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Valuing water quality tradeoffs at different spatial scales: An integrated approach using bilevel optimization

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ABSTRACT

This study evaluates the tradeoff between agricultural production and water quality at both the watershed scale and the farm scale, using an integrated economic-biophysical hybrid genetic algorithm. We apply a multi-input, multi-output profit maximization model to detailed farm-level production data from the Oregon Willamette Valley to predict each producer's response to a targeted fertilizer tax policy. Their resulting production decisions are included in a biophysical model of basin-level soil and water quality. Building on a general regulation problem for nonpoint pollution, we use a hybrid genetic algorithm to integrate the economic and biophysical models into one bilevel multiobjective optimization problem, the joint maximization of farm profits and minimization of Nitrate runoff resulting from fertilizer usage. This approach allows us to more fully endogenize fertilizer reduction cost, rather than assume an average cost relationship. The solution set of tax rates generates the Pareto optimal frontier at the watershed level. We then measure the tradeoffs between maximum profit and Nitrogen loading for individual farms, subject to the solution fertilizer tax policy. We find considerable variation in tradeoff values across the basin, which could be used to target incentives for reducing Nitrogen loading to agricultural producers under non-uniform control strategies.

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1. Introduction

Nutrient runoff from agriculture is a leading contributor to water quality impairment, inland eutrophication, and coastal hypoxia. The integration of biophysical models of these processes with economic models of agricultural producer behavior constitutes an important area of research related to nonpoint pollution policy. Examples of integrated economic and biophysical models for agriculture include modeling the biophysical outcomes of alternative economic scenarios [55,34] or the solution to a single-objective economic optimization model [52,65] and linking both single and multiobjective economic optimization models to biophysical models in a model chain [31,38,40,70,67,46,29].

In the model chain approach, information passes only in one direction, so that the optimal decision at any point in the chain is constrained by any previous decisions or outcomes in the chain. A simultaneous optimization of all objectives can inform the calculation of tradeoffs between multiple objectives. Several studies employ genetic algorithms to simultaneously optimize multiple objectives by allowing information to pass between each objective in both directions [7,2,44,45,47]. These studies illustrate the use of genetic algorithms to calculate the Pareto optimal frontier for both economic and environmental objectives.

We build on the use of genetic algorithms for nonpoint pollution policy analysis by integrating a realistic biophysical model with a detailed economic optimization model that more fully endogenizes each producer's response to the search for an optimal targeted nonpoint pollution policy. Our use of genetic algorithm computation methods to more freely integrate the economic and biophysical models is detailed in a related study of targeted policy design [73].

Our approach contributes to existing work on integrated modeling for nonpoint pollution in several important ways. First, we include both a detailed, spatially explicit biophysical model and a complete model of profit maximization, with minimal restrictions to solution values and without imposing an *a priori* production technology relationship. Second, we apply an adaptive modeling framework to allow for two-way feedback between our economic and environmental objectives. We formulate our multiobjective optimization as a bilevel optimization problem, which we show is amenable to the more general regulation problem underlying much of the nonpoint policy literature. This framework

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endogenizes fertilizer usage, making economic cost endogenous and better updating the search for an efficient allocation of fertilizer reduction. The resulting policy generates a set of Pareto optimal tradeoffs that can be evaluated across objectives. Third, we evaluate the resulting tradeoffs at varying spatial scales, for individual producers and for the basin as a whole.

This integrated economic-biophysical model simulates a rich set of agent-level decisions, made in response to the Pareto optimal policy, and corresponding environmental outcomes that can be used to evaluate tradeoffs at the individual level. We examine these decisions for a set of grass seed farms situated in the Calapooia River watershed, a predominantly agricultural watershed in Oregon's Willamette Valley. We also make use of detailed micro-level farm production data, which further enhances the evaluation of individual tradeoffs between farm profit maximization and watershed Nitrogen loading.

To value these tradeoffs, we jointly model profit-maximizing crop production and Nitrogen loading levels, simulated by the economic-biophysical model, as outputs in a production process using the directional output distance function [10]. In economic production theory, the directional output distance function is dual to the revenue function, which we exploit to derive shadow price estimates for Nitrogen loading in the basin [5,19,20].

We find that the tradeoff between farm profit and Nitrogen loading varies greatly across farmers in the watershed, due to differences in farm productivity and location in the basin's hydrologic network. This general result is consistent with previous studies that consider environmental heterogeneity from the nonpoint pollution literature [30,53,54]. In practice, managers could use this information to target incentives for fertilizer reduction or reduced Nitrate runoff, such as easement payments or funding for best management practices, to farms that have a lower opportunity cost of reducing eventual Nitrogen loading in the basin. Randhir and Shriver [48] demonstrate the potential gains from using multi-attribute shadow price values to target restoration incentives across a watershed.

Moreover, analysis of the tradeoff at the farm level offers a better picture of the distribution of costs across producers in the region, which could be added to existing information on environmental heterogeneity. This spatial distribution may be of concern for equity considerations and could affect the feasibility of implementing prospective agri-environmental policies in practice. For instance, variation in compliance costs across producers is a form of heterogeneity that could undermine ambient pollution policies targeted at the group level [61,63]. Differences in tradeoff values at the farm level could also help us to explain why some producers participate in voluntary management practice programs while their neighbors opt out, as well as identify areas where uniform policies are likely to generate large efficiency losses [30,69,54].

2. Background on nonpoint source pollution

Information asymmetries between producers and regulators, as well as uncertainty regarding individual emissions, complicate nonpoint source pollution policies for agriculture [75]. As a result, common output-oriented policy options, including Pigouvian taxes and output quantity standards, can no longer be generally expected to generate efficient pollution levels. Two key early insights motivate much of the related literature. First, while individual emissions levels may be unknown, the use of polluting inputs, such as fertilizer and pesticides, can be more easily observed [26]. This gives rise to greater focus on input-oriented policy instruments and extensions to management practices on the farm [49]. Second, while farm-level emissions may not be directly observable, ambient pollution levels can be monitored at regional receptor sites. It may still be possible to use group-level policies directed to ambient pollution concentrations to indirectly target individual emissions and achieve a desired pollution level [56,57,68,61,62].

2.1. Biophysical models and nonpoint policy

Biophysical models that account for factors such as hydrology, soil drainage, and climate, can serve to narrow the information gap for nonpoint source pollution, by identifying the relationship between input use, nutrient runoff, and ambient concentration levels. Understanding this relationship is particularly important for policy targeting and policy tradeoff analysis.

Numerous studies link agricultural production to a biophysical model, commonly using linear programming methods to estimate the resulting policy tradeoffs between emissions reductions and production value. Important innovations include the introduction of dynamic optimization for fertilizer and irrigation timing decisions [35,36,66]; the use of cost-effectiveness and the theory of second best for policy comparison [30,37]; incorporating producer heterogeneity [30,24,66,53,54,74]; allowing for stochastic processes in an ambient tax scheme [56,9,32]; allowing for substitution effects in response to input-oriented policies [33,39]; and the use of evolutionary algorithms to simultaneously optimize over production and water quality objectives [7,2,44,45,47].

Examined policy instruments include fertilizer input taxes [35,12,30,25,39]; quantity controls for fertilizer and irrigation [66], irrigation fees [36]; emissions taxes [69,36]; drainage standards [69]; emissions standards [53]; management practice standards [54]; and voluntary-threat approaches [56,57,68,62].

Across policy instruments, spatial heterogeneity emerges as an important factor in the relative inefficiency of alternative policy options [30,69,53,54]. Differences in soil quality, topography, farm productivity and location in the hydrology network affect key determinants, such as plant nutrient uptake, drainage rates, compliance costs and pollution transfer coefficients. In general, uniform approaches, whether in the form of standards, fees, or management practices, impose higher costs than alternatives that incorporate heterogeneity in some form. We build on this area of the literature by considering heterogeneity at the farm level, in both the production technology and biophysical characteristics, and then evaluating policy tradeoffs at both the farm level and for the basin as a whole. We briefly describe the nonpoint pollution problem in our study below, and outline our multiobjective policy analysis framework in the next section.

2.2. Nitrogen loading in the Calapooia River Basin

Our study area, the Calapooia River Basin, lies just west of the Cascades Mountain range, in the Oregon Willamette Valley. Agriculture comprises the majority of land use, and though small in size, this watershed accounted for roughly 40% of all perennial ryegrass production in the United States during our study period. Perennial ryegrass production is relatively fertilizer-intensive, and this area is known (at least locally) as the “grass seed capital of the world.”

The environmental effects of agricultural land use in the Calapooia have been previously studied as part of the USDA Conservation Effects Assessment Project (CEAP) [15,41]. A recent National Water Quality Assessment of the watershed identifies Nitrate Nitrogen as a particular concern, due to the increasing trend of stream and groundwater concentrations in excess of human health and aquatic life standards [41,18]. Recent sampling confirms that these Nitrogen concentrations vary greatly across the basin, even for areas with over 90% of land in agriculture [41], making this a particularly interesting case to consider for spatial heterogeneity and policy targeting.

3. Modeling nonpoint pollution regulation

In a recent review of the economic theory related to nonpoint pollution, Xepapadeas [75] presents a general theoretical representation of the nonpoint pollution regulator's problem underlying much of the literature. In this, the regulator chooses an ambient tax scheme to achieve the socially optimal ambient pollution concentration, allowing both the tax rate and emissions levels to vary across producers. Before introducing our own extension, we start with this general problem, given farms $k = 1, \ldots, K$,

$$\max_{\alpha} \quad \sum_{k=1}^{K} B_k(E_k) - D(Z) \text{s.t.} \quad Z = g(E_1, \ldots, E_K, \mathbf{b})$$
$$E_k \in \arg \max_{E_k} [B_k(E_k) - \alpha[g(E_k E_{-k}, \mathbf{b}) - Z^*]], \tag{1}$$

where $\alpha = \alpha_1, \ldots, \alpha_K$ is the ambient tax scheme for emissions, $E = E_1, \ldots, E_K$, $B_k(E_k)$ is the net benefit of farm k's emissions, Z is the ambient concentration governed by the biophysical relationship, $g(E_1, \ldots, E_K; \mathbf{b})$, $\mathbf{b}$ represents parameters for factors such as environmental characteristics, and $D(Z)$ represents the value of total damages from ambient pollution. The socially optimal ambient concentration is Z^*, so that each farm pays a tax on their increase in the concentration level above Z^*, given the emissions of other farms, E_{-k}. The solution tax scheme sets each farm's individual marginal benefit of emissions equal to the total marginal damages of emissions.

With assumed functional forms for the benefits, damages and biophysical relationship, along with standard monotonicity and concavity assumptions, there is a unique social optimum. In practice, emissions are generally unobserved and the damage function is unknown, although it is reasonable to assume that damages increase with the ambient concentration level. The net benefits depend on each farm's respective production technology. and the biophysical relationship may change depending on the spatial distribution of emissions. We address each of these in our modeling framework below.

3.1. Bilevel multiobjective optimization problem

For empirical analysis, we begin by shifting regulation from emissions to fertilizer use. We use farm profit for each farm's net benefit of fertilizer use, and total Nitrogen loadings at the basin receptor site as our ambient pollution measure. Lacking adequate information on damage values, we do not attempt to identify the socially optimal level of Nitrogen loading. Instead, we characterize the joint, and often competing, objectives of farm-level profit maximization and basin-level Nitrogen loading minimization as a multiobjective optimization problem. These objectives are constrained by the farm production technology and by the biophysical processes that determine the fate and transport of Nitrogen through the basin. The solution includes a set of farm-level tax schemes and corresponding fertilizer use that generate the Pareto frontier for profit and Nitrogen loading. In practice, a policy maker could use the resulting frontier to compare the tradeoffs associated with alternative nutrient reduction levels.

The solution, (Z^*, α^*), to the general problem in (1) depends on the optimizing behavior of individual firms. Similarly, in our case the regulator's solution set of optimal tax rates and fertilizer usage depends on the profit-maximizing behavior of individual producers. To account for this form of nested decision-making, inherent to the problem of nonpoint regulation, we formulate the multiobjective problem as a bilevel optimization [6]. A bilevel optimization nests one optimization inside of another, so that the solution to the outer non-nested optimization, typically referred to as the upper level, depends on the solution to the inner nested optimization, typically referred to as the lower level [60]. In our case, the joint maximization of total profit and minimization of basin-level Nitrogen constitutes the upper level while producer level profit maximization makes up the lower level.

For tax rate t and fertilizer input x_N, we represent the nested nature of this problem in general form, following Sinha et al. [60] as

$$\max_{t, xN} \quad F(t, xN) = [\pi(t, xN), -N(xN)] \text{s. t.} \quad xN \in \arg \max_{xN} \begin{cases} \pi(t, xN) = py(xN) - w_N x_N - t w_N x_N \\ \pi(t, xN) \geq 0 \end{cases}$$
$$xN \geq 0, \quad t \geq 0, \tag{2}$$

where N denotes basin-level Nitrogen loading, π represents farm profit, and w_N is the market price for fertilizer. This bilevel optimization framework allows for iterative feedback effects between the profit-maximization and biophysical models, making fertilizer usage endogenous, and thus, also endogenizing economic cost.

We note several important points underlying this general representation. First, the optimal tax rates and fertilizer usage for total profit and Nitrogen loading at the upper level depend on how individual producers respond to the tax, in terms of fertilizer use, at the lower level. The profit-maximizing fertilizer usage, in turn, depends on the production technology. Second, total Nitrogen loading at the upper level also depends on individual fertilizer usage in response to the tax at the lower level, as well as the spatial distribution of fertilizer usage by producers in the watershed. The spatial dynamics of fertilizer usage and Nitrogen loading are governed by biophysical processes in the basin. Third, the nested nature of this problem, coupled with multiple production inputs and many profit-maximizing producers, makes the solution to (2) complex. We employ a hybrid genetic algorithm to iteratively optimize the lower and upper levels of our problem. We explain the production technology specification, biophysical model and genetic algorithm solution method in more detail below.

3.2. Profit maximization at the farm level

In our economic model, each producer chooses inputs and outputs to maximize profit subject to the production technology and the fertilizer tax rate policy. We use nonparametric linear programming methods known as data envelopment analysis (DEA) [11] to estimate the production technology and to simulate the profit maximization decision for each farm. In the DEA representation of the production technology, each of the K producers uses inputs $x = (x_1, \ldots, x_N)$ to produce outputs $y = (y_1, \ldots, y_M)$. The production technology T is defined as $T = \{(x, y)\colon x \text{ can produce } y\}$.

Given input prices $w = (w_1, \ldots, w_N)$ and output prices $p = (p_1, \ldots, p_M)$, we compute the maximum profit for each farm as the solution to

$$\pi(p, w) = \max \quad \sum_{m=1}^{M} p_m y_m - \sum_{n=1}^{N} w_n x_n, \text{ s. t.} \quad \sum_{k=1}^{K} z^k y_m^k \geq y_m, \quad m = 1, \ldots, M,$$
$$\sum_{k=1}^{K} z^k x_n^k \leq x_n, \quad n = 1, \ldots, N$$
$$\sum_{k=1}^{K} z^k \leq 1,$$
$$z^k \geq 0, \quad k = 1, \ldots, K. \tag{3}$$

where the variables z^k, known as intensity variables in this framework, are constrained to allow for non-increasing returns to scale. Fig. 1 illustrates profit maximization for a DEA representation of a single input/single output production technology with three observations, a, b and c. These frontier observations also lie on the profit lines, π_1^*, π_2^* and π_3^*, which represent maximum profit levels for input and output prices $\{(p_1, w_1), (p_2, w_2), (p_3, w_3)\}$.

To simulate each producer's response an input tax policy, we add a targeted proportional tax to the profit maximization model

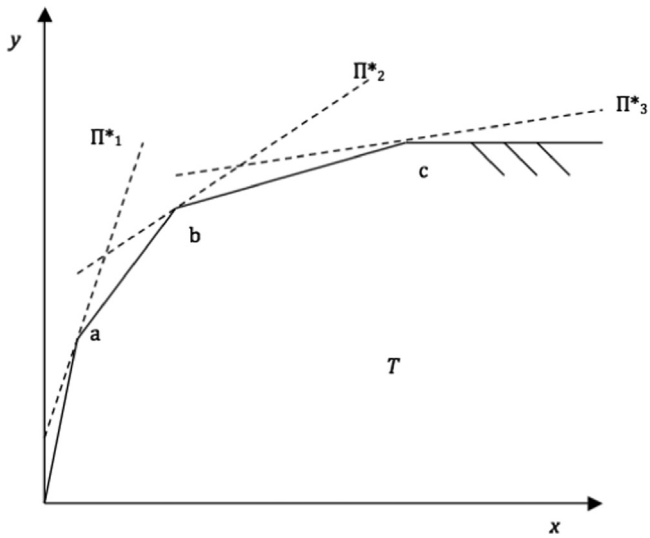

Fig. 1. DEA profit maximization for three different price ratios.

in (3). Each farm's objective function under the targeted tax, t^k, on Nitrogen fertilizer, the Nth input, is

$$\pi(p, w) = \max \sum_{m=1}^{M} p_m y_m - \sum_{n=1}^{N-1} w_n x_n - t^k w_N x_N, \tag{4}$$

subject to the technology representation in (3). Here the tax rate for each farm, t^k, is multiplied by the quantity and price of the Nth input, Nitrogen fertilizer. Note that a tax value of $t=1$ is equivalent to having no tax on fertilizer and that a given policy consists of K different tax rates for each of the K farms. Solving this problem for each producer allows for heterogeneity in farm-level technologies, which underlies variation in producer compliance costs.

Much of our focus in this study lies in more fully integrating the nested decision process in the economic model with a spatially explicit biophysical model, in order to examine tradeoffs at both the basin and the producer level. While farm-level tax rates on fertilizer may not represent a very realistic policy option, we use them in this framework as a general incentive to reduce fertilizer. We could easily replace them with payments for fertilizer reduction, and with additional data on management practices (*e.g.*, vegetative filter strips; buffer zones), we could also include multiple policy incentives. Allowing the tax to vary at the farm-level is analogous to varying ambient tax rates across producers. We use them here to identify the frontier for Nitrogen reductions, based on decreased fertilizer use. It is important to note that allowing for multiple policy options would provide an even fuller representation of the frontier.

3.3. The biophysical model

The environmental objective in this case is to minimize Nitrogen loading in the basin resulting from profit-maximizing fertilizer use. We use the Soil and Water Assessment Tool (SWAT) [3] to specify the environmental objective. SWAT is a biophysical model that can be used to simulate the effects of agricultural production processes at the river basin scale [4]. The model divides the entire watershed into subbasins, where each subbasin is further divided into hydrological response units (HRUs), which represent unique combinations of topography, land use and soil properties. Farm-level production decisions in each of the HRUs can then be included to model the spatial distribution of Nitrogen loadings throughout the watershed.

We use the digital elevation model ArcSWAT, which adds a GIS interface to SWAT, to input and designate land use, soil, weather, groundwater, water use management, pond and stream water quality data. SWAT simulates hydrology, soil erosion, plant growth, as well as multiple fate and transport processes, including that of Nitrogen. This framework is specifically designed to simulate the environmental effects of agricultural production practices, thus providing a method to test the effectiveness of agri-environmental policy [4]. SWAT is widely used and numerous studies apply it specifically to agri-environmental policy analysis [7,50,45]

3.4. The hybrid genetic algorithm

We employ genetic algorithm computational methods to solve the multiobjective optimization problem for the case of a targeted environmental policy, in this case a proportional Nitrogen fertilizer tax. This problem is computationally intensive, but relatively easy to implement with parallel execution [71].

A genetic algorithm (GA) is an iterative algorithm based on retention of the best or 'fittest' members of a population until a stopping condition is satisfied [27]. In an optimization application, the GA consists of an initial randomly generated population that is evaluated for fitness using an objective function, a test for convergence, and application of the GA operations of selection, crossover and mutation. These elements are followed iteratively until an optimum is obtained.

Although GAs generally find promising solution regions quickly, convergence to an optimum can be much slower. In response, a hybrid genetic algorithm (HGA) model adds a local search method to speed convergence [59]. Fig. 2 adapts the more general explanation of genetic algorithms from Goldberg [27] to illustrate the HGA used to solve our maximum-profit and minimum-Nitrogen loading problem in this case.

We use the non-dominated sort genetic algorithm (NSGA-II) [16] to assign a fitness value to each individual in the GA population, based on the evaluation of the individual for each objective. The result is an estimate of the Pareto optimal set of our objectives, farm profit and Nitrogen loading, at convergence. In our case, a linear program for the DEA model is solved in the evaluation step, which limits the space that is searched by the GA. The DEA results are then passed to NSGA-II, which finds the set of values available across the Pareto optimal frontier. It is important to note that this HGA uses information from both the economic and environmental models used in the integrated simulation of the tax policy during the optimization. Whittaker et al. [73] provide more computational details on implementing the HGA.

4. Evaluating the individual tradeoffs

We specify the HGA to maximize total basin-wide profit while also minimizing total basin-wide Nitrogen loadings. However, individual tax rates are applied to each farm. Therefore, for this targeted tax policy, it is also important to understand the tradeoffs that exist for individual producers. To evaluate the tradeoff between Nitrogen loading and crop production at the farm level, we first calculate each farm's share of total basin Nitrogen loading as a function of their fertilizer application rate and HRU location. We then use a directional distance function approach to model individual Nitrogen loading as an undesirable output, produced jointly with the desirable output, crop production.

4.1. The underlying theory

We let $P(x)$ denote the feasible output set for the vector of farm outputs $y = (y_1, \ldots, y_M)$ and undesirable outputs $u = (u_1, \ldots, u_J)$ given inputs $x = (x_1, \ldots, x_N)$, so that

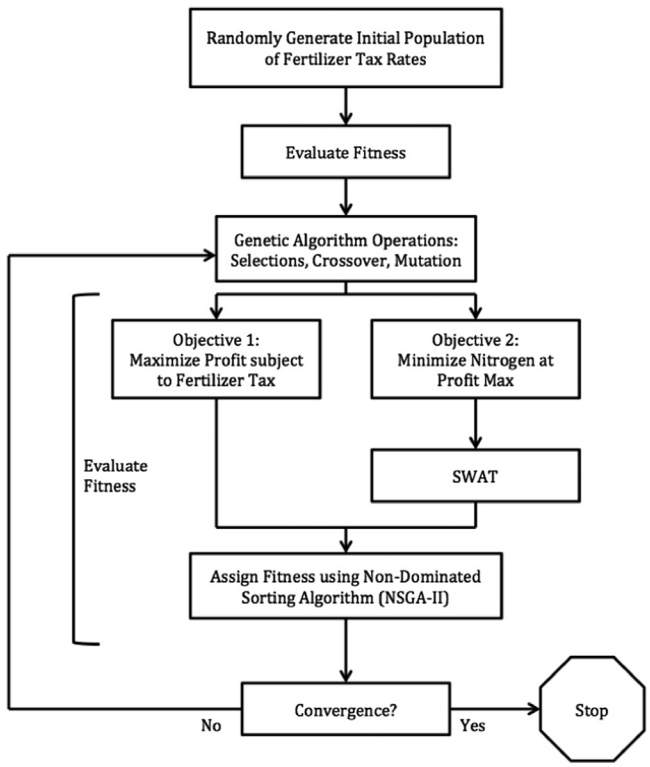

Fig. 2. The hybrid genetic algorithm.

$$P(x) = \{(y, u)\colon x \text{ can produce } (y, u)\}. \tag{5}$$

In this case, y represents each farm's crop production output, u its Nitrogen loading and x the vector of inputs, including acreage, labor, equipment and fertilizer.

We make the standard assumption that $P(x)$ is compact and convex, acknowledging that output is scarce and thus, tradeoffs exist at the frontier. We also assume that good and bad outputs are weakly disposable, which allows for their proportional scaling up or down over $P(x)$, meaning that for $(y, u) \in P(x)$ and $0 \le \theta \le 1$, $(\theta y, \theta u) \in P(x)$. We relax the usual assumption of null jointness, that if $(y, u) \in P(x)$ and $u = 0$, then $y = 0$, due to its violation in practice by one of the farms in our study. Given these assumptions, we use the directional output distance function to represent the feasible output set [10], as well as individual measures of performance. Fig. 3 illustrates the feasible output set for the joint production of good and bad output and the directional output distance function, defined as

$$\vec{D}_O(x, y, u; g_y, g_u) = \max\{\beta\colon [(y + \beta g_y, u - \beta g_u)] \in P(x)\}, \tag{6}$$

where $(g_y \in \Re_+^M, g_u \in \Re_+^J)$ is a directional vector that specifies the simultaneous expansion of desirable output and contraction of undesirable output. This model measures each observation's distance, in a particular direction, to the production frontier. Thus, for observations on the frontier, $\vec{D}_O(x, y, u; g_y, g_u) = 0$, and for any observation below the frontier, $\vec{D}_O(x, y, u; g_y, g_u) > 0$. Individual performance deteriorates with distance to the frontier, so that the directional output distance value can be interpreted as a measure of inefficiency for each observation.

The directional output distance function can be used to account for the undesirable nature of some outputs of a production process, in this case Nitrogen loading, by specifying a negative direction for those outputs [13]. This enables the simultaneous expansion of desirable output and contraction of undesirable output in the measurement of performance. The properties of the

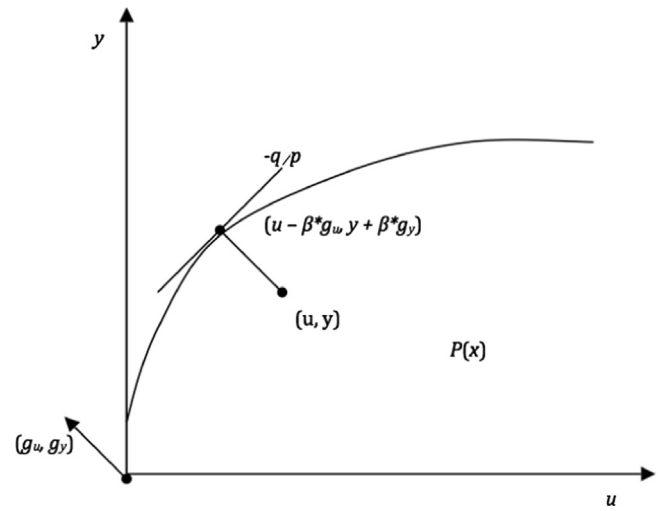

Fig. 3. The directional output distance function for desirable output, y, and undesirable output, u.

directional output distance function follow from the assumptions made to characterize $P(x)$, and include Representation, Monotonicity and Translation. Chambers et al. [10] prove these properties for the input oriented case and we outline their use for estimation purposes in the next section.

We use this model to construct the feasible output set for crop production and Nitrogen loading, which allows us to measure the physical tradeoffs for individual producers in the watershed. Given the market value of grass seed, it is also possible to value these tradeoffs in monetary terms [20,21,8] by exploiting the duality that exists between the directional output distance function and the revenue function:

$$R(x, p, q) = \max_{y,u}\{py - pu\colon (y, u) \in P(x)\}, \tag{7}$$

where $p = (p_1, \ldots, p_M) \in \Re_+^M$ is the vector of output prices corresponding to y and $q = (q_1, \ldots, q_J) \in \Re_+^J$ is the vector of output prices corresponding to u. By definition,

$$R(x, p, q) \ge py - qu, \quad \forall\ (y, u) \in P(x), \tag{8}$$

and this, along with the definition of the directional output distance function from (6) and the representation property, implies

$$\begin{aligned} R(x, p, q) &\ge (p, q)(y + \vec{D}_O(x, y, u; g_y, g_u) \\ &\quad g_y, u - \vec{D}_O(x, y, u; g_y, g_u)g_u) \\ &\ge (py - qu) + \vec{D}_O(x, y, u; g_y, g_u) \\ &\quad pg_y + \vec{D}_O(x, y, u; g_y, g_u)qg_u. \end{aligned} \tag{9}$$

Rearranging terms in (9),

$$\vec{D}_O(x, y, u; g_y, g_u) \le \frac{R(x, p, q) - (py - qu)}{(pg_y + qg_u)}. \tag{10}$$

The directional output distance function can then be recovered from the right-hand side in (10) as the solution to

$$\vec{D}_O(x, y, u; g_y, g_u) = \min_{p,q} \frac{R(x, p, q) - (py - qu)}{(pg_y + qg_u)}. \tag{11}$$

The vector of shadow prices is derived by applying the envelope theorem to (11), so that

$$\nabla_u \vec{D}_O(x, y, u; g_y, g_u) = \frac{q}{(pg_y + qg_u)} \ge 0, \tag{12}$$

and

$$\nabla_y \vec{D}_O(x, y, u; g_y, g_y) = \frac{-p}{(pg_y + qg_u)} \leq 0. \tag{13}$$

For a single observation, the shadow price ratio is

$$-\frac{q_j}{p_m} = \frac{\partial \vec{D}_O(x, y, u; g_y, g_u)/\partial u_j}{\partial \vec{D}_O(x, y, u; g_y, g_u)/\partial y_m}, \quad \forall\, m \in M \text{ and } \forall\, j \in J. \tag{14}$$

The shadow price ratio values the tradeoff in relative terms between the desirable and undesirable output. If at least one of the outputs y_m in $P(x)$ is marketed, in this case crop production, the shadow price of the nonmarketed undesirable output, in this case Nitrogen loading, can be recovered in absolute terms as

$$q_j = -\, p_m \frac{\partial \vec{D}_O(x, y, u; g_y, g_u)/\partial u_j}{\partial \vec{D}_O(x, y, u; g_y, g_u)/\partial y_m}, \quad \forall\, m \in M \text{ and } \forall\, j \in J. \tag{15}$$

We note that in this application, the desirable output, crop production, is measured in terms of total sales, so that a unit of output is \$1.00. This normalizes the price of output, p_m, to equal \$1.00 as well.

4.2. Estimating the tradeoffs in practice

To compute the marginal effects and shadow prices of each output in practice requires parametrization of the output frontier. In choosing a functional form for that parametrization, we are guided by the properties of the directional output distance function. Only two forms are known to satisfy the translation property, and of these, only the quadratic form contains the first order parameters necessary to compute marginal effects [21]. More recently, Färe et al. [22] use Monte Carlo simulations to demonstrate the ability in practice of the quadratic directional output distance function to characterize the output set. The quadratic (also as in [1]) directional output distance function [19,20] is estimated as

$$\begin{aligned}
&\vec{D}_O(x, y, u; g_y, g_u) \\
&\quad = \alpha_0 + \sum_{n=1}^{N} \alpha_n x_n + \sum_{m=1}^{M} \beta_m y_m + \sum_{j=1}^{J} \gamma_j u_j \\
&\qquad + \frac{1}{2} \sum_{n=1}^{N} \sum_{n'=1}^{N} \alpha_{nn'} x_n x_{n'} \\
&\qquad + \frac{1}{2} \sum_{m=1}^{M} \sum_{m'=1}^{M} \beta_{mm'} y_m y_{m'} \\
&\qquad + \frac{1}{2} \sum_{j=1}^{J} \sum_{j'=1}^{J} \gamma_{jj'} u_j u_{j'} + \sum_{n=1}^{N} \sum_{m=1}^{M} \delta_{nm} x_n y_m \\
&\qquad + \sum_{n=1}^{N} \sum_{j=1}^{J} \nu_{nj} x_n u_j + \sum_{m=1}^{M} \sum_{j=1}^{J} \mu_{mj} y_m u_j.
\end{aligned} \tag{16}$$

We estimate the quadratic directional output distance function as a constrained linear programming problem, choosing the parameters to minimize each observation's distance to the frontier. The solution to this problem, the optimal parameter values and $\vec{D}_O^{\,k}$ minimize $\sum_{k=1}^{K} \vec{D}_O^{\,k}(x^k, y^k, u^k; g_y, g_u)$ subject to the properties of the production technology. Färe et al. [19,20] outline the associated technology constraints in more detail.

5. Empirical application

We apply the bilevel multiobjective optimization framework outlined above to a set of 87 real grass seed farms in the Calapooia river watershed, a tributary of the Willamette river basin west of the Cascades Mountain range in Oregon. These farms are situated in the lower portion of the watershed, which has a drainage area of 682 km^2. The vast majority of the watershed is used for agricultural crop production (83%) with virtually all of this in grass seed farming. This is followed by hay/pasture/range areas (12%). Wetlands, water bodies and urban areas comprise the remaining (5%) watershed area.

5.1. The SWAT model

We use the SWAT model to divide the study area into 381 subbasins and 533 HRUs. We calibrated the SWAT model with daily streamflow data at the basin outlet near Albany, OR, obtained from the U.S. Geological Survey (USGS) National Water Information System (NWIS) website (http://nwis.waterdata.usgs.gov/nwis/discharge). We obtained the 10-m DEM used to delineate the watershed from the Regional Ecosystem Office (http://www.reo.gov/reo/data/DEM_Files/indexes/orequadindex.asp). We used soil data from the SSURGO state soil geographic database for Oregon, obtained from the U.S. Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) (http://soils.usda.gov/survey/geography/ssurgo/), land use data from the USGS National Water Quality Assessment (NAWQA) program (http://or.water.usgs.gov/projs_dir/pn366/landuse.html), and climate data from the Oregon Climatic Service (OCS) (http://www.ocs.oregonstate.edu). We calibrated the model using the automatic calibration method described in Confessor and Whittaker [15] and Whittaker et al. [72]. Fig. 4 depicts the Calapooia watershed stream system. Our analysis focuses on the lower portion of the river basin, between the Holley and Albany weather stations. Beyond Holley, the upper watershed extends into the Cascades Mountain range, an area unsuitable for the type of intensive agricultural production studied here.

5.2. The Pareto optimal tax policy

Due to USDA confidentiality restrictions, agricultural policy studies commonly model the decisions of a representative farm, and are applied to aggregated production data. The USDA National Agricultural Statistics Service (NASS) granted us access to detailed farm-level records from the 2002 Census of Agriculture with the confidentiality restriction that the data could only be accessed from NASS computers.

The HGA requires parallel computation, and could not be run using available NASS computing capability. To maintain the confidentiality of individual producers, we constructed a synthetic data set from the original records for application of the economic model. Fully synthetic data sets are constructed by multiple imputation [51] of all observations for all variables in the data set, and are generally considered protection against disclosure of confidential data. Bayesian networks provide a useful method for imputation and creation of synthetic data sets, particularly in high dimensions [64,17].

The estimated Bayesian network satisfies the confidentiality restrictions and can be copied to non-secured computers. We construct the synthetic microdata for use in the profit maximization model using constrained draws from the Bayesian network. Our constructed synthetic microdata has the same statistical properties as the original census records and protects the confidentiality of the individual producers. The synthetic data were also shown to generate the same results for the profit maximization model, which can be run in isolation using NASS computers, as the original census records. Table 1 provides descriptive statistics for the input and output data listed in expenditure and revenue form, with the exception of acreage. We note that producers in our sample do not

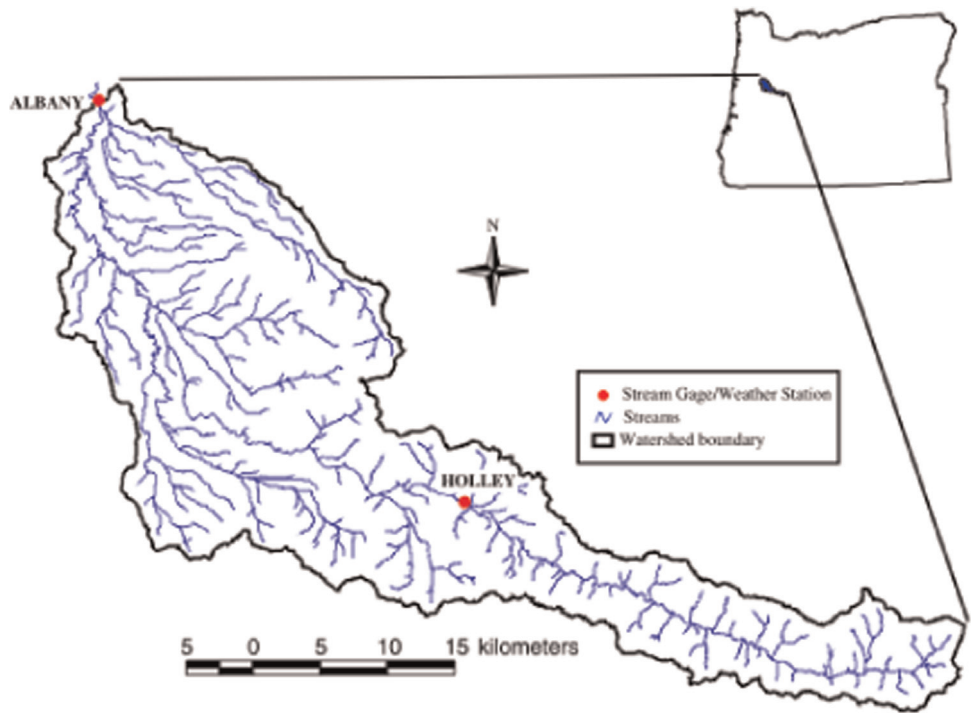

Fig. 4. The SWAT delineation of the Lower Calapooia watershed.

typically employ irrigation, as the growing season for perennial rye coincides with the annual rain season in the Willamette Valley, which can often last from October to May.

According to NASS records, Nitrogen fertilizer sold for $191/ton in 2002, which implies that farms in our sample applied roughly 486.5 tons of fertilizer on average. Using the most commonly applied 46–0–0 N-concentration, for a farm with average acreage and fertilizer expenditure, this translates to roughly 260 lbs Nitrogen per acre. This value exceeds local agricultural extension recommendations for annual N application to perennial rye in the Willamette Valley, which ranged from 120 to 160 lbs during our study period [28]. We also note that reported fertilizer use is skewed toward upper end values in our sample. This intensive rate of fertilizer application further highlights the policy concern for Nitrogen reductions in the basin.

For the targeted tax policy solution HGA, we set up a population of 200 individuals (the number of cluster nodes). Each individual genome consists of 87 targeted tax rates, one for each farm in the watershed. The tax rate values range from 1 to 10, so that the optimal tax payments could range from 0 to up to 9 times the total fertilizer expenditure for a given farm. The HGA runs and tests the fitness of different individuals for their ability to simultaneously optimize both environmental and economic objectives. After several thousand generations, only the fittest solutions are retained. These resulting non-dominated solutions approximate the Pareto optimal frontier.

Fig. 5 depicts the Pareto optimal frontier for Nitrogen Loading and Profit at the basin level, summing over all 87 farms for the 200 individual candidate solutions to the targeted tax policy HGA. We summarize the Pareto optimal tax rates in Table 2. The curvature reflects the changing tradeoffs facing policy makers at the basin level, in choosing between alternative tax schemes. The frontier indicates that reductions to Nitrogen loading below approximately 1.025 ($\times 10^7$) correspond to substantially greater profit losses, compared to equal reductions from higher Nitrogen values. Likewise, reductions to loading levels above 1.15 impose relatively low profit losses.

Not surprisingly, solution tax rates steadily decrease with increasing Nitrogen and profits, but also at a decreasing rate. For Nitrogen loading levels between 1.000 and 1.025, average tax rates range from 3.11 to 5.86, while between 1.025 and 1.050, they range from 2.47 to 3.11. in the mid-region of the frontier, between Nitrogen levels of 1.05 and 1.15, average solution tax rates range from 1.38 to 2.52, while for loadings greater than 1.15, they range from 1.06 to 1.56. Important for policy decisions, these solution values suggest that over much of the frontier, relatively minor tax increases could generate considerable reductions to Nitrogen loading at proportionately lower costs to basin profits. We could also use these results, along with additional information on the social costs of Nitrogen loading to determine the optimal level (or range, depending on precision) of Nitrogen for the basin. In the absence of known costs, understanding the sensitivity of loading and profit losses to alternative prospective tax rates at different loading levels could also be useful for setting a policy goal for loading in the basin.

We illustrate the spatial distribution of the solution tax rates over different regions of the Pareto frontier in Fig. 6. Moving clockwise from the top left, regions I, II, III, and IV correspond to Nitrogen loadings lower than 1.000, between 1.000 and 1.025, 1.025 and 1.050, and greater than 1.050, respectively. The different shaded areas correspond to zip code areas in the basin, and grow

Table 1
Descriptive statistics for the Calapooia synthetic microdata.

87 Obs.[a]	Mean	Min	Max	Std. Dev
Crop sales ($)	731,800.63	7744.39	3,404,889.01	591,995.20
Acres	1715.48	27.54	6972.44	1370.35
Labor	112,772.43	241.37	484,628.39	101,673.74
Fertilizer	92,911.99	6524.38	342,890.26	72,011.17
Seed	16,903.00	4.58	104,308.10	21,278.89
Chemicals	60,243.97	27.21	565,094.90	90,974.07
Fuel	25,720.85	283.84	169,372.22	27,747.60
Utilities	13,392.67	0.00	82,088.85	14,950.13
Maintenance	43,410.06	21.20	159,912.51	37,177.90
Other expenses	204,159.40	8411.60	716,892.97	154,316.76

[a] Note, all input data with the exception of acreage is listed in expenditure form.

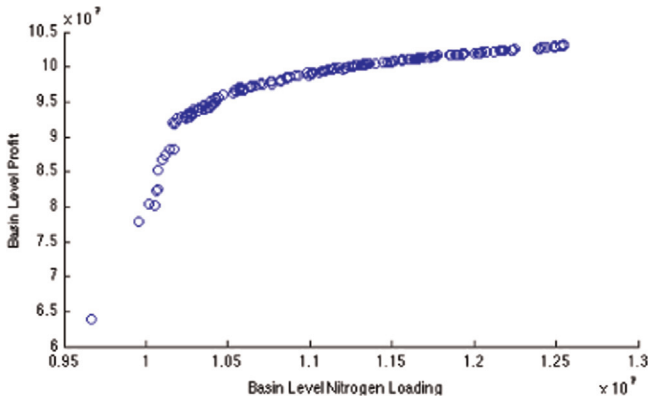

Fig. 5. The Pareto optimal frontier for the targeted tax policy.

Table 2
Calapooia simulated microdata and distance results.

17,400 Obs.	Mean	Min	Max	Std. Dev
Acres	1715.47	27.54	6972.40	1362.48
Labor expenditures	112,772.43	241.37	484,628.39	101,090.62
Other expenditures	363,829.96	19,981.10	977,014.99	232,010.46
Fertilizer (tons)	253.83	0	8928.30	374.89
Crop sales	734,068.28	0.47	2,834,500	573,605.17
Nitrogen loading (lbs)	128,978.06	0	3,462,393.05	162,294.89
Distance	0.62	0.00	5.20	0.38
Tax rate	2.03	1	10	1.90
q elasticity	0.98	0.00	3.01	0.42
q price	5.58	0.00	17.11	2.39

darker with increasing average solution tax values. Not surprisingly, we find that areas closest to the mouth of the basin in Albany, where final loadings are measured, and areas along the main branch of the stream system, tend to have the highest solution tax rates, across regions of the frontier. Next, we examine variation in solution tax rates across the Pareto frontier, at the farm level.

5.3. Farm level tradeoff results

The targeted tax policy HGA generates the Pareto optimal tax rate and corresponding profit-maximizing production decisions and Nitrogen loading for each of the 87 farms in each of the 200 frontier solution tax schemes from the HGA computation. This yields a data set of 17,400 simulated observations. For this second stage of analysis, where the profit-maximizing input and output quantities have already been chosen, we also combine some of the inputs to reduce the number of parameters that must be estimated.

For computational purposes, we convert each observation's input and output level to a mean-weighted amount. Weighting each input and output by its respective sample mean insures independence of unit of measurement [58] and corrects for differences in scale.

Thus, the distance value for a hypothetical observation at the mean can be interpreted as the percent increase in desirable output ${y_m}^k$ and decrease in undesirable output ${u_j}^k$ required to reach the corresponding point (y_m^{k*}, u_j^{k*}) on the output frontier. The marginal effects of each output can then be interpreted as percent changes in inefficiency, so that the shadow price ratio provides a measure of the elasticity of the tradeoff between crop sales and Nitrogen loading for each producer. The simulated microdata, Pareto optimal tax rates, directional output distance function results and Nitrogen loading shadow price ratios are summarized in Table 2.

The average Pareto optimal tax rate from the HGA is 2.03 times the price of fertilizer. We note that the minimum and maximum tax values reflect imposed tax bounds, which were specified for two initial tax schemes in our HGA population. While our results indicate solution values at the lower bound of 1 for a number of farms in the basin, we find a solution value at the upper bound of 10 for just one of the farms. In practice, upper-extreme tax values are likely infeasible, but they could be used to target other policy incentives, including payments for land retirement or the construction of riparian buffers.

The market price of fertilizer in this study is $191 per ton, making the average Pareto optimal fertilizer cost equal to roughly $380 per ton. Profit-maximizing fertilizer application decreases substantially, falling from an average of 486.6 tons per farm to an average of 253.8 tons per farm under the tax policy. While crop sales decrease for more than half of the farms in our sample under the tax policy, average crop sales increase slightly, from roughly $732,000 to $734,000 per farm. This is due to a shift in optimal production intensities under the tax policy and our estimate of the production technology for the basin.

To provide additional context for these results, in 2013 the state of California considered a fertilizer tax policy to reduce Nitrate loading to groundwater and fund improvements to drinking water supplies. While this tax ultimately did not pass, Mérel et al. [39] use a bioeconomic model and positive mathematical programming to simulate the effects of proposed taxes between $100 and $180 per ton at the regional level. Using input shadow prices to calibrate substitution elasticities, they find that intensive margin effects (reduced fertilizer use per acre) account for much of the behavioral response.

In terms of production efficiency, the distance value of 0.62 suggests that, on average, producers in the basin could increase their crop sales and decrease their Nitrogen loading by 62% from mean levels, based on the production levels of other farms in the basin. For a hypothetical observation at the mean, this corresponds to a feasible reduction of roughly 80,000 lbs of Nitrogen loading and an increase of roughly $450,000 in crop sales. We caution that differences in location within the basin stream system, as well as unobserved differences in soil quality, may be driving these relatively high estimated inefficiencies.

Along the frontier, the tradeoff between crop sales and Nitrogen loading, measured in elasticity form, is close to one on average. This implies that, on average, a one percent reduction in Nitrogen loading (from mean levels) corresponds to a one percent reduction in crop sales (from mean levels). To convert this value to monetary terms,

$$q = -p\frac{\partial \vec{D}_O(x, y, u); g_y, g_u)/\partial u}{\partial \vec{D}_O(x, y, u); g_y, g_u)/\partial y}\frac{\bar{y}}{\bar{u}}. \tag{17}$$

The desirable output, grass seed sales, is measured in dollars, so that the price for an additional dollar of grass seed sales, p, is normalized to equal $1.00. Thus, the average estimate for the shadow price of Nitrogen loading, q, in monetary terms is $ 5.58 per lb, and q ranges from 0.00 to $17.11 per lb across individual producers. These values should be interpreted with caution, particularly given that they are derived from simulated outcomes. They do however shed some light on the possible range of values for Nitrogen loading in the basin, as well as how these values vary across the farms. We also note that shadow price values for Nitrogen loading, as opposed to reductions in fertilizer use, could be used to inform ambient emissions schemes, such as group voluntary-threat approaches and pollution permits, as well as identify critical areas for management practice adoption.

Fig. 7 illustrates the distribution of estimated tradeoff elasticities, which lie between 0.5 and 1.5 for the majority of

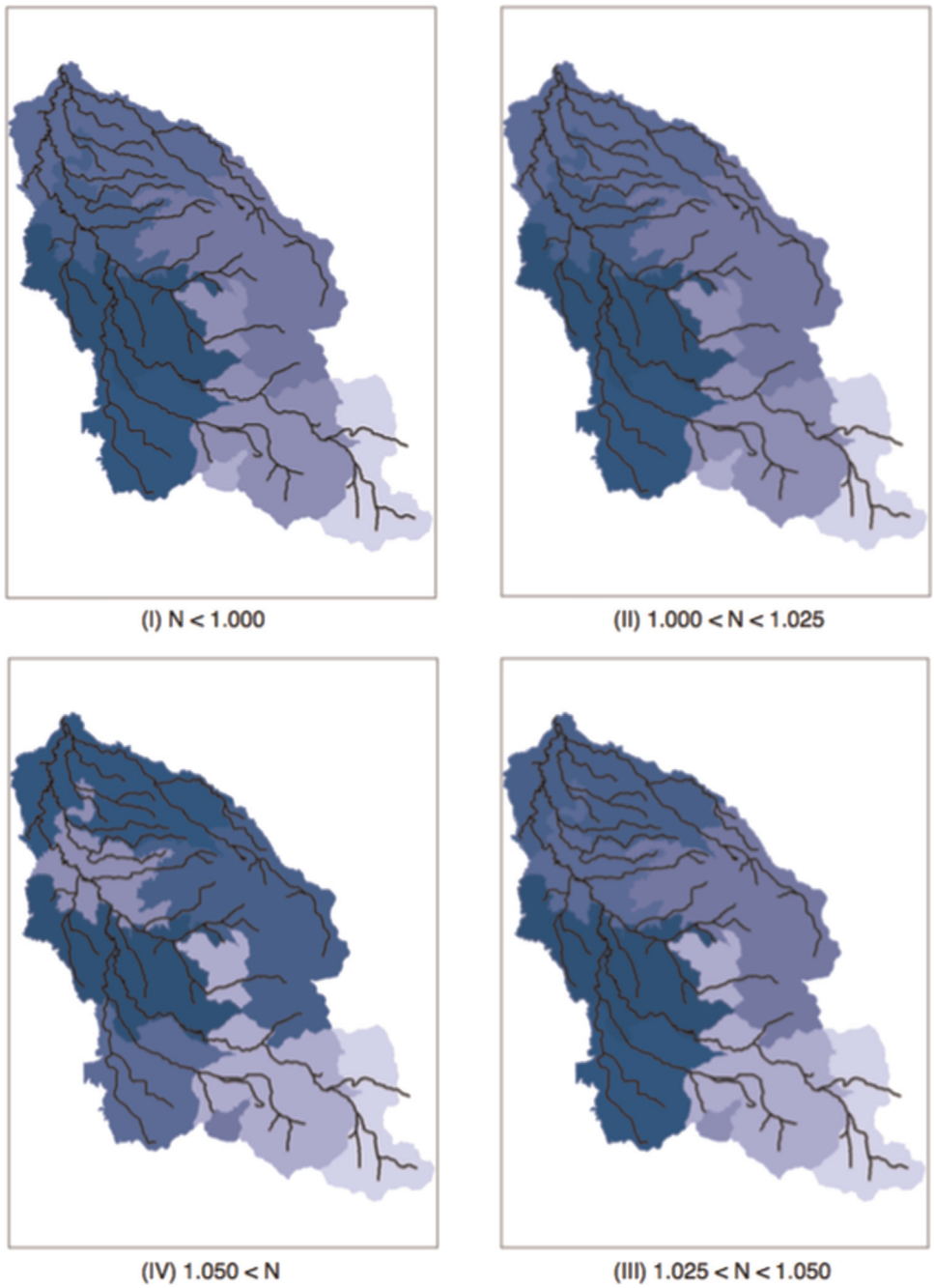

Fig. 6. Spatial distribution of solution tax rates for frontier regions I–IV.

observations in our sample. For relatively inelastic observations, a one percent reduction in Nitrogen loading corresponds to more than a one percent reduction in crop sales. The opportunity cost of reductions to Nitrogen loading is greatest for these farms under the tax policy. Several factors could explain a more inelastic tradeoff. These farms may be situated on more productive land in the basin, on land where applied fertilizer is less apt to run off due to gradient conditions, or they may also be located at a point in the stream network where runoff has less of an effect on basin-level Nitrogen loading.

These results on variation in tradeoffs at the farm level highlight the potential for inefficiency under uniform control policies, consistent with previous findings in the literature. For instance, in a comparison of nonpoint pollution control strategies for the Neuse River basin in North Carolina, Schwabe [54] finds that for a 30% basin-level reduction to Nitrogen loadings, uniform reductions result in control costs of more than three times the least-cost solution, while a uniform vegetative filter strip policy increases those costs even further. He also finds that considerable variation in acreage responses at the county level to three common management practices, controlled drainage, vegetative filter strips, and reduced tillage. He attributes much of this variation to environmental heterogeneity, namely differences in soil type across counties, affecting both yield levels and nutrient uptake. Ultimately, the state implemented a plan that sets a uniform 30% reduction goal, but allowed for county-level management strategies that currently include a combination of fertilizer reductions, crop rotation, and management practices [42]. The mix of strategies varies across counties, depending on crop type, soil differences, and farm size, and primary management practices include buffer

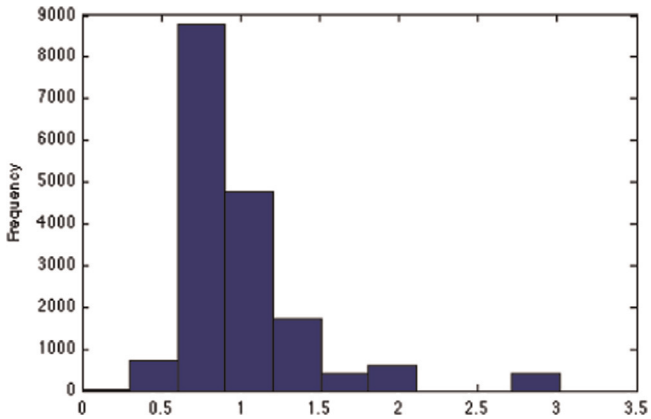

Fig. 7. Distribution of nitrogen loading shadow price elasticities.

strips and managed drainage.

In the Calapooia, the primary management practices under consideration by the USDA CEAP program are conservation tillage and riparian buffers. Moving from farm-level to more realistic regional targeting, the spatial distribution in Fig. 6 suggests offering additional incentives for these practices to areas near the mouth of the watershed and along the main branch of the stream network. Information on the distribution of elasticities in Fig. 7 could be used to further tailor incentives, by better understanding the level of heterogeneity among producers within each region.

6. Conclusion

The tradeoff between agricultural production and water quality is widely acknowledged. The effectiveness of any policy incentive to address this problem depends not only on how farmers respond, but also on the physical relationship between their production activities and the surrounding watershed. This linkage between producer behavior and the environment has long been acknowledged, particularly for soil condition [69,54] and stream flow [43,54]. Recent computational advances in bilevel multi-objective optimization [60] allow for more detailed two-way model integration in the simultaneous consideration of both objectives.

The ability to account for feedback effects between producers, the environment, and the regulating authority adds to the tool set for nonpoint pollution policy analysis. In this study, we take just such an integrated approach by employing a hybrid genetic algorithm to solve for an optimal tax policy that jointly maximizes agricultural profit and minimizes basin-level Nitrogen loading. Our framework advances the integrated economic and biophysical literature by incorporating realistic models of both farm production and the basin hydrology, by more freely optimizing over both objectives, and by fully endogenizing economic cost without imposing an *a priori* production technology. More generally, bilevel optimization accommodates the often nested nature of the regulation problem for nonpoint pollution. We believe that this offers a useful tool for solving this problem in practice.

We use our framework to better understand the tradeoffs that result at both the basin level and the farm level under a prospective fertilizer input tax policy. Working with a set of grass seed farms from Oregon's Calapooia River watershed, we estimate an average shadow price of $5.58 per lb for Nitrogen loading, providing information on the cost to farmers of decreasing current loadings in the basin. We also find that this tradeoff varies across farms, from relatively elastic for some to relatively inelastic for others. The distribution of tradeoff values likely depends on several factors, including differences in farm productivity, soil quality, topography, and location in the basin's hydrological network. This spatial heterogeneity suggests the need for more adaptive, non-uniform management policies [30,69,53,54] in conjunction with the fertilizer tax, such as incentives for the use of best management practices on more productive working land and taking some marginal, or critically located land out of production altogether. The distribution of tradeoff values would also likely affect the feasibility of implementing these policies in practice. For instance, a policy that concentrates Nitrogen reduction costs among producers in one are of the basin may be less feasible than one that would spread costs more evenly across the watershed. Individual tradeoff values could be used to assess the distributional implications of prospective agri-environmental policies, which may determine the efficacy of group-based policies [61,63].

While our results at the farm level underscore the importance of spatial heterogeneity, our results at the basin level suggest the potential to substantially reduce total Nitrogen loading within a relatively narrow range of total profit losses. In practice, policy makers often lack sufficient information on nonuse values for water quality to set a socially optimal ambient pollution objective. Information on the tradeoffs associated with various prospective reduction amounts could be used to instead set an objective range of ambient pollution levels. Also, while it may not be feasible to fully account for spatial heterogeneity by targeting incentives at the farm level, information on spatial heterogeneity could inform more realistic regional targeting, for instance at the county level [53,54], or the designation of priority areas.

We also note several limitations of this study. Perhaps most importantly, we focus on a single fertilizer reduction policy. A more realistic analysis would consider a range of policies to address Nitrogen loading, including best management practices and land retirement [44,29]. Allowing for more policy options would likely lower the overall cost of Nitrogen reduction [23,14]. We emphasize that our bilevel optimization framework does not preclude multiple policies. With additional data on management practice adoption for the production technology, one could add multiple policy incentives to the nested profit maximization problem and use SWAT to model their physical effects. Here we focus on the overall framework to endogenize policy response, and leave the question of multiple policies for a separate application. We also do not attempt to estimate the causal determinants of tradeoff differences across farms. Likely determinants include on-farm practices, topographical characteristics and location in the basin system. A better understanding of how these factors affect tradeoff differences would also be useful for targeting policies in practice.

While our application focuses on a small agricultural watershed in the Pacific Northwest, this framework could be adapted to analyze nonpoint pollution tradeoffs for larger and more policy-relevant watersheds, in both the U.S. and internationally. It is also possible to expand the analysis to include additional environmental objectives, such as biodiversity measures or water flow by using an integrated HGA approach. We are interested in adapting this framework to model changing environmental tradeoffs over time, in response to a variety of factors, including efficiency and technology change, prospective agri-environmental policies, and projected climate change.

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