge-of-field abatement function around baseline abatement: $r_i(\boldsymbol{x_i}) \cong r_i(\boldsymbol{x_i^0}) + \nabla_r\boldsymbol{x_i} + \boldsymbol{x_i}'\nabla_r^2\boldsymbol{x_i} = 0 + w_i\boldsymbol{x_i} + \boldsymbol{x_i}'\nabla_r^2\boldsymbol{x_i}$, which implies that $r_i(\boldsymbol{x_i}) < (>) w_i\boldsymbol{x_i}$ if $r_i(x_i)$ is concave (convex). We are mostly interested in the resulting ambient approximation $A(\mathbf{wx})$, which depends on the performance of all field-level approximations and their interactions, specified by $A(\cdot)$.

[21] However, in some cases optimal trading ratios (trading policy parameters) have been shown to be a function of a regulator's information on abatement costs (Rabotyagov and Feng 2010; Yates and Rigby (2012); http://www.webmeets.com/AERE/2012/prog/viewpaper.asp?pid=99).

convex case. The direction and magnitude of this adjustment is an empirical question to which we subsequently return.

The appeal of trading in terms of its ability to achieve cost-efficiency without imposing information collection and optimization burdens on the regulator leads us to consider and evaluate a Montgomery-type trading program where we sacrifice the ability of state-of-the-art $A(\cdot)$ to capture nonlinearities and nonseparabilities and rely on a potentially imperfect linear approximation. That is, we add another layer of linearization to the PS policy by imposing fixed and constant delivery coefficients for the ambient impact of edge-of-field abatement (on top of the edge-of-field linearization employed in implementing a PS policy):

$$A(r(\mathbf{x})) \cong \sum_{i}^{N} d_i r_i(\boldsymbol{x_i}) = \sum_{i}^{N} \sum_{j=1}^{J} d_i w_{ij} x_{ij}. \tag{7}$$

Policy Design Using an Approximation to the Water Quality Production Function

Suppose the regulator utilizes a single linear approximation of the effect of abatement actions on both the edge-of-field and ambient water quality:

$$A(r(\mathbf{x})) \simeq \sum_{i}^{N} \sum_{j=1}^{J} d_i w_{ij} x_{ij} = \sum_{i}^{N} \sum_{j=1}^{J} a_{ij} x_{ij} \tag{8}$$

where edge-of-field reductions are given by $r_i(\boldsymbol{x_i}) \equiv \sum_{j=1}^{J} w_j x_{ij}$, and a farmer undertaking an abatement action earns a credit of $\sum_{j=1}^{J} a_{ij} x_{ij}$, where a_{ij} provides the weight given to a conservation practice j at farm i. We refer to a_{ij} as a "points coefficient" and refer to the credits earned by farmer and the constraints imposed under PS or the trading programs in point totals.[22] Under the adopted approximation, the points coefficient can be interpreted simply as the approximate marginal benefit, in terms of water quality abatement, of practice j at location i. In the empirical section below, we describe an approach for estimating the vector of multiple a_{ij} for our study watershed.

The CAC policy does not require the use of points, as each farmer is assumed to be directly required to undertake abatement actions. For the PS policy, the regulator needs to choose the appropriate farm-level point requirements. Under this approach, a farmer is free to choose the conservation practices that solve the cost-minimization problem:

$$\min_{x_{ij}} C_i^P(x_{ij}, \boldsymbol{\theta_i}) \text{ s.t. } \sum_{j=1}^{J} a_{ij} x_{ij} \geq b_i^o \tag{9}$$

where the performance requirement is specified by b_i^o. The performance requirements differ under satisficing and optimizing PS approaches.

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

$$\min_{x_{ij}, b_i} C_i^P(x_{ij}, \boldsymbol{\theta_i}) + p b_i \tag{10}$$

$$\text{s.t. } \sum_{j=1}^{J} a_{ij} x_{ij} + b_i \geq b_i^o$$

and the point price is determined in a points market equilibrium, where $\sum_i b_i = 0$. The overall cap is specified by $\sum_i b_i^0$. Conceptually, the proposed trading approach is a combination of an emission permit system where rights are defined in terms of what firms can emit, and an ambient permit system where rights are defined in terms of pollution contributions to a receptor point (Montgomery 1972; Baumol and Oates 1988). As in an emission permit 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 ambient permit system, the point values 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 (an effective trading ratio between action j in location i, and an action k in location l is given by $t_{ij,kl} = \frac{a_{kl}}{a_{ij}}$).[23]

[22] The "points" terminology is not crucial, but the terminology is chosen to be consistent with Kling's (2011) proposal, as well as some existing water quality crediting programs (e.g., Florida Everglades) and other environmental benefit scoring systems such as the Conservation Reserve Program's Environmental Benefits Index.

[23] As a point of conjecture, the fact that farmers would simply see how many points accrue per acre for a particular abatement action, and would participate in a market for a single commodity ("point") traded on one-to-one basis, may serve to simplify market

A substantial amount of literature exists related to 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, Shortle, and Abler 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

Boone Watershed River is located in the north-central part of Iowa, and covers more than 237,000 acres (960 km^2) in six counties. Land use in the watershed is dominated by agriculture, with nearly 90% of the area covered by row crops, and another 6% retired from crop production. The data for populating the watershed-based model (Soil and Water Assessment Tool, SWAT) was collected at the scale of a "Common Land Unit (CLU)" level, which can best be thought of as an agricultural field; there are more than 16,300 CLUs in the Boone sample. Data concerning crop rotations, tillage, and conservation practices were provided by a field level survey conducted by Kiepe (2005).[24] Weather, soils, management, and the approach for simulating the water quality impact of conservation practices are detailed in Gassman (2008).

Conservation Practices, Costs, and the Water Quality Production Function

The set of conservation practices selected includes nutrient management (reducing the rate of fertilizer application), conservation tillage (no till), cover crops, and land retirement. The above set is expanded into a set of mutually exclusive abatement actions (i.e., the combination of no till and cover crops is considered an independent abatement action). The baseline is also considered as a choice alternative, which allows us to consider the cases where keeping the baseline is optimal.

Costs for each conservation practice were drawn from several sources, and are expressed as dollars per acre. The cost of adopting no till (drawn from Kling et al. 2005) is \$9.62 per acre if the baseline has assigned conventional tillage, and \$4.81 if the baseline is assigned mulch tillage. Cover crop cost estimates averaged \$25 per acre.[25]

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 (Rabotyagov 2007). The cost of reducing fertilization is given by multiplying a 20% reduction in the baseline fertilizer rate by the price of corn, and by subtracting the cost savings from applying less fertilizer.[26]

The cash rental rates (Edwards and Smith 2009) in conjunction with the available corn suitability ratings were used to compute the cost of land retirement. The cost of abatement actions consisting of a combination of the primary conservation practices (i.e., no-till and reduced fertilizer) are obtained by summing per acre cost of each conservation practice considered in the combination. Table 1 summarizes the costs used in this application.

The Soil and Water Assessment Tool (SWAT) is a water quality, watershed-based hydrological model developed by the U.S. Department of Agriculture to simulate the impact of point and nonpoint source emissions (Arnold et al. 1998; Arnold and Fohrer 2005; and Gassman 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 sub-basins.

The Characterization of the First-best Solution

To evaluate the performance of our three second-best regulatory approaches, we first

participation and price discovery. Market complexity has been identified as one of the obstacles to a robust water quality trading market (e.g., Shortle 2013).

[24] Mr. Charles Kiepe, a private consultant from Hamilton, Iowa, conducted the watershed survey and recorded the land use, crop rotation, tillage practice, and other conservation actions at the field level. Details are provided in Gassman (2008).

[25] Provided by T. Kaspar personal communication.

[26] An extensive body of literature on how farmers might value fertilizer reductions under uncertainty exists (e.g., Lichtenberg 2002). The policy-relevant implication is that the cost of fertilizer reductions is private information in general. An issue of hidden action is also present in the case of fertilizer applications, and the programs we propose can easily be formulated only for directly observable abatement actions. In practical terms, however, nutrient management is very likely to be considered as a part of any NPS water quality policy.

Table 1. Mutually Exclusive Abatement Actions and Costs

	Conservation Practice	Conservation Practice Description	Assumed Cost Used in Application, Mean $/acre
1	Baseline	Baseline agricultural practices	0.0
2	No till (NT)	No till, no more than 30% of crop residue is removed.	4.9
3	Reduced Fertilizer (RF)	Reducing fertilizer application rate by 20%.	7.4
4	Cover Crops (CCr)	Establishment of cover crops between crop rotations.	24.9
5	Land retirement	Retirement of land from production.	206.5
6	NT RF	No till and 20% reduction in nitrogen application rate.	12.3
7	NT CCr	No till and establishment of cover crops.	29.8
8	RF CCr	20% reduction in nitrogen application rate, establishment of cover crops.	32.32
9	NT RF CCr	No till, 20% reduction in N application rate and cover crops.	37.22

solve for the first-best solutions: the least-cost placement of conservation practices across the watershed to achieve any given level of ambient water quality. 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; Randhir et al. 2000) and mixed integer programming (Khanna et al. 2003). Evolutionary algorithms (Arabi et al. 2006; Rabotyagov et al. 2010) have been used in the simulation-optimization approach.

Hydrologic models such as SWAT, calibrated with watershed-specific data, can be used to determine the expected level of ambient water quality that can be achieved by a given placement of conservation practices in a watershed. However, solving for the least-cost approach to achieving a given water quality level is nontrivial; a watershed is divided into hundreds of fields, and each field may have multiple agricultural practices that are suitable for its type of soils. In our example, for a set of 9 abatement actions and 2,968 fields, there are a total of $9^{2,968}$ possible watershed scenarios. Even with fast computing, evaluating all possible combinations and selecting the lowest cost is not possible. However, using an evolutionary algorithm provides one way to deal with the combinatorial nature of the watershed simulation-optimization model to solve for least-cost solutions. 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." These computer-intensive methods address the combinatorial nature of the problem by intelligently covering the search space.

We use a simulation optimization system using SWAT and a modification of the Strength Pareto Evolutionary Algorithm 2 presented by Zitzler, Laumanns, and Thiele (2002), and described in Rabotyagov et al. (2010) to approximate the solution to a two-objective minimization problem that simultaneously minimizes the 5-year mean annual nitrogen loadings and the costs of abatement practices for the examined watershed.[27] The solution to this multiple objective problem is a set of Pareto-nondominated points in the objective space, where each point on the frontier, called an individual, is a specific watershed configuration that achieves a particular level of nitrogen loadings in the

[27] The simulation period used in optimization is 1997–2001. We later present the results on the potential variability of solutions across a longer time frame (1990–2009).

least-cost way. The generated Pareto frontier can be interpreted as the set of approximate first-best solutions—the least cost watershed configurations to achieve any given ambient water quality.[28]

Obtaining the Point Coefficients

To implement the proposed PS or trading program, a linear approximation to the water quality production function and the edge-of-field abatement effectiveness is needed. The nonlinear water quality production function is thus:

$$(11) \quad A(\mathbf{x}) \simeq \sum_{i}^{N} \sum_{j=1}^{J} d_i w_{ij} x_{ij} = \sum_{i}^{N} \sum_{j=1}^{J} a_{ij} x_{ij} = \mathbf{x}\boldsymbol{a}$$

where $\mathbf{x}$ is the vector of specific abatement actions, and $\boldsymbol{a}$ is the vector of point coefficients. We construct point coefficients at the level of a sub-basin (but we note that different point values for conservation practices for every farm could be computed following the same steps). There are 30 sub-basins in the watershed, $(N = 30)$, and 9 abatement actions are considered ($J = 9$, table 1). Thus, we need to estimate 270×1 the vector of $\boldsymbol{a}$. To do so, 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, denoted by A_s, are combined with the $3{,}000 \times 270$ matrix of abatement action assignments, denoted by $\mathbf{x}_s$, to generate a data set that is in turn used to estimate the points coefficient vector a by ordinary least squares: $\min_a (A_s - \mathbf{x}_s\boldsymbol{a})'(A_s - \mathbf{x}_s\boldsymbol{a})$. Table 3 presents estimation results.[29]

In general, the results are quite sensible and conform closely to prior expectations. Practices that are known to be highly effective at reducing nitrogen loss are awarded higher points than less effective practices.[30] A somewhat unexpected result is that nitrogen fertilizer reductions alone are not always significant, but they are significant when combined with no-till (and no-till with cover crops), and are significant in all but one (sub-basin 27) when combined with cover crops. Consistent with the presence of nonlinearities, the points associated with adopting several conservation practices are not simply the sum of the points for each practice separately. In 22 out of 30 sub-basins, a farmer receives less than an additive credit for adopting no-till and cover crops jointly, while in the remaining sub-basins, a farmer is awarded additional points for joint adoption. 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 sub-basins with sub-additive point credits. In terms of practical implementation, farmers in different sub-basins need only to be provided with one row of table 2, which specifies the credits earned from adopting a practice. Thus, the cognitive burden on the participants is likely to be low.

Once the regulatory agency has assigned point values to a particular abatement action in a specific sub-basin, the total points associated with any watershed configuration can be computed. For both the performance standard and the tradable credit programs, the total points value chosen by the regulator will have a direct impact on the watershed abatement levels achieved.

Having obtained a set of points, 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 is given by the approximate Pareto frontier in nitrogen abatement-cost space (watershed-level total cost of abatement curve), obtained using the simulation-optimization approach described above (figure 2).

[28] Supplementary appendix material describes the optimization parameters. Deb (2001) provides a general background on evolutionary algorithms, and Rabotyagov et al. (2010) and Nicklow et al. (2010) discuss some recent applications for watershed optimization.

[29] Feng, Jha, and Gassman (2009) use SWAT to estimate delivery ratios by changing N application rates in each sub-basin of a watershed, holding rates constant in other sub-basins, obtaining the implied "delivery ratio," and solving for the least-cost allocation of N abatement across sub-basins. As discussed above, such an 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.

[30] Table S.3 in the supplementary appendix summarizes the effectiveness of each abatement action for N reduction under a uniform application (i.e., the same abatement action is assigned to each field in the watershed). The point value estimates are qualitatively similar.

Table 2. Estimated Point Values Coefficients by Sub-basin (expressed as approximate expected annual kg N reduction from 1 acre of abatement action treatment)

	Abatement Actions (practice combinations)							
	No Till	Cover Crops	No Till, Cover Crops	Red. Fertilizer	Red. Fert., No Till	Red. Fert., Cover Crops	Red. Fert., No Till, Cover Crops	Land Retirement
Subbasin1	3.4*	1.9*	5.4*	0.2	4.5*	2.7*	6.2*	10.3*
Subbasin2	4.0*	2.4*	5.3*	0.7	4.5*	2.5*	5.9*	9.6*
Subbasin3	3.5*	1.9*	4.6*	0.3	3.9*	2.6*	4.8*	7.5*
Subbasin4	2.5**	2.8**	4.5*	0.3	3.8*	2.1**	4.2*	5.8*
Subbasin5	2.0*	2.0*	4.0*	0.6**	2.6*	2.5*	4.7*	6.4*
Subbasin6	2.2*	2.2*	4.4*	0.7**	2.4*	2.9*	5.0*	7.0*
Subbasin7	6.3*	3.3**	6.5*	1.3	6.6*	3.3**	7.8*	10.1*
Subbasin8	2.8*	3.1*	5.2*	0.8	3.9*	3.2*	5.2*	7.5*
Subbasin9	0.9**	1.0*	2.0*	0.3	1.1*	1.8*	2.3*	4.3*
Subbasin10	1.7*	2.3*	3*	0.5	2.2*	2.7*	4.5*	5.9*
Subbasin11	2.1*	1.8*	3.4*	0.1	3.2*	2.8*	5.3*	7.3*
Subbasin12	2.9*	2.3*	4*	0.0	3.2*	3.0*	5.1*	7.0*
Subbasin13	2.2*	2.5*	3.5*	0.3	2.3*	2.5*	3.4*	5.8*
Subbasin14	2.0*	2.0*	3.2*	1.0**	2.5*	3.2*	4.0*	5.7*
Subbasin15	2.4*	1.7*	4.0*	0.1	2.7*	1.7*	3.8*	5.1*
Subbasin16	1.1**	1.1*	2.5*	0.2	1.6*	1.5*	2.8*	3.9*
Subbasin17	1.8*	1.9*	3.2*	1.0**	2.1*	2.5*	3.6*	4.4*
Subbasin18	2.9*	3.1*	4.1*	1.5**	3.4*	3.4*	4.8*	7.1*
Subbasin19	3.4*	2.0**	4.8*	0.0	3.0*	2.8*	4.8*	7.5*
Subbasin20	1.9*	2.6*	4.3*	0.9**	2.7*	2.5*	4.5*	6.6*
Subbasin21	4.1*	2.8*	6.7*	0.9**	4.9*	3.6*	7.0*	12.2*
Subbasin22	2.3*	3.1*	4.4*	0.6	3.7*	3.5*	5.4*	8.5*
Subbasin23	2.6*	3.1*	4.4*	0.4	3.6*	3.5*	5.8*	7.9*
Subbasin24	2.2*	2.1*	4.4*	0.8***	3.5*	3.1*	4.7*	7.8*
Subbasin25	1.5**	1.7**	4.5*	0.2	2.5*	1.9**	4.2*	6.7*
Subbasin26	3.3*	3.7*	8.1*	0.7	5.6*	4.8*	7.3*	12.7*
Subbasin27	5.5**	5.1**	9.2*	1.5	3.9***	3.2	9.1*	12.2*
Subbasin28	2.0*	2.1*	4.4*	0.0	2.6*	1.9*	3.9*	5.5*
Subbasin29	3.5*	2.7*	4.5*	0.5	3.7*	4.1*	5.2*	9.3*
Subbasin30	3.8*	2.2*	5.4*	1.2**	3.6*	3.4*	5.5*	8.3*

Note: Asterisk (*), double asterisk (**), and triple asterisk (***) denote significance at the 1%, 5%, and 10% levels, respectively. $R^2 = 0.993$.

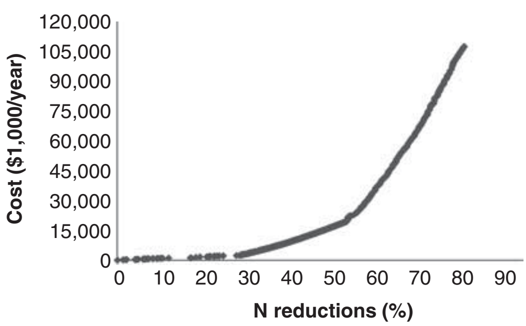

Figure 2. Total abatement cost curve (tradeoff frontier)

Setting the Points Targets under the Three Approaches

The final step in implementing one of the three policies described is to set the relevant on-farm target. In the case of CAC, this is the required conservation practice for each field; for the PS, the target is the number of points each farm is required to accrue and the watershed-level points total is the target for the trading policy. As discussed above, the regulator has an option to use either a satisficing or optimizing approach. Implementing CAC involves requiring $\mathbf{x}_{CAC}^{sat}$ for the satisficing case and $\mathbf{x}_{CAC}^{opt}(\bar{\boldsymbol{\theta}})$ for the optimizing case.

It is also straightforward to compute the number of points (a linear approximation to watershed-level abatement) that these two solutions represent. The points associated with an individual performance standard can be constructed as $b_i^{os} = \sum_{j=1}^{J} a_{ij} x_{ij}^{sat}$ for the satisficing case, and as $b_i^{oo} = \sum_{j=1}^{J} a_{ij} x_{ij}^{opt}$ for the optimizing case, where the x_{ij} terms represent the corresponding element of $\mathbf{x}^{sat}_{CAC}$ or $\mathbf{x}^{opt}_{CAC}(\bar{\boldsymbol{\theta}})$, respectively, for each farm. Similarly, the total points for the watershed for the satisficing and optimizing target can be written, respectively, as $P^{sat} = \sum_i b_i^{os} = \sum_i \sum_j a_{ij} x_{ij}^{sat}$, and $P^{opt} = \sum_i b_i^{oo} = \sum_i \sum_j a_{ij} x_{ij}^{opt}$. Total points can be translated into an initial farm-level allocation of points requirements in any number of ways. One approach is for the initial allocation of points to equal the requirements imposed under the on-farm performance standard. Another approach is to equally divide the total watershed points equally amongst all farms. Obviously, numerous other initial allocations are possible.

Policy Simulations

The performance of the three policies and the two approaches to define points targets (satisficing vs. optimizing) results in six different policies to simulate. Results are summarized in table 3 for three levels of desired water quality improvements: 20%, 30%, and 40% reductions in mean annual loadings of nitrogen (N). In this first set of simulations, we assume that the costs of conservation practices are known to both the farmer and the regulator. Under the CAC approaches, abatement actions are mandated, so non-attainment of the expected 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.[31] Since the points are approximations to the effectiveness and fate-and-transport of nutrients, the reallocation of points resulting from optimization (on the level of the farm for PS, and on the watershed level for trading) can potentially result in nonattainment of the abatement goal. In other words, for this case, when costs are assumed to be known, the PS and the simulated trading outcomes serve as (hopefully good) approximations for the first-best solution (represented by CAC-optimizing in this case) in terms of water quality goal attainment. The reported N reductions in table 3 indicate that the point allocation in the PS-satisficing and PS-optimizing cases lead to a slight over-achievement of abatement goals for the ranges specified.[32]

In contrast, a clear pattern of non-attainment is found under the trading approaches, regardless of whether total watershed point targets are specified using the satisficing or the optimizing approaches. Although we do not use a differentiable abatement function, this is consistent with concavity of $A(\cdot)$ in edge-of-field abatement (equation 6). However, the magnitude of non-attainment is fairly small (never exceeding 4 percentage points of abatement). In this case, the total point requirement at the watershed level may require an upward correction.

We now turn to the cost-effectiveness of the approaches. We expect that the least-flexible CAC approach will perform least favorably on this criterion. We also expect the more flexible approaches to become 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, with costs of meeting the three target N reductions ranging from 3 to 6 times higher than the first-best solutions. The cost effectiveness of the performance standards is better than CAC, with the PS optimizing approach doing much better than PS satisficing. The trading outcomes are quite cost-effective. Although a direct comparison between their outcomes and the first best is inappropriate since they do not achieve the same level of N reduction, they are largely non-dominated by solutions in the Pareto-frontier.[33,34] The fact that PS-optimizing and trading outcomes are

[31] Note that the outcomes are not identical because the abatement action allocations used to construct the trading programs under the satisficing and the optimizing approaches involve somewhat different total point values (table 4). Under the same total point values, the simulated outcomes are identical.

[32] Recall that PS approaches involve linearizing the edge-of-field abatement function, and that a linearization would underestimate true abatement in the case of the edge-of-field function being convex in abatement actions.

[33] This is non-dominated in N-cost space (meaning we do not find a solution in the tradeoff frontier that offers the same or larger N reductions at the same or lower cost).

[34] To assess cost-effectiveness, all CAC, PS, and trading outcomes have been compared with the solutions on a Pareto-frontier; CAC satisficing solutions are highly cost ineffective, and dominated by a large number of Pareto-frontier solutions (dominated by 164 (20% N reduction target), 435 (30%), and 323 (40%)). Similar numbers are observed for the PS satisficing solutions. The PS optimizing solutions are non-dominated. Trading solutions are non-dominated under both approaches for 20% and 30 % goals, and dominated by one solution (satisficing approach) and two solutions (optimizing approach) for the 40% water quality goal. Interestingly, this is consistent with the Randhir et al. (2000) finding that simple linear approximations do a poorer job of approximating complex watershed relationships at larger levels of abatement.

Table 3. Simulated Program Performance under Varying Nitrogen Abatement Targets (abatement action costs assumed known)[†]

Target N Reduction, % From Baseline (mean Annual Loading, 1997-2001)	Approximately Optimal Solution (CAC, 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.	$, Million	N Red.	$, Million	N Red.	$, Million	N Red.	$, Million	N Red.	$, Million	N Red.	$, Million
20	20.73	1.8	20.8	7.2	22.2[a]	5.0	*20.8*	*1.7*[‡]	*17.3*	*1.2*	*17.0*	*1.2*
30	*30.12*	*3.2*	30.1	19.8	31.2[a]	17.8	*30.2*	*3.1*	*27.8*	*2.3*	*28.6*	*2.4*
40	*40.00*	*9.0*	40.0	29.6	40.8[a]	28.0	*39.7*	*8.7*	36.1[§]	6.7	36.2[§]	6.7

[†]Given that the costs are assumed to be known, the optimizing CAC case represents the first-best solution, and the comparisons are made with respect to effectiveness (achieving N abatement target) and efficiency (whether the simulated policies are a part of the efficient N abatement curve (Pareto-frontier)). Non-dominated outcomes are italicized (with specific results reported in the supplementary material online).

[‡]For the 20% abatement goal, we see that the CAC-optimizing approach is Pareto-dominated by the PS-optimizing approach. This is due to the fact that the empirical first-best is not exact, and that the solution obtained by optimization heuristics (evolutionary algorithm) is being improved upon, locally, by linear programming. This kind of result has been noted in operations research literature (Whittaker et al. 2009). This was not observed for other N reduction targets.

[§]Note that the quality of linear approximation appears to decrease at higher levels of abatement. A similar finding was reported (for a different watershed model) by Randhir et al. (2000).

[a]Note that our results support the conjecture of $A(\mathbf{x}_{PS}^{Sat}(\mathbf{w})) \geq A(\mathbf{x}_{PS}^{Opt}(\mathbf{w}))$, which would arise if higher-cost practices were generally more effective. The correlation between abatement action costs (table 1) and their effectiveness in reducing N when applied in a uniform fashion (table S3) is 0.81.

comparable to CAC-optimizing solutions (approximating the first-best) suggests that the overall mix of abatement actions and their spatial distribution is similar to the solutions discovered by the evolutionary algorithm. This is indeed the case: both the mix and the spatial distribution of abatement actions are similar (table S.4 and figure S.3 of the Supplementary Material).[35] The results presented in table 3 provide us with useful information on the performance of the points-based approximation to $A(\cdot)$ when abatement action costs are assumed to be known. That is, table 3 describes how effective (in terms of abatement) or cost-efficient (in terms of lying on the Pareto-frontier) the approximations are. Of course, under asymmetric information, the potential gains from the two more flexible approaches come from the ability of the farmer who knows his/her true costs to optimize abatement choices.

We now explore how the programs behave in the presence of significant cost heterogeneity and under simulated information asymmetry, where the regulator has some information about the costs of conservation practices (unbiased estimate of the mean), but the costs vary across the farms in the watershed. To simulate this case, we generate 1,000 random draws of $u \sim U[-0.8\ 0.8]$ and multiply the mean estimate of costs by $(1+u)$. When simulating cost heterogeneity, we assume that for a given farm the cost of each conservation practice receives the same shock, u.

Some caution is warranted when interpreting the policy simulation results. The results presented are based on the theoretical performance of both the PS and the trading program (whereby we solve the optimization problems in equations (8) and (9) subject to the appropriate point target constraints).[36] This approach may overstate the efficiency gains in reality, where transaction costs, bounded rationality, and the sequential and bilateral nature of trading or non-monetary preferences may hinder the performance of incentive-based policies (Stavins 1995; Atkinson and Tietenberg 1991; Netusil and Braden 2001; Peterson et al. 2011; Smith et al. 2012; Nguyen et al. 2013; Shortle 2013).

Table 4 and figures S.2–S.4 in the supplementary online appendix present the simulation results for the three chosen abatement goals for the cost heterogeneity findings. The CAC (both the optimizing and the satisficing approaches) do not allow any variation in abatement that would result from re-optimizing abatement practices due to variation in costs. The satisficing CAC approach will 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 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, we present 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 (200,556 for the satisficing and 38,705 for the optimizing approaches under a 20% N abatement target). The only possible attractive feature of a CAC-satisficing approach (the approach that often echoes in policy questions such as "What would it take to achieve the water quality goal?") is that abatement does not depend on the realizations of costs. However, in the case that the 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 target 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), which supports our earlier expectation that $\mathrm{A}(\mathbf{x}_{PS}^{Sat}(\mathbf{w})) \geq \mathrm{A}(\mathbf{x}_{PS}^{Opt}(\mathbf{w}))$ when higher-cost abatement actions tend to be generally more effective. In terms of costs, once again the optimizing approach dramatically outperforms the satisficing approach. Should a regulator possess good information on the costs of abatement actions, using on-farm performance standards appears to be an attractive approach.

[35] Particularly striking is the similarity between the maps of solutions (figure S.3) discovered by the evolutionary algorithm (CAC-optimizing) and the solution found via linear programming (simulating the trading outcome).

[36] We thank an anonymous reviewer for this caveat.

Table 4. Simulated Outcomes under Cost Heterogeneity and Asymmetric Information[†,††]

	Command and Control and Performance Standard Outcomes, 20% Goal					
	PS, optimizing		CAC, optimizing (20.7% N red.)	PS, satisficing		CAC, satisficing (20.7% 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	22.3	7,231,175
StdDev	38,090	0.1	38,705	184,403	0.1	200,556
	Trading Outcomes, 20% Goal					
	Optimizing Points		Satisficing Points		$P_{satisficing} * (K = 1.075)$	
	Cost, $/yr	N, % red.	Cost, $/yr	N, % red.	Cost, $/yr	N, % red.
Mean	927,373	17.7	950,499	17.9	1,113,597	19.5
StdDev	29,253	0.3	29,583	0.3	31,850	0.3
	Command and Control and Performance Standard Outcomes, 30% Goal					
	PS, optimizing		CAC, optimizing (30.1% N red.)	PS, satisficing		CAC, satisficing (30.1% N red.)
	Cost, $/yr	N, % red.	Cost, $/yr	Cost, $/yr	N, % red.	Cost, $/yr
Mean	3,081,106	30.3	3,232,261	17,814,415	30.3	19,804,107
StdDev	60,465	0.1	59,303	644,392	0.1	645,923
	Trading Outcomes, 30% Goal					
	Optimizing Points		Satisficing Points		$P_{satisficing} * (K = 1.075)$	
	Cost, $/yr	N, % red.	Cost, $/yr	N, % red.	Cost, $/yr	N, % red.
Mean	2,260,722	27.9	2,188,889	27.5	2,653,474	29.9
StdDev	48,061	0.2	46,943	0.2	56,049	0.7
	Command and Control and Performance Standard Outcomes, 40% Goal					
	PS, optimizing		CAC, optimizing (40.0% N red.)	PS, satisficing		CAC, satisficing (40.0% N red.)
	Cost, $/yr	N, % red.	Cost, $/yr	Cost, $/yr	N, % red.	Cost, $/yr
Mean	8,654,175	39.9	9,010,815	27,910,009	40.9	29,573,330
StdDev	163,169	0.1	162,446	897,480	1.3	900,772
	Trading Outcomes, 40% Goal					
	Optimizing Points		Satisficing Points		$P_{satisficing} * (K = 1.075)$	
Mean	5,382,613	37.1	5,350,838	37.1	6,907,911	39.9
StdDev	123,255	0.2	122,218	0.2	166,865	0.2

[†] PS and trading programs are simulated by solving equations (8) and (9), respectively. The resulting solutions' water quality impacts are simulated in SWAT over the fixed time interval (1997-2001). The source of N variation is solely reallocation of optimal abatement actions resulting from re-solving equations (8) and (9).

[††] 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 the 20% goal, $4.64 ($5.65) for the 30% goal, and $11.92 ($11.92) for the 40% goal (price per kg N annual reduction).

As expected, either trading approach performs equally well in terms of cost efficiency and simulated variability in program costs and abatement outcomes. 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 potential drawback to the trading approach is the possible non-attainment of the abatement goal.

Indeed, the results indicate that the mean-simulated trading outcomes underachieve the specified abatement goals by 2.5–3.4 percentage points. This is expected under a nonlinearity in the abatement function. By adjusting the required watershed points target upward by 7.5%, we find that this value results in simulated trading outcomes where the mean is approximately equal to the N reduction goal. Clearly, without some knowledge of abatement costs (so that trading outcomes can be simulated), such inflation coefficients cannot be obtained by the regulator. However, if the regulator has some cost information, trading outcomes and consequent non-attainment likelihood can be simulated. The potential need for the regulator to carry out such simulations represents one of the tradeoffs associated with using a linear approximation to the complex water quality production process in order to be able to use a simple trading program.

To evaluate the ability of a regulator who has some, albeit inaccurate, cost information to come close to selecting the right point inflation coefficient, we investigate how sensitive the empirically derived 7.5% inflation coefficient is to a range of trading outcomes. To do so, we model a regulator who has biased information regarding abatement action costs (underestimates the true abatement costs by as little as 10% and as much as 110%). When simulating trading outcomes using this biased cost information, we find that the unmodified total point value yields, on average, 36.9% nitrogen abatement for the 40% abatement target, which is similar to the 37% 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 39.5%. 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. This suggests that a sophisticated regulator could simulate trading outcomes using potentially biased cost information prior to trading program implementation, use the results to assess the impact of nonseparability and nonlinearity, and construct similar approximation corrections.

Ex Post Assessment of Policies with Respect to Abatement Risk

The actual abatement realization will be subject to the stochastic influences of weather, climate, and other factors, and those influences may result in the proposed policies being quite different in terms of risk.[37] We formulated the objective (equation 1) in terms of minimizing expected pollution, and the regulator's problem does not involve preferences over risk.[38] However, we are able to provide some empirical assessment, *ex post*, of variability in attaining 5-year mean nitrogen abatement targets using historical climate data for a longer time frame. It could be that the satisficing CAC and PS policies that select high-cost practices might result in lower variance of abatement. To determine to what extent the ambient outcomes of the three types of policies depend on historically-observed weather variability, and to establish whether some policies may be preferred over others based on risk considerations, we simulate the abatement outcomes for a time period spanning from 1990 to 2009, based on water quality and weather data availability for the watershed.

By computing the five-year moving average from 1990 to 2009, we obtain sixteen additional annual mean N values for each policy. The mean and the standard deviation for each of these distributions are summarized in table 5.[39] The standard deviations are relatively small, representing around 15% on the mean values. Moreover, these are similar across abatement targets and policies. Testing for difference in variances across satisficing policies within the same abatement target shows that, given the observed historical data, policies are equally risky in terms of abatement. Similar results are obtained for the optimizing policies, with the standard deviations representing around 15% on the mean values. Testing for the difference in variances *across* satisficing and optimizing policies further shows that there is no difference in terms of risk.[40]

Policy Implications, Extensions, and Conclusions

We evaluated three simple approaches to regulating agricultural nonpoint-source water

[37] We thank the editor for pointing this out.

[38] Controlling the variance of abatement (even under the assumption of linear and separable ambient abatement function) would also introduce nonlinearities (e.g., Shortle and Horan 2013) and additional approximations would be required.

[39] Detailed tables with these distributions are provided in the supplementary material.

[40] The null hypothesis for a test of equal variances is not rejected (p-value > 0.3).

Table 5. The Five-Year Moving Average of 1990-2009 N Loadings Distribution

	Satisficing Policies			Optimizing Policies		
	CAC	PS	Trading	CAC	PS	Trading
20% goal						
Mean (kg,N)	3,866,809	3,756,183	4,024,971	3,824,371	3,817,882	4,037,307
St.dev. (kg,N)	607,153	569,630	599,178	575,141	573,963	601,386
Average N reduction (N)	20.5	22.8	17.23	21.4	21.5	17.0
30% goal						
Mean (kg,N)	3,424,873	3,356,720	3,453,769	3,337,541	3,332,835	3,412,061
St.dev. (kg,N)	549,779	527,071	508,943	491,356	490,390	499,974
Average N reduction (N)	29.6	31.0	28.98	31.4	31.5	29.8
40% goal						
Mean (kg,N)	2,987,899	2,918,844	3,116,531	2,922,795	2,940,443	3,114,093
St.dev. (kg,N)	489,257	465,417	481,662	462,606	463,449	481,523
Average N reduction (N)	38.6	40.0	35.91	39.9	39.5	36.0

pollution control: the CAC, the on-farm performance standard (PS), and a trading system based on abatement action credits (which we call "points") under the case where on-farm abatement actions interact in a nonseparable and nonlinear fashion to produce (expected) water quality outcomes. The potential for a complex and interdependent pollution process creates endogeneity in marginal impacts of individual abatement actions, and largely precludes any simple incentive-based policy from achieving first-best (cost-efficient) outcomes, even if one assumes that the environmental process is known to the regulator without error. Given perfect information on costs, the regulator could implement a first-best solution via a command-and-control policy, but information asymmetries preclude such solutions. Rather, we consider three second-best approaches by first identifying the simplifications to the true pollution process needed to implement them. In progressing from CAC to a performance standard and then to a trading program, the regulator employs increasingly simple approximations to the pollution process, but in exchange can capitalize on private incentives to gain cost efficiency. The relative impact of the two effects is an empirical question that is likely dependent on the pollution process modeled, and on the degree of private cost heterogeneity.

We provide an empirical assessment for a large agricultural watershed focusing on nitrogen abatement, but the proposed policies apply more generally to cases where the pollution process may have to be simplified or approximated to yield workable incentive-based policies, and where the regulator has limited information on the distribution of private costs of abatement actions. Property rights are assumed to belong to the regulator, but the presented issues find ready counterparts in the extant assignment of rights for nonpoint-source pollution.

In our proposed PS and trading programs, we rely on subsequent linear approximations to the complex and nonlinear water quality production function to simplify the abatement process at the edge-of-field (PS) or both at the edge-of-field and across farms (trading). Under a highly nonseparable and nonlinear environmental process, we could expect that a PS (and some cost information) might be needed to represent the desired spatial distribution of abatement actions, but in our application we find that an approximation where nonseparabilities and nonlinearities are omitted performs well. We also find that a well-functioning trading program would produce cost-efficient outcomes, although we do find that setting the total points value (akin to a cap in a cap-and-trade program) requires a correction for the approximation error. In our application, we argue that by employing the tradable abatement action 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), and where a simple correction ensures the attainment of the expected abatement goal.[41] The goal is to make the market simple for the polluters, with the understanding that careful initial analysis is needed on the part of the regulator.

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*) bring cropping choices into the point credit system (Collentine and Johnsson 2012); (*c*) create sub-watershed-scale markets; or (*d*) 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 and including large storms, which can be responsible for a significant share of nutrient loadings. Then the share of simulation years where the water quality target is reached would serve as an estimate of the reliability of reductions, and would subsequently be used to construct the "risk-modified" set of points. A different set of abatement actions (e.g., constructed wetlands, which may be able to retain nutrients even under high flow conditions (Fink and Mitsch 2004)) may receive high credit under targets incorporating risk. However, we leave these extensions to future work. Furthermore, other environmental processes may exhibit a much greater degree of nonseparability and nonlinearity, and free trading based on assumptions of independence and linearity may lead to unacceptable environmental performance. In those cases, perhaps a PS approach (or even a CAC) may prove to be a more attractive second-best policy. In the case that trading is not able to reach the theoretically predicted outcome (Shortle and Horan's (2013) "kryptonite" to trading proposals), a PS may present a lower cognitive burden and transactions cost alternative.

Many caveats regarding the water quality modeling process, data availability, uncertainty over the changing climate and hydrologic regimes, political feasibility, and monitoring and compliance issues apply. We believe, however, that these caveats should not serve as an impediment to more thorough consideration of the proposed flexible approaches by the research community. Rather, perhaps they warrant serious consideration for possible implementation by watershed managers.

[41] And which does not require any good information on the part of the regulator, since even severely biased cost information can be used to simulate trading program outcomes in order to find a good empirical approximation to the correction factor *k*.

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