Valuing Water Quality Tradeoffs Under a Targeted Pollution Policy: An Integrated Economic-Biophysical Hybrid Genetic Algorithm Approach

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Introduction

In this study, we examine the use of policy incentives to reduce Nitrogen pollution from agriculture.

We connect an economic production model to a spatially explicit biophysical model to:

- Estimate Nitrogen loading levels for farms in the Willamette Valley
- Determine the optimal allocation of Nitrogen reduction using a fertilizer tax policy
- Understand the tradeoffs that individual farmers would face under this policy
Introduction

Agricultural runoff is a leading water quality stressor:

- Nitrogen Fertilizer and Eutrophication
- Non-point Source Pollution
Introduction

Things can get really bad... The Gulf of Mexico Hypoxic Area, 15,000 $km^2$ Summer 2013

- N and P runoff from the Mississippi River Basin.
- Reducing to 5,000 $km^2$ by 2015 is estimated to require 30 - 60 percent reductions in N and P loadings.
Introduction

The effectiveness of policies to reduce agricultural runoff depends on:

- How producers respond to the policy
- The physical relationship between their production and the surrounding watershed

These relationships are connected, and not necessarily in just one direction.
Introduction

Two main approaches to linking economic and biophysical models:

▷ Model Chain Approach (Moore and Tindall, 2005; Volk et al., 2008)

\[ \text{Economic Objective} \rightarrow \text{Environmental Objective} \]

(Secchi and Babcock, 2007; Jha et al., 2010)

\[ \text{Environmental Objective} \rightarrow \text{Economic Objective} \]

(Schönert et al., 2011; Uthes et al., 2010)

▷ Simultaneous Optimization Approach (Rabotyagov et al, 2010a; 2010b; Whittaker et al., 2014)

\[ \text{Economic Objective} \leftrightarrow \text{Environmental Objective} \]
We build on the Simultaneous Optimization literature by:

- Integrating a realistic economic production model with a detailed and spatially explicit biophysical model
- Allowing for a more adaptive two-way feedback between the environmental objective and the economic objective
- Analyzing the distribution of tradeoffs for individual producers, in addition to aggregate tradeoffs for the basin
Introduction

In the rest of this talk, I will:

- Explain the modeling framework
  
  Stage 1: Linking the Economic and Environmental Objectives to find the Pareto Optimal allocation of Nitrogen reduction

  Stage 2: Estimate the tradeoff between production and Nitrogen reduction at the farm level

- Apply the framework to farmers in the Willamette Valley

- Consider the use of these results to inform policy decisions
Stage 1: Economic Objective

We model each farm, $k$, as a decision making unit, that chooses inputs and outputs to maximize profit subject to the production technology and the fertilizer policy.

- Let $x = (x_1, \ldots, x_N) \in \mathbb{R}_+^N$ and $y = (y_1, \ldots, y_M) \in \mathbb{R}_+^M$ denote the associated inputs and outputs, so that the production technology, $T = \{(x, y) : x \text{ can produce } y\}$.

- We use linear programming methods known as Data Envelopment Analysis (DEA) to estimate the production technology and then maximize profit for each farm.
Stage 1: Economic Objective

The corresponding DEA representation of the technology is

\[ T = \{(x, y) : y_m \leq \sum_{k=1}^{K} z^k y^k_m, \quad m = 1, \ldots, M, \] 
\[ x_n \geq \sum_{k=1}^{K} z^k x^k_n, \quad n = 1, \ldots, N, \] 
\[ \sum_{k=1}^{K} z^k \leq 1, \] 
\[ z^k \geq 0 \}, \]

where the variables \( z^k \) are used to construct a convex combination of observed inputs and outputs.
Stage 1: Economic Objective

Figure: DEA Technology Representation
Stage 1: Economic Objective

Given input prices $w = (w_1, \ldots, w_N)$ and output prices $p = (p_1, \ldots, p_M)$, the profit of the $k^{th}$ farm is computed as the solution to

$$\pi(p^k, w^k) = \max \sum_{m=1}^{M} p^k_m y^k_m - \sum_{n=1}^{N} w^k_n x^k_n,$$

subject to

$$\sum_{k=1}^{K} z^k y^k_m \geq y_m, \quad m = 1, \ldots, M,$$

$$\sum_{k=1}^{K} z^k x^k_n \leq x_n, \quad n = 1, \ldots, N,$$

$$\sum_{k=1}^{K} z^k \leq 1,$$

$$z^k \geq 0, \quad k = 1, \ldots, K.$$
Stage 1: Economic Objective

Figure: DEA Profit Maximization for Three Different Price Ratios
Stage 1: Economic Objective

We simulate each producer’s response to a ‘green’ tax policy by adding a targeted proportional tax on Nitrogen fertilizer, the $N^{th}$ input,

$$
\pi(p^k, w^k) = \max \sum_{m=1}^{M} p^k y^k_m - \sum_{n=1}^{N-1} w^k_n x^k_n - t_k w^k_N x^k_N,
$$

s.t. $T = \{(x, y) : x \text{ can produce } y\}$.

- The tax rate for each farm, $t_k$, is multiplied by the quantity and price of Nitrogen fertilizer.
- Note that a given policy consists of $K$ different tax rates for each of the $K$ farms.
Stage 1: Environmental Objective

We use the Soil and Water Assessment Tool (SWAT) to simulate the effects of agricultural production on Nitrogen loading at the basin scale.

- SWAT is a detailed spatially explicit biophysical model.

- Each subbasin of the watershed is divided into hydrological response units (HRUs)

- Each HRU represents topography, land use, and soil properties

- Farm-level production in each HRU is used to model the spatial distribution of nitrogen loadings throughout the watershed.
Stage 1: Environmental Objective

Figure: Lower Calapooia SWAT HRU Delineation
Stage 1: Environmental Objective

We use the GIS ArcSWAT interface to:

- input land and water use, soil and water quality, weather and groundwater
- simulate hydrology, soil erosion, plant growth and Nitrogen loading
- identify the spatial distribution of fertilizer usage that minimizes nitrogen loading for a given fertilizer tax policy
Stage 1: The HGA

For computation, we use a genetic algorithm to jointly maximize profit and minimize Nitrogen loading at the basin level, under the fertilizer tax policy.

- Initial population of tax rates is generated
- Draws are evaluated, based on profit and Nitrogen objectives
- Best draws are kept iteratively until convergence to optimum
- The *hybrid* genetic algorithm (HGA) adds a local search method to speed convergence
Stage 1: The HGA

Figure: The hybrid genetic algorithm
Stage 1: The HGA

Figure: The Beowulf Cluster
Stage 2: The Individual Tradeoffs

- In Stage 1, we solve for the optimal tax rates to maximize profit and minimize Nitrogen loading at the basin level.

- In Stage 2, we evaluate the tradeoffs between profit and reductions to Nitrogen loading for *individual* farms.

- We use a directional distance function framework to model the joint production of agricultural output and Nitrogen loading at the farm level.

- We apply the envelope theorem to value the tradeoffs in production for individual farms.
Stage 2: The Individual Tradeoffs

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

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

- $y$ represents each farm’s crop production output
- $u$ represents each farm’s Nitrogen loading
- $x$ includes each farm’s acreage, labor, equipment and fertilizer.
Stage 2: The Individual Tradeoffs

We make the standard assumptions that,

i. $P(x)$ is compact.

Output is scarce; Nitrogen loading and agricultural production are finite.

ii. $P(x)$ is convex.

There is a physical tradeoff between reductions to Nitrogen loading and agricultural production.

iii. *Weak Disposability* of outputs:
For $(y, u) \in P(x)$ and $0 \leq \theta \leq 1$, $(\theta y, \theta u) \in P(x)$

Nitrogen loading and agricultural production can be proportionally scaled up or down over the output set.
The Underlying Theory

The *Directional Output Distance Function* is defined as

\[ D_O(x, y; g_y) = \max \{ \beta : [y + \beta g_y] \in P(x) \} . \]

- \( g_y \) is a directional vector that specifies the path of output expansion.
- \( D_O(x, y; g_y) = 0 \) for observations on the output frontier.
- Performance diminishes with distance to the frontier.
- Given assumptions *i*, *ii*, and *iii*, \( D_O(x, y; g_y) \) provides a complete representation of \( P(x) \) (Chambers et al., 1996).
The Underlying Theory

\[ \tilde{D}_O(x, y; g_y) = \max \{ \beta : [y + \beta g_y] \in P(x) \} \]
Numerical Example

\[
g \vec{y} = (1, 1)
\]

<table>
<thead>
<tr>
<th>Obs.</th>
<th>( x )</th>
<th>( y_1 )</th>
<th>( y_2 )</th>
<th>( \vec{D}_O )</th>
</tr>
</thead>
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<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>0.5</td>
</tr>
<tr>
<td>2</td>
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<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
The Underlying Theory

\[ \vec{D}_O(x, y, u; g_y, g_u) = \max \{\beta : [(y + \beta g_y, u - \beta g_u)] \in P(x)\} \]
The Underlying Theory

\( \vec{D}_O(x, y, u; g_y, g_u) \) also satisfies the following properties:

i. **Representation**
\[ \vec{D}_O(x, y, u; g_y, g_u) \geq 0 \text{ if and only if } (y, u) \in P(x). \]

ii. **Monotonicity**
\[ \vec{D}_O(x', y, u; g_y, g_u) \geq \vec{D}_O(x, y, u; g_y, g_u), \text{ for } x' \geq x \]
\[ \vec{D}_O(x, y', u; g_y, g_u) \geq \vec{D}_O(x, y, u; g_y, g_u), \text{ for } y' \leq y \]
\[ \vec{D}_O(x, y, u'; g_y, g_u) \geq \vec{D}_O(x, y, u; g_y, g_u), \text{ for } u' \geq u \]

iii. **Translation**
\[ \vec{D}_O(x, y + \alpha g_y, u - \alpha g_u; g_y, g_u) = \vec{D}_O(x, y, u; g_y, g_u) - \alpha \]

iv. **Directional Homogeneity of degree -1**
\[ \vec{D}_O(x, y, u; \lambda g_y, \lambda g_u) = \lambda^{-1} \vec{D}_O(x, y, u; g_y, g_u), \text{ for } \lambda > 0. \]
Valuing the Tradeoffs using Duality Theory

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

\[ R(x, p, q) = \max_{y, u} \{ py - pu : (y, u) \in P(x) \} \]
Valuing the Tradeoffs using Duality Theory

- \( \widetilde{D}_O(x, y, u; g_y, g_u) \) is dual to the Revenue Function,

\[
R(x, p, q) = \max_{y, u} \left\{ py - pu : (y, u) \in P(x) \right\}.
\]

- It is possible to recover the shadow price ratio by exploiting the duality between \( \widetilde{D}_O(x, y, u; g_y, g_u) \) and \( R(x, p, q) \).

- First, note that

\[
R(x, p, q) \geq py - qu, \forall (y, u) \in P(x).
\]
Valuing the Tradeoffs using Duality Theory

- The definition of the directional output distance function,

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

and the Representation property,

\[
\vec{D}_O(x, y, u; g_y, g_u) \geq 0 \iff (y, u) \in P(x),
\]

imply

\[
R(x, p, q) \geq (p, q)(y + \vec{D}_O())g_y, u - \vec{D}_O()g_u) \\
\geq (py - qu) + \vec{D}_O()pg_y + \vec{D}_O()qg_u.
\]
Valuing the Tradeoffs using Duality Theory

Rearranging terms,

\[ \vec{D}_O(x, y, u; g_y, g_u) \leq \frac{R(x, p, q) - (py - qu)}{(pg_y + qg_u)}. \]

Moreover, the directional output distance function can be recovered from the right hand side as the solution to

\[ \vec{D}_O(x, y, u; g_y, g_u) = \min_{p, q} \frac{R(x, p, q) - (py - qu)}{(pg_y + qg_u)}. \]
The vector of shadow prices, \((p, q)\) can then be derived by applying the envelope theorem to

\[
\vec{D}_O(x, y; g_y) = \min_{p, q} \frac{R(x, p, q) - (py - qu)}{(pg_y + qg_u)},
\]

so that

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

and

\[
\nabla_u \vec{D}_O(x, y, u; g_y, g_u) = \frac{q}{(pg_y + qg_u)} \geq 0.
\]
Valuing the Tradeoffs using Duality Theory

For a single observation,

\[-q / p = \frac{\partial \vec{D}_O(x, y, u; g_y, g_u)}{\partial u} / \frac{\partial \vec{D}_O(x, y, u; g_y, g_u)}{\partial y}.\]

The shadow price of the nonmarketed undesirable output, in this case Nitrogen loading, can be recovered in absolute terms as

\[q = -p \frac{\partial \vec{D}_O(x, y, u; g_y, g_u)}{\partial u} / \frac{\partial \vec{D}_O(x, y, u; g_y, g_u)}{\partial y}.\]
Valuing the Tradeoffs using Duality Theory

- The shadow price ratio values the tradeoff in relative terms between the desirable and undesirable output.

- Note that crop production is measured in terms of total sales, so that a unit of output is $1.00. This normalizes the price of output, $p$, to equal $1.00$ as well.

- $q$ differs conceptually from the notion of implicit value using Hedonic Methods.

- The shadow price vector values the opportunity cost of reductions Nitrogen Loading in terms of foregone agricultural production at the farm level.
Estimating the Output Frontier

To compute the marginal effects and shadow price of each output in practice requires parameterization of the output frontier.

- Only two functional forms are known to satisfy the translation property for $\vec{D}_O$.

- Of these, only the quadratic form contains the first order parameters necessary to compute marginal effects (Färe and Lundberg, 2006).

- Färe et al. (2010) use Monte Carlo simulations to show the quadratic directional model outperforms the translog radial model in estimating $P(x)$. 
Estimating the Output Frontier

The quadratic directional output distance function is estimated as

\[
\vec{D}_O(x, y, u; g_y, g_u) = \alpha_0 + \sum_{n=1}^{N} \alpha_n x_n + \sum_{m=1}^{M} \beta_m y_m + \sum_{j=1}^{J} \gamma_j u_j
\]

\[
+ \frac{1}{2} \sum_{n=1}^{N} \sum_{n'=1}^{N} \alpha_{nn'} x_n x_{n'} + \frac{1}{2} \sum_{m=1}^{M} \sum_{m'=1}^{M} \beta_{mm'} y_m y_{m'}
\]

\[
+ \frac{1}{2} \sum_{j=1}^{J} \sum_{j'=1}^{J} \gamma_{jj'} u_j u_{j'} + \sum_{n=1}^{N} \sum_{m=1}^{M} \delta_{nm} x_n y_m
\]

\[
+ \sum_{n=1}^{N} \sum_{j=1}^{J} \nu_{nj} x_n u_j + \sum_{m=1}^{M} \sum_{j=1}^{J} \mu_{mj} y_m u_j.
\]
Estimating the Output Frontier

Given the quadratic form, the marginal effect of the $m^{th}$ desirable output is then derived as

$$\frac{\partial \vec{D}_O(x, y, u; g_y, g_u)}{\partial y_m} = \beta_m + \sum_{m'=1}^{M} \beta_{mm'} y_{m'} + \sum_{n=1}^{N} \delta_{nm} x_n + \sum_{j=1}^{J} \mu_{mj} u_j,$$

and the marginal effect of the $j^{th}$ undesirable output is derived as

$$\frac{\partial \vec{D}_O(x, y, u; g_y, g_u)}{\partial u_j} = \gamma_j + \sum_{j'=1}^{J} \gamma_{jj'} u_{j'} + \sum_{n=1}^{N} \nu_{nj} x_n + \sum_{m=1}^{M} \mu_{mj} y_m.$$
Estimating the Output Frontier

We estimate each observation $k$’s distance by choosing the parameters to minimize

$$\sum_{k=1}^{K} \mathbf{D}_{O}^{k}(x^{k}, y^{k}, u^{k}; g_{y}, g_{u}) \text{ s.t.}$$

i. Representation

$$\mathbf{D}_{O}^{k}(x^{k}, y^{k}, u^{k}; g_{y}, g_{u}) \geq 0, k = 1, \ldots, K,$$

ii. Monotonicity

$$\frac{\partial \mathbf{D}_{O}^{k}(x^{k}, y^{k}, u^{k}; g_{y}, g_{u})}{\partial y_{m}^{k}} \leq 0, m = 1, \ldots, M, k = 1, \ldots, K,$$

$$\frac{\partial \mathbf{D}_{O}^{k}(x^{k}, y^{k}, u^{k}; g_{y}, g_{u})}{\partial u_{j}^{k}} \geq 0, j = 1, \ldots, J, k = 1, \ldots, K,$$

$$\frac{\partial \mathbf{D}_{O}^{k}(x^{k}, y^{k}, u^{k}; g_{y}, g_{u})}{\partial x_{n}^{k}} \geq 0, n = 1, \ldots, N, k = 1, \ldots, K,$$
iii. Translation

\[ \sum_{m=1}^{M} \beta_m - \sum_{j=1}^{J} \gamma_j = -1; \]

\[ \sum_{m'=1}^{M} \beta_{mm'} - \sum_{j=1}^{J} \mu_{mj} = 0, \; m = 1, \ldots, M; \]

\[ \sum_{j'=1}^{J} \gamma_{jj'} - \sum_{m=1}^{M} \mu_{mj} = 0, \; m = 1, \ldots, M; \]

\[ \sum_{m=1}^{M} \delta_{nm} - \sum_{j=1}^{J} \nu_{nj} = 0, \; n = 1, \ldots, N. \]
Application to the Calapooia Watershed
The Calapooia watershed is an agriculturally intensive region that serves as a tributary to the Willamette River basin.

The environmental effects of agricultural land use in the Calapooia have been previously studied as part of the USDA Conservation Effects Assessment Project (CEAP).

We use the HGA to solve the first stage (profit max/N min) model for 87 grass seed farms in the watershed.

Our study area represents the lower portion of the watershed, with a drainage area of 682 km².
Application to the Calapooia Watershed

- We use the SWAT model to divide the study area into 381 subbasins and 533 HRUs.

- The land use is: 83% Agricultural crop production, 12% pasture and range, 5% wetland and urban

- We calibrated the physical model with: USGS streamflow and land use data, USDA NRCS soil data, Oregon Climatic Service climate data.
Application to the Calapooia Watershed

Figure: The SWAT delineation of the Lower Calapooia watershed
Application to the Calapooia Watershed

We gained permission to work with detailed farm-level production data from the USDA National Agricultural Statistics Service (NASS) 2002 Census of Agriculture

- The data can only be accessed from NASS Computers.
- NASS computing capability insufficient for HGA.
- We used Bayesian network methods to construct synthetic microdata with the same statistical properties as the original data, but cleared for public use.
## Table: Descriptive Statistics for the Calapooia Synthetic Microdata

<table>
<thead>
<tr>
<th></th>
<th>87 Obs.*</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Std. Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crop Sales ($)</td>
<td>731,800.63</td>
<td>7,744.39</td>
<td>3,404,889.01</td>
<td>591,995.20</td>
<td></td>
</tr>
<tr>
<td>Acres</td>
<td>1,715.48</td>
<td>27.54</td>
<td>6,972.44</td>
<td>1,370.35</td>
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</tr>
<tr>
<td>Labor</td>
<td>112,772.43</td>
<td>241.37</td>
<td>484,628.39</td>
<td>101,673.74</td>
<td></td>
</tr>
<tr>
<td>Fertilizer</td>
<td>92,911.99</td>
<td>6,524.38</td>
<td>342,890.26</td>
<td>72,011.17</td>
<td></td>
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<tr>
<td>Seed</td>
<td>16,903.00</td>
<td>4.58</td>
<td>104,308.10</td>
<td>21,278.89</td>
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<tr>
<td>Chemicals</td>
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<td>27.21</td>
<td>565,094.90</td>
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</tr>
<tr>
<td>Fuel</td>
<td>25,720.85</td>
<td>283.84</td>
<td>169,372.22</td>
<td>27,747.60</td>
<td></td>
</tr>
<tr>
<td>Utilities</td>
<td>13,392.67</td>
<td>0.00</td>
<td>82,088.85</td>
<td>14,950.13</td>
<td></td>
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<tr>
<td>Maintenance</td>
<td>43,410.06</td>
<td>21.20</td>
<td>159,912.51</td>
<td>37,177.90</td>
<td></td>
</tr>
<tr>
<td>Other Expenses</td>
<td>204,159.40</td>
<td>8,411.60</td>
<td>716,892.97</td>
<td>154,316.76</td>
<td></td>
</tr>
</tbody>
</table>

*Note, all input data with the exception of acreage is listed in expenditure form.
We implement the HGA in the first stage for 200 cluster nodes.

- Each cluster node serves as an individual genome.

- Each individual genome consists of 87 targeted tax rates, one for each farm.

- The tax rates range from 1 (no tax) to 10, so that optimal tax payments could range from 0 to up to 9 times the total fertilizer expenditure for each farm.

- Over several thousand generations, the HGA repeatedly tests random tax rate draws, retaining solutions that jointly optimize both objectives.
Application to the Calapooia Watershed

**Figure:** The Pareto optimal frontier for the targeted tax policy
Application to the Calapooia Watershed

In the second stage, we apply the directional distance framework to the production decisions and Nitrogen loading levels from the first stage.

- The first stage generates a data set of 17,400 simulated observations (87 farms for 200 cluster nodes).

- For computational purposes, we weight each variable by the sample mean.

- The distance value for a hypothetical observation at the mean can be interpreted as the percent increase in desirable output $y^k_m$ and decrease in undesirable output $u^k_j$ required to reach the output frontier.

- The marginal effects of each output can be interpreted as percent changes in inefficiency.
## Application to the Calapooia Watershed

<table>
<thead>
<tr>
<th>17,400 Obs.</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Std. Dev</th>
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<td>Acres</td>
<td>1,715.47</td>
<td>27.54</td>
<td>6,972.40</td>
<td>1,362.48</td>
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<tr>
<td>Labor</td>
<td>112,772.43</td>
<td>241.37</td>
<td>484,628.39</td>
<td>101,090.62</td>
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<td>Other Exp.</td>
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<td>19,981.10</td>
<td>977,014.99</td>
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<tr>
<td>Fertilizer (tons)</td>
<td>253.83</td>
<td>0</td>
<td>8,928.30</td>
<td>374.89</td>
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<tr>
<td>Crop Sales</td>
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<td>0.47</td>
<td>2,834,500</td>
<td>573,605.17</td>
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<td>N Loading (lbs)</td>
<td>128,978.06</td>
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<td>3,462,393.05</td>
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<td>Distance</td>
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<td>0.00</td>
<td>5.20</td>
<td>0.38</td>
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<td>Tax rate</td>
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<td>1.90</td>
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<td>$q$ elasticity</td>
<td>0.98</td>
<td>0.00</td>
<td>3.01</td>
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<tr>
<td>$q$ price</td>
<td>5.58</td>
<td>0.00</td>
<td>17.11</td>
<td>2.39</td>
</tr>
</tbody>
</table>
Results for the Calapooia Watershed

- The average optimal tax rate from the first stage is 2.03; For a market price of $191 per ton, this makes the optimal fertilizer cost equal roughly $380 per ton.

- Profit maximizing fertilizer usage decreases from 486.6 tons per farm to 253.8 tons per farm under the tax policy.

- Average crop sales increase slightly, from $732,000 to $734,000 per farm.

- The increase in crop sales is due to a shift in optimal production intensities under the tax policy.
Results for the Calapooia Watershed

- The distance value of 0.62 suggests that on average, farms could jointly increase crop sales and decrease N loading by 62 percent from mean levels.

- For a hypothetical farm at the mean, this corresponds to roughly $450,000 in crop sales and 80,000 lbs of N loading.

- The elasticity of the tradeoff between crop sales and N loading is close to one on average.

- The average shadow price of N loading, $q$, is $5.58 per lb,

\[
q = p \frac{\partial \tilde{D}_O(x, y, u; g_y, g_u)}{\partial u} \frac{\tilde{y}}{\bar{u}}.
\] (2)
Results for the Calapooia Watershed

Figure: Distribution of Nitrogen Loading Shadow Price Elasticities
Results for the Calapooia Watershed

It’s important to consider how these tradeoff estimates could be used from a policy perspective.

▶ For relatively inelastic observations, a one percent reduction in N loading corresponds to more than a one percent reduction in crop sales.

▶ Relatively inelastic farms could be situated on more productive land, on land where applied fertilizer is less apt to run off or at a point in the stream network where runoff has less effect on basin-level N loading.

▶ It may be advantageous to provide increased incentives for best management practices, such as buffers or grass strips, to these farms given that their reductions in N loading are so costly when solely dependent on decreased fertilizer usage.
Results for the Calapooia Watershed

- For relatively elastic farms, a one percent reduction in N loading corresponds to less than a one percent reduction in crop sales.

- These farms may be situated on less productive land, on land where applied fertilizer is more likely to run off, or at a point in the stream system where runoff has more of an effect on basin-level N loading.

- It may be advantageous to provide incentives for land retirement to these farms.
Conclusions

The success of agri-environmental policies to improve water quality depends both on how farmers respond and on the physical relationship between their production and the surrounding watershed.

- Numerous economic studies include a physical model relating agricultural production to water quality.

- Few studies allow for feedbacks between the physical model and the economic model.

- This study advances the integrated economic/biophysical literature by i) incorporating realistic production and hydrology models, ii) more freely optimizing over both objectives, and iii) evaluating individual tradeoffs.
Conclusions

We find in our application to the Calapooia River, that the tradeoff between N loading reductions and crop sales varies considerably across farms.

▶ In addition to differences in productivity, the tradeoffs likely differ due to differences in soil quality, topography, and location in the basin’s hydrological network.

▶ This suggests the need for more adaptive management policies, such as incentives for the use of best management practices on more productive working land and retirement of more marginal or critically-located lands.

▶ The distribution of tradeoff values may also affect the feasibility of implementing a targeted tax policy in practice.
Conclusions

Future extensions of this framework include:

▶ Application to the more policy-relevant Mississippi River Basin and the problem of Gulf Hypoxia

▶ Inclusion of additional environmental objectives, such as biodiversity measures or water flow

▶ Analysis of changing tradeoffs over time due to efficiency and technology change, prospective agri-environmental policies, or projected climate change