USING TRADING RATIOS TO CORRECT FOR SYSTEMATIC SELECTION IN PERFORMANCE-BASED WATER QUALITY TRADING PROGRAMS

by

Wenbo Liu

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Wenbo Liu

Approved: ____________________________________________
Joshua M. Duke, Ph.D.
Professor in charge of thesis on behalf of the Advisory Committee

Approved: ____________________________________________
Thomas W. Ilvento, Ph.D.
Interim Chair of the Department of Applied Economics and Statistics

Approved: ____________________________________________
Mark Rieger, Ph.D.
Dean of the College of Agriculture and Natural Resources

Approved: ____________________________________________
Ann L. Ardis, Ph.D.
Interim Vice Provost for Graduate and Professional Education
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ABSTRACT

Scientific-based water quality models are used in water quality trading programs to assess nutrient loadings. Maryland Nutrient Trading Tool (MDNTT) calculates loading reductions on a land use, land cover map of all fields in the Maryland and Delaware portion of the Chesapeake Bay Watershed for a host of potential best management practices (BMPs). However, uncertainty remains. This work hypothesizes that the BMP projects with largest overestimated abatement error would be supplied first into trading program, which is called as a “first-worst” selection.

An algorithm is developed to perform the simulation of abatement error and four alternative systematic selection mechanisms: “first-worst” selection, “first-best”, acreage targeting and benefits targeting. There are 100 treatments consisting of 10 possible levels of abatement heterogeneity and 10 possible levels of budget. The rule of prioritization of the four mechanisms is different. The outputs of the simulation experiment are the sum of error, the proportion of error of selected projects, and the predicted values of the percentage of error from nonlinear model estimation.

As for “first-worst” selection, the results show that there is a convex relationship between error and the budget ratio. Holding heterogeneity constant and in each level of heterogeneity, total error of selected projects will increase as the budget ratio increase from 10% to 50%, reaching the peak value, and then it will decrease as budget ratio continues to rise. Holding the budget constant, the error will experience an unstable growth as heterogeneity increases. The results offer an empirical estimate
of how best to vary trading ratios. When it comes to “first-best” selection, the results show that under the largest level of abatement heterogeneity and in a thin market, there is 50% more abatement than the estimates. This indicates that if policymakers can target those underestimated projects, they can expect more abatement than estimation with just a small amount of budget. However, trading cannot achieve the “first-best” solution due to the information asymmetry. The results of two targeting strategies show that benefit targeting can be regarded as a “second-best” solution.
Chapter 1

INTRODUCTION

Nonpoint source pollution is a leading cause of water quality problems in the U.S., and agricultural activities contribute a large share of nonpoint source nutrient emissions (Bonham et al., 2006). The Chesapeake Bay has endured a high level of nitrogen and phosphorus for decades. Nonpoint sources deliver 60 percent of the nitrogen reaching the Bay, with agricultural runoff being the largest single source (U.S. Environmental Protection Agency [U.S. EPA], n.d.). According to the Chesapeake Bay Program, 107.38 million lb of nitrogen in the Bay originated from agricultural activities in 2013, contributing 40 percent total basin nitrogen load\(^1\).

A Total Maximum Daily Load (TMDL) was established by the U.S. Environmental Protection Agency (U.S. EPA) on December 29, 2010, under the Clean Water Act. The TMDL sets the daily maximum amount of nitrogen, phosphorus, and sediment that can enter the Bay, and also specifies a loading cap for a seven jurisdictions (U.S. EPA, 2010, p. ES-3). In order to fulfill the nutrient reduction goals, EPA also recommends a water quality trading program (U.S. EPA, 2010, p. 10-3). Several state-specific trading programs in the Chesapeake Bay area have begun (Chesapeake Bay Commission, 2012), like the *Maryland Water Quality Trading*

\(^1\) This is calculated based on the data “2013_reducingpollution_031414final” from Chesapeake Bay Program, http://www.chesapeakebay.net/indicators/indicator/nitrogen_loads_and_river_flow_to_the_bay1.
Program and the Pennsylvania Nutrient Credit Trading Program (Horan and Shortle, 2005).

In order to determine credits from nonpoint source sellers, water quality models are used to assess loadings in certain watersheds. Modeling is needed because it is not possible to observe nonpoint pollutions at a reasonable cost (Shortle and Horan, 2013, p.114). Various modeling approaches are used, like Soil and Water Assessment Tool (SWAT) model (Rabotyagov et al., 2010; Feng et al., 2008), Watershed Assessment Model (WAM) (Corrales et al., 2014) and NTRADER models (Cox et al., 2013). Generally, these models estimate pollutant loadings based on physical characteristics of soil, the hydrogeological system, agricultural production, and pollution abatement activities (Corrales et al., 2014, p.163; Rabotyagov et al., 2010, p.416). In the Chesapeake Bay Watershed, a web-based tool, Chesapeake Bay Nutrient Trading Tool or so-called NutrientNet was developed for nutrient trading. NutrientNet estimates current loadings and loadings after BMP implemented on field level, and therefore the credits of nitrogen and phosphorous after inputting agronomic information and conservation practices via an online worksheet.

However, uncertainty remains even though the models are built on monitoring data, which has been calibrated and validated (Feng et al., 2008, p.185). Multiple factors may cause uncertainty. Shortle and Horan (2013) pointed out four main factors: “stochasticity of weather drivers”, like rainfall and temperature (Fisher-Vanden and Olmstead, 2014, p.159), is one of the major factors. The second factor is “imperfect information on production and pollution control practices” or “moral hazard” (Horan, 2001, p.396). This is true in our case, as farmers input their own crop management and BMP practices in Nutrient Net and monitoring of these practices is incomplete (Miller
and Duke 2013). The third factor is the “imperfect measurements of site characteristics”. Actual field tests are required for many inputs in Nutrient Net, like soil P, soil type, manure P and N concentration, moisture content, etc. However, there is no data about field’s characteristics tested on the spot used for Chesapeake Bay trading program. The fourth factor is that the true relationship between runoff reaching the Bay and the above three elements used for nutrient estimation is unknown. In other words, neither the true model functional form, nor the variables incorporated into the model are known perfectly, which leads to inevitable uncertainty. Except for modeling uncertainty, the BMP’s performance is also uncertain, due to heterogeneous “on-farm conditions” and “maintenance practices” (Wainger et al., 2013, p.216). In addition, there still may be “institutional uncertainty”, even though the estimation is correct (Fisher-Vanden and Olmstead, 2014, p.159).

Trading ratios have been regarded as the approach to deal with uncertainty in water quality trading (Nguyen et al., 2013, p.63). Adjusting for spatial variations is another role of trading ratio (Shortle and Horan, 2013, p.131). Moreover, Horan and Shortle (2005) argue that trading ratio should reflect the “relative marginal transaction cost” in trading (Horan and Shortle, 2005, p.341). However, a few key problems have not been addressed by trading ratios. The most important one is the determination of the value of trading ratios. A larger than one ratio is more often used in regulations, but the optimal trading ratio can be “greater or less than one” (Fisher-Vanden and Olmstead, 2013, p.160). Another problem about trading ratio is that the uniform trading ratio may have negative impacts on trading efficiency (Shortle, 2013, p.68). There are multiple types of trading ratios, in this research, the concept of trading ratio is more close to “uncertainty ratio” (Greenhalgh and Selman, 2012, p.114), which
specifies how many units of nutrient reductions from nonpoint sources can be traded as one credit. We will provide the actual estimates of this type of trading ratio in different market scenarios and for different errors of load estimation.

A few studies simulate uncertainty in nutrient trading models. First, when it comes to what has been simulated, two uncertain parameters in water quality models are studied the most: BMP efficiency and abatement cost. That is because the heterogeneity of BMP efficiency and abatement cost may bring about underlying errors in predicting nutrient loadings and so impede optimum trading. Second, two methods are commonly used in uncertainty simulation: Listing combinations of possible values of parameters and Monte Carlo simulation. Caplan and Sasaki (2014) assigned a probability for each possible estimate of BMP efficiency and abatement cost, and get nine combinations of the two parameters for all the fields inputted in the model. Obviously, it is not possible to list all the values of uncertain parameters, so Monte Carlo simulation has been used widely in research. In Caplan’s other research (Caplan et al., 2013), in order to solve the uncertainty of BMP effectiveness and per-acre cost of BMP, 5,000 draws are generated based on uniform and normal distribution with parameters including means, standard deviation and supports (p.374). Nguyen et al. (2012) also simulated buyer’s cost and seller’s cost in the market separately. They think that buyer’s marginal abatement cost follows Lorenz curve, and the parameter that controls the shape of the curve follows the uniform distribution. On the other hand, the seller’s per unit abatement cost is assumed to be uniform. In addition, Smith et al. (2012) generated costs and nutrient loadings for each trading participant, plants and farms, by randomly drawing from independent lognormal distributions. The draw is iterated for each scenario 10,000 times under different prices
and quantities, so that the results are not just based on any particular draws (p.165). Another example more like our method comes from the research of Rabityagov et al. (2013), which assessed first-best solution and three second-best approaches for nonpoint water pollution control under nonlinear emission aggregation. In order to simulate the heterogeneous abatement cost, they assumed that the cost of conservation practices for any farm would get the same shock, $\mu$. They firstly randomly draw 1,000 $\mu$ with distribution of $U [-0.8 0.8]$, and then “multiply the mean estimated cost by $(1+\mu)$”. Similarly, in our algorithm, we also have a parameter like the “shock”, while the intuition and the distribution we used are quite different from those of this research.

Duke et al. (2012) studied nonadditionality in performance-based nutrient trading program by innovatively simulating abatement error in different budget scenarios. The core ideas are that the estimates from NTT may be greater than or less than the actual abatement, and the “true” load reductions followed triangular distribution. The abatement errors of 78 fields are ordered from the lowest in figure 1. Based on the idea that those projects with error above zero trade first, their results show that there is 57% nonadditiationality error if 25% of possible reductions is traded.
Based on Duke’s research, we develop an algorithm to simulate abatement error based on real data and to perform systematic projects selections in the presence of ten levels of abatement heterogeneity and ten extents of market participation. First we investigate the total error and the proportion of error in various market scenarios in “first-worst” selection, and provide corresponding trading ratios based on predictions of error. Second, “first-best” selection is discussed. Then, we compare two targeting policies, “acreage targeting” and “benefit targeting”, with “first-best” and “first-worst” to see whether the two strategies can perform close to “first-best” selection or perform better than trading. This research extends Duke’s research from the following aspects:
first, there are 100 treatments or scenarios totally in the simulation; second, this paper also explores “first-best” solution; and third, we incorporate two targeting strategies to make a comparison. This research differs from the current literature from the following aspects.

1. We develop an algorithm of abatement error and give actual estimates of trading ratios using real field-level data.

2. The probability distribution used in current papers are uniform distribution, normal distribution, lognormal distribution, or kind of discrete triangular distribution with only three values, while our simulation of abatement is randomly draw from triangular distribution. There are three advantages of using triangular distribution. First, it can prevent infinite values which normal distribution may bring about. Second, it will avoid the potential bias from truncating negative values generated from normal distribution. Finally, we assume that the “true” abatement is more likely to be near the average values.

3. The current literature generates BMP effectiveness from random draw, but we can obtain it from Nutrient Net.

The rest of the thesis is organized as follows. Chapter two describes the procedures of systematic selection in detail, chapter three explains the simulation results of the four selection mechanisms, and chapter four offers conclusions.
Chapter 2

METHODOLOGY

2.1 Systematic Selection Mechanisms

When not all of the potential nonpoint source traders are allowed participate in trading program due limited budget—or when we would like to simulate the trading market where there are different numbers of suppliers—a selection mechanism is needed to choose the specific participants. Ideally, regulators want to target those projects with smallest abatement error or even those abatement is underestimated, this kind of selection can be called as “first-best” selection. However, in reality, performance-based trading program cannot target those projects that can produce more abatement than estimated because of asymmetric information. If behavior is systematic, then even worse nutrient trading may lead to a “first-worst” selection because of uncertainty. Our first key assumption is:

Assumption 1: the projects with largest error (i.e., “positive error” in this study), or whose estimated abatement larger than the true abatement will be selected first into trading program, because of corresponding larger incentive. We will explain this in detail.

As for the potential nutrient abatement sellers (e.g., farmers), the revenue of trading is an increasing function of estimated abatement, while abatement cost is an increasing function of “true” abatement. The larger profit means the larger incentive for farmers to participate in trading; furthermore, the largest profit may occur when
overestimation happens or in other words the estimated abatement exceeds “true” abatement.

Suppose two prospective participants have implemented the same type of BMP on their own fields, and the estimated abatement per-acre can be obtained from Nutrient Net. The revenue and cost curve are displayed in figure 2, and the slope of revenue is credit price. Participant A has estimated abatement at level $a'_1$, but the “true” abatement $a_1$ is lower than $a'_1$; participant B’s estimated abatement $a'_2$ equals to the “true” abatement $a_2$ also at level $a'_1$. The revenue of trading for the two participants are the same ($R_1=R_2$), but the cost are different, participant A’s cost is $C_1$ which is lower than participant B’s cost $C_2$. The profit of trading is the distance between revenue and cost, so the profit of participant A is larger than that of participant B, $\pi_1 > \pi_2$ in figure 1. As larger profit leads to larger incentive, A would participate in trading program first relative to the incentives facing B.

![Figure 2 Revenue, cost and profit of trading](image)

It is a rational generalization that the projects whose abatement is being overestimated participate in trading first due to uncertainty (Duke 2012). In our study,
we will fulfill the prioritization of participation through a programmed systematic selection.

The targeting methods also have been regarded as a way to prioritize participation in water quality programs, say, from a purchase of environmental services program. We will discuss two targeting strategies, acreage targeting and benefit targeting, to compare them with “first-worst” and “first-best” selection. Acreage targeting selects the fields with largest acreage, while benefit targeting prioritizes fields based on benefit (Duke et al., 2014), indicating nutrient abatement in this study. The prioritization of these two targeting methods is based on fields’ feature and estimations of nutrient rather than abatement error, so we will provide the simulation of error they may bring about. We explore whether trading or the two targeting strategies are more close to “first-best” selection. Actually, targeting methods are not restricted to the above two; cost targeting and benefit-cost ratio targeting are also discussed (Duke et al., 2014). However, in our study, we will not discuss the latter two, because the abatement cost is unknown in our case.

Overall, this paper will discuss four alternative systematic selection mechanisms. Firstly, “first-worst” selection is simulated and actual estimates of trading ratios are displayed in different market scenarios; then “first-best” selection is discussed; next, acreage targeting and benefit targeting are simulated as comparison.

2.2 Systematic Selection Algorithm

Generally, the systematic selection includes two major steps: abatement error simulation and project selection. In abatement error simulation, Monte Carlo draws are applied to simulate “true” abatement and abatement error under ten levels of
heterogeneity, representing a range of ten levels of uncertainty. Here, we have our second key assumption:

Assumption 2: “true” abatement follows triangular distribution, based on the idea that the estimated abatement are more likely to be correct. We will randomly generate “true” abatement for a certain type of BMP, with a new heterogeneity assigned to all fields for each time of iteration. For simplicity, a symmetric triangular distribution is used. The triangular distribution has three parameters, the minimum value $a$, the maximum value $b$, and the peak value $c$ (figure 3), often the peak value is the mode or mean value of the sample. With the probability density function formula listed below and pre-defined three parameters, we can generate random numbers following triangular distribution.

$$f(x) = \begin{cases} \frac{2(x-a)}{(b-a)(c-a)} & a \leq x \leq c \\ \frac{2(b-x)}{(b-a)(b-c)} & c < x \leq b \end{cases}$$ (1)

![Figure 3 Triangular distribution]

Then, project selection is performed at ten levels of market scenarios, where 10%, 20%, …, 100% of total abatement is traded, for each draw of error under all ten levels of heterogeneity. Specifically, if we create ten different error levels under each
level of heterogeneity, we have 100 possible values of error for each field. After selecting projects ten times, we have 1,000 values of total error of selected projects.

All of the four alternative selection mechanisms follow the same procedures, except that the rule of prioritization is different. The projects with largest error (smallest error) would be selected first in “first-worst” selection (“first-best” selection), while acreage targeting and benefit targeting prioritize fields with largest acreage and benefit, respectively. The Algorithm was performed with SAS (Statistical Analysis System) 9.3, and for each selection mechanism, it took about 1 minute to run the program.

2.2.1 Abatement Error Simulation

(1) Determine parameters of triangular distribution

In our data, there are total 141 potential nonpoint source participants, with the same type of BMP implemented on all fields. The estimated per-acre abatement $antt_m$ obtained from Nutrient Net is given by:

$$antt_m = \frac{LC_m - LBMP_m}{S_m}$$

where $LC_m$ is the current nutrient loading on m field, $LBMP_m$ is the loading after BMP implemented, $S_m$ is fields’ acreage (see table 1 for the description of notations of variables). These data were obtained from Nutrient Net.
### Table 1 Description of notations of variables

<table>
<thead>
<tr>
<th>Simulation Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{m}$</td>
<td>Estimated per-acre abatement obtained from Nutrient Net on field m</td>
</tr>
<tr>
<td>$a_{true}^{m}$</td>
<td>&quot;True&quot; abatement generated from triangular distribution on field m</td>
</tr>
<tr>
<td>$L_{C}^{m}$</td>
<td>Current nutrient loading on field m</td>
</tr>
<tr>
<td>$L_{BMP}^{m}$</td>
<td>Loading after BMP implemented on field m</td>
</tr>
<tr>
<td>$S_{m}$</td>
<td>Acreage of field m</td>
</tr>
<tr>
<td>$\sigma_{k}$</td>
<td>Heterogeneity, defining triangular distribution parameter, a measure of uncertainty</td>
</tr>
<tr>
<td>$r_{j}$</td>
<td>Budget ratio or market share</td>
</tr>
<tr>
<td>$z_{k}^{m}$</td>
<td>The $t^{th}$ random number generated from triangular distribution for each field m under each $\sigma_{k}$</td>
</tr>
<tr>
<td>$e_{k}^{m}$</td>
<td>The $t^{th}$ abatement error on field m under each $\sigma_{k}$</td>
</tr>
<tr>
<td>$A$</td>
<td>A constant number represents total nutrient abatement of 141 fields</td>
</tr>
<tr>
<td>$R_{k,j}^{p}$</td>
<td>Rank operator for $p^{th}$ field give the $t^{th}$ draw of error, at $k^{th}$ heterogeneity and $j^{th}$ budget ratio</td>
</tr>
<tr>
<td>$TE_{k,j}$</td>
<td>Total error of selected projects at $k^{th}$ heterogeneity and $j^{th}$ budget ratio</td>
</tr>
<tr>
<td>$PE_{k,j}$</td>
<td>The proportion of error of selected projects at $k^{th}$ heterogeneity and $j^{th}$ budget ratio</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Regression Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Terror$</td>
<td>Dependent variable, total error (1000lbs) of selected projects.</td>
</tr>
<tr>
<td>$Perror$</td>
<td>Dependent variable, the proportion of error (Error/Budget) of selected projects.</td>
</tr>
<tr>
<td>heter</td>
<td>Independent variable, representing heterogeneity.</td>
</tr>
<tr>
<td>heter2</td>
<td>Independent variable, representing the quadratic term of heterogeneity.</td>
</tr>
<tr>
<td>ratio</td>
<td>Independent variable, representing budget ratio.</td>
</tr>
<tr>
<td>ratio2</td>
<td>Independent variable, representing the quadratic term of budget ratio.</td>
</tr>
<tr>
<td>heter_ratio</td>
<td>Independent variable, representing the interaction term between heterogeneity and budget ratio.</td>
</tr>
</tbody>
</table>

In order to make sure that all fields achieve the same level of uncertainty, which means the same triangular distribution is used for each time of generation for all fields, we use a variable $\sigma_{k} \in [0.1,1]$, reflecting heterogeneity, to determine the parameters of triangular distribution. $\sigma_{k}$ will be selected by every 0.1 increment each time, such as $\sigma_{1}=0.1$, $\sigma_{2}=0.2$, $\sigma_{3}=0.3$,..., $\sigma_{10}=1.0$, so we have ten heterogeneity
treatments. The parameters of the symmetric triangular distribution are: minimum value $= -\sigma_k$, maximum value $b = \sigma_k$, and mean value equals to zero. So, the range of heterogeneity is $[-\sigma_k, \sigma_k]$. Specifically, $\sigma_k = 0$ indicates that there is no heterogeneity or no uncertainty, and as $\sigma_k$ increases, the heterogeneity becomes larger.

(2) Generation of random numbers

After defining the distribution, a standard deviation is needed next, so Monte Carlo draws are applied here. For all 141 fields, under each level of heterogeneity, a standard deviation is generated ten times based on the triangular distribution, so we have a random number $z_{ktm} \in [-\sigma_k, \sigma_k]$, representing the $t^{th}$ random number draw for the $m^{th}$ field at $\sigma_k$.

(3) Calculation of abatement error

With the random number $z_{ktm}$, we can get the $t^{th}$ “true” abatement $a_{true_{ktm}}$ for each field $m$ under a certain level of heterogeneity $\sigma_k$:

$$a_{true_{ktm}} = antt_{ktm}(z_{ktm} + 1)$$  \(3\)

So $a_{true_{ktm}} \in [0, antt_{ktm}] \forall \sigma_k$, which means that the largest range of “true” abatement is from zero and two times of estimated abatement. According to the definition that error is the difference between estimated abatement and “true” abatement, we have abatement error $e_{lm}$ represented as:

$$e_{ktm} = antt_{ktm} - a_{true_{ktm}} = -antt_{ktm}z_{ktm}$$  \(4\)

If abatement is overestimated, the error will be positive. If abatement is underestimated, the error will be negative.

2.2.2 Project Selection

(1) Determine the budget
First, we get the total estimated abatement \( A = \sum_{m=1}^{141} antt_m \), which is a constant value because the number of fields is certain. So the budget is given by

\[
A \cdot r_j,
\]

where \( r_j = 0.1, 0.2, \ldots, 1 \) represents the \( j^{th} \) budget ratio or market share. This is our second treatment variable, also there are ten levels. The concept of budget here is not exactly the same with its meaning in a purchase of environmental services program. We use budget to indicate scenarios where different percentage of abatement is traded. All projects represent 100% of the budget and 100% of the possible abatement.

(2) Systematic selection

As mentioned above, the rule of selection of the four alternative strategies is different. Here, we use “first-worst” selection as an example to illustrate the detailed procedures of selection. The rule of “first-worst” selection is that the projects with largest error are selected first until budget exhausted. The reminder of budget is accounted into the money spent on the last selected project. The number of selected projects is determined by budget.

First, we assign rank operators to all fields under each ten levels of heterogeneity. All fields are ranked by the descending order of error \( e_{ktm} \), and the field with the highest \( e_{ktm} \) receives a rank of 1, etc. (Duke, 2014). Let \( R_{k,j^th} = R(e_{1111}, e_{1112}, \ldots, e_{1110p}) \) represents the rank operator for the \( p^{th} \) field given the \( t^{th} \) draw of error, at \( k^{th} \) heterogeneity and \( j^{th} \) budget ratio. As there are ten draws of error, so all the fields are assigned ten sets of rank operators under 10 levels of heterogeneity. Then, we begin the first selection according to the rank defined by first draw given \( \sigma_k = 0.1 \) and \( r_j = 0.1 \), and record the sum of error of selected projects, and the proportion of error over budget. Then, we perform the selection to the next set of rank
given $\sigma_k = 0.1$ and $\tau_j = 0.1$ until finish ten times selection, and move on to the next set of treatment of heterogeneity and budget ratio. The iteration continues for all 100 treatments. In the end, we get the average of the ten summation of total error (lbs), and the average of ten proportions for each set of heterogeneity and budget ratio. So in the final dataset, there are four variables, heterogeneity $\sigma_k$, budget ratio $\tau_j$, total error of selected projects $TE_{kj}$, and the proportion of error of selected projects $PE_{kj}$.

Mathematically, the functions of total error $TE_{kj}$ and the proportion of error $PE_{kj}$ can be expressed as:

\[
TE_{kj} = f(k, j, i, t) = \frac{1}{10} \times \sum_{t=1}^{10} \sum_{i=1}^{p} e_{kjilt}, \quad k = 1, 2, ..., 10, \quad j = 1, 2, ..., 10
\]  
\[
PE_{kj} = \frac{f(k, j, i, t)}{A \cdot r_j}
\]

s.t. $A \cdot r_j \geq \sum_{p=1}^{n} \text{antt}_i, \quad j = 1, 2, ..., 10, n \leq 141$

\[
A = \sum_{m=1}^{141} \text{antt}_m
\]

where $TE_{kj}$ and $PE_{kj}$ are the total error (lbs), and proportion of error of selected projects for a given level of heterogeneity and budget ratio; $A$ is the total estimated reductions(lbs), which is a constant. From the constraint function, we can get the value of $p$ given a certain $j$, so that we know how many and which projects are selected; from function 6, we can get the average of total $p$ error, given a certain $k$ and $j$. Results are derived by the above functions, and outputs include two-dimensional plots, surface plots, and regressions which are built with the four variables in the final dataset.

### 2.3 Hypotheses

We have four hypotheses regarding to “first-worst” selection:

First, as $\sigma_k$ increases, $TE_{kj}$ will increase holding budget ratio constant, which means that higher heterogeneity will lead to higher error, mathematically expressed as:

\[
H_0^j: \frac{\partial TE_{kj}}{\partial \sigma_k} > 0.
\]
Second, as $r_j$ increases, $TE_{kj}$ will increase first and then goes down beyond a point, and reach at zero when $r_j = 1$, holding heterogeneity constant, because the positive error and negative error would be cancelled out, mathematically expressed as:

$$H_0^2: \left\{ \frac{\partial TE_{kj}}{\partial r_j} > 0 \quad \text{and} \quad \frac{\partial^2 TE_{kj}}{\partial r_j^2} < 0, \quad 0.1 \leq r_j < r_j^* \right\}$$

$$H_0^2: \left\{ \frac{\partial TE_{kj}}{\partial r_j} < 0 \quad \text{and} \quad \frac{\partial^2 TE_{kj}}{\partial r_j^2} > 0, \quad r_j^* \leq r_j \leq 1 \right\}$$

Third, as $\sigma_k$ increases, $PE_{kj}$ will increase holding budget ratio constant, which means that higher heterogeneity will lead to higher proportion of error, mathematically expressed as:

$$H_0^3: \frac{\partial PE_{kj}}{\partial \sigma_k} > 0.$$

Forth, as $r_j$ increases, $PE_{kj}$ will decrease holding heterogeneity constant, which means the proportion of error will decrease as market gets thicker, mathematically expressed as:

$$H_0^4: \frac{\partial PE_{kj}}{\partial r_j} < 0.$$

The confirmation of the above hypotheses will testify that the performance-based incentive approach still cannot solve the nonadditionality problem due to the asymmetric information of nonpoint sources.

### 2.4 Data

The population of interest is corn fields in Kent County and Sussex County in Delaware within Chesapeake Bay boundaries. According to the 2012 Census report (U.S. Department of Agriculture, 2012), the total croplands of the two counties are 147,402 acres, standing for 87.23% croplands in Delaware. Specifically, the area of Kent County is about 375,246 acres, with 39.28% cropland; and the area of Sussex County is 599,089 acres with cropland accounting for 39.34%. The area within the Bay watershed, however, is smaller.
2.4.1 Parcel Sample Selection

A geo-spatial method was used to create parcel sample with the application of QGIS, an open source Geographic Information System. Several GIS layers were added in QGIS, including a Delaware crop layer, Delaware watershed layer, County tax parcel layers, stream layer, roads layer, and zip-code layer. Some of the GIS layers are obtained from National Agriculture Statistics Service (2012), State of Delaware (2012), the Delaware Department of Transportation (2014), Sussex County Mapping and Addressing Department (2007) and U.S. Census Bureau (2010). One GIS layer of Kent tax parcels was obtained by lab member’s personal contact with professor in Water Resources Agency in University of Delaware. First, the raster crop layer was converted to vector layer, so that different types of crops can be extracted into separate strata. Then, only the corn polygons within Bay boundaries were kept to make sure the parcels were exclusively from the two counties within Bay area. The acreage of population of interests is 34,459 hectares. Next, 200 points were randomly scattered on the corn polygons in Kent County, and 250 points were randomly draw in Sussex County using the inherent tool in QGIS, respectively. There were several types of unused points. If more than one point located in one polygon, the points with larger ID were deleted. Further, the points located in small polygons, like one to five pixels, were also removed. In the end, there are 96 usable points in Kent County, and 174 usable points recorded in Sussex County. Further, 144 points, 72 in Kent and 72 in Sussex were randomly selected, so 144 parcels containing the 144 points were extracted as our research sample (figure 5). The total area is 3,555.06 hectares and 5,752.08 hectares in Kent and Sussex County, respectively.
2.4.2 Nutrient Related Data Collection

After determining sample parcels, the next step was to get nutrient related data from Nutrient Net. Based on zip code we navigated the location of each parcel roughly, and then delineated the parcel boundary and field boundary within it by hand looking at the field from a satellite map according to the GIS layer. Multiple fields were connected as one field in a parcel, because according to the application design, there should be one field in one parcel.

Next, agronomic and BMP information were inputted into Nutrient Net, like general field information, field and soil characteristics, and crop management practices. Specifically, general information included crop type and whether field was adjacent to stream or water body, which could be identified from GIS map. In the Soil
module, tillage type, irrigation situation, and soil test data were required to input. In the Current Crop Management Module, requisition of inputs were basic crop information (e.g., crop planting date, planting method), manure fertilizer applications (e.g., application date, manure type, consistency, total N concentration, P concentration, application rate, moisture content, incorporation date and incorporation depth), and harvest type and date. In the module of Future Crop Management, all of the set ups were the same with Current Crop Management.

We assumed that no BMP is implemented currently on the fields, and the BMP applied would be Land Use Conversion, where 25% of area would be converted to forest. After inputting this information, Nutrient Net displayed the estimates of nitrogen and phosphorus emissions for each field, including baseline load, current load, future load, reductions, delivery ratio, and reductions to the Chesapeake Bay. Three fields were removed because of negative reduction, which suggested an error in the model, so there were 141 fields (3,598.50 hectares) in final sample. The sample area covers about 15% of population area. This is an approximation because the area of population is recorded from GIS layer of 2007, while the sample area is recorded from Nutrient Net, so two different statistical sources may lead to statistical error.
Chapter 3

RESULTS

3.1 “First-worst” Selection

The experiment produces observations on four variables: heterogeneity, budget ratio, total error (lbs) of selected projects and the proportion of error (error/budget) of selected projects. The results are first presented graphically in a three dimensional relationship. The surface plot in figure 5 shows the relationship between total error (lbs), heterogeneity and budget ratio.

The plot suggests a concave relationship between error and the budget ratio. For instance, holding heterogeneity constant and in each level of heterogeneity, total error of selected projects will increase as the budget ratio increase from 10% to 50%, reaching the peak value, and then it will decrease as budget ratio continues to rise. Because as more and more projects with negative error enter into the market, overall the positive error and negative error in the market will be canceled out. Moreover, as heterogeneity increases, the slope of the convex surface gets steeper, and the peak value of error also increases progressively. On the other hand, holding the budget constant, the error will experience an unstable growth as heterogeneity increases. The reason is that larger uncertainty will lead to larger positive error. But the peak values vary corresponding to the ratio.

Figure 6 shows the relationship between the proportion of error and the other two variables. Generally, the proportion of error will constantly increase as
heterogeneity increase, while the increasing rate will diminish as budget ratio gets larger. By contrast, the proportion of error will continuously decrease as budget ratio increases, and will decrease more rapidly under a larger level of heterogeneity.

Figure 5 Total error (lbs) in “first-worst” selection

Figure 6 The proportion of error in “first-worst” selection

Next, we will construct regressions to examine the exact relationships among the three variables. We built two regressions with same independent variables but different dependent variables. In the first regression, the dependent variable is error (1,000 lbs). In the second regression, the dependent variable is the proportion of error. The independent variables include heterogeneity, budget ratio, the quadratic terms of
heterogeneity and budget ratio, and the interaction term of heterogeneity and budget ratio. The theoretical models are as follows:

\[
\text{Error} = a_{10} + a_{11} \cdot \text{Heterogeneity} + a_{12} \cdot \text{Heterogeneity}^2 + a_{13} \cdot \text{Ratio} \\
+ a_{14} \cdot \text{Ratio}^2 + a_{15} \cdot \text{Heterogeneity}_\text{Ratio} + e_{11}; \quad (9)
\]

\[
\text{Perror} = a_{20} + a_{21} \cdot \text{Heterogeneity} + a_{22} \cdot \text{Heterogeneity}^2 + a_{23} \cdot \text{Ratio} \\
+ a_{24} \cdot \text{Ratio}^2 + a_{25} \cdot \text{Heterogeneity}_\text{Ratio} + e_{22}; \quad (10)
\]

where Error is the total error divided by 1,000, Perror is the proportion of error.

Table 2 presents the coefficients of estimate with heteroscedasticity-consistent standard errors.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Error(1000lbs)</th>
<th>Error/budget</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Parameter</td>
<td>Standard Error</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.19051***</td>
<td>0.01840</td>
</tr>
<tr>
<td>heter</td>
<td>0.43698***</td>
<td>0.04912</td>
</tr>
<tr>
<td>heter2</td>
<td>-0.13507***</td>
<td>0.03999</td>
</tr>
<tr>
<td>ratio</td>
<td>0.83516***</td>
<td>0.04912</td>
</tr>
<tr>
<td>ratio2</td>
<td>-0.73428***</td>
<td>0.03999</td>
</tr>
<tr>
<td>heter_ratio</td>
<td>-0.21066***</td>
<td>0.03522</td>
</tr>
<tr>
<td>R^2</td>
<td>0.88</td>
<td>0.99</td>
</tr>
<tr>
<td>N</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

From the R-squared, we know that both of the models fit well. In the first regression, all of the independent variables are significant, while in the second regression, Ratio and Ratio^2 are not significant. There is a significant interaction between heterogeneity and budget ratio. Since there are quadratic and interaction terms in the model, the explanation of coefficients will not be straightforward as linear model. We will examine the relationship by viewing the predicted values of dependent variables from model estimation with confidence intervals in figure 7. Here the proportion of error is converted to percentage of error by multiplying 100%.
Note: The confidence intervals in this plot are the confidence intervals for the parameter from regression or for a given value of budget ratio in this case. The range between the point on the line and upper bound/lower bound represents the margin of error, which can be produced by SAS 9.3. The confidence level is 95%.

Figure 7 Prediction of percentage of error (%) in “first-worst” selection

In Figure 7, the vertical axis is the percentage of error (%), and the horizontal axis is budget ratio. The three lines show how the percentage of error would change as budget ratio increases, given a certain level of heterogeneity. The red line has the smallest heterogeneity (0.1), while the yellow line has the largest heterogeneity (1.0). The green line in the middle has the heterogeneity of 0.55, which is the mean of heterogeneity.

When both heterogeneity and budget ratio equal to 0.1, the largest percentage of error is about 5%. As budget ratio increase, which means more and more suppliers enter into the market, the percentage of error decrease slightly, and reach at 0 if all of the projects are in the market. Holding budget ratio constant at 0.1, we can see that the
increase of percentage of error stems from the increase of heterogeneity. At the largest level of heterogeneity, we will have 44.52% of error out of total estimation in the market, which is also the potential largest percentage under all scenarios. As budget ratio increases, the percentage is decreasing because of the offset of positive and negative error. However, the percentage of error is not reaching at 0 when budget ratio is 1. One of the reasons may be that in our simulation, we only do ten draws, so the randomness is not smoothed thoroughly.

With the predictions of percentage error, one gains information about the value of compensating trading ratios. In the extreme case, the trading ratio can be set up at 1.45. So in a similar way, we can deduct every trading ratio along the three lines in the figure. Thus, for policy makers, given the information of the market and an estimation of the uncertainty, they can pick a compensating trading ratio based on figure 7 to deal with the error in trading market.

3.2 “First-best” Selection

The “first-worst” results are comparable to optimal or “first-best” selection. An important feature of “first-best” is that it can be treated as a targeting policy, meaning that projects are selected that produce more “true” abatement than the estimation suggests.
Figure 8 Total error (lbs) in “first-best” selection

Figure 9 The proportion of error in “first-worst” selection

Figure 8 shows the relationship among total error in the market (lbs), heterogeneity and budget ratio. We can see that the surface plot is the inverse of the plot in “first-worst” selection. Specifically, as heterogeneity increases, the absolute value of total error would also increase; however, the error is negative, indicating that “true” abatement is larger than the estimated abatement. This is because projects with smallest error or negative error would be selected first in the “first-best” selection.
Second, as budget ratio increases, there is increasing negative error; however, then the negative error shrinks as half of budget being used and finally turns into positive error. The reason is that in the initial stage, only projects with negative error are chosen into trading program and the later participations bring more error than previous projects.

As with the “first-worst” selection, two nonlinear regressions are run. We also display the predictions of percentage of error.

Table 3 The estimations on error and error/budget in “first-best” selection

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Error(1000lbs)</th>
<th>Error/budget</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Parameter Estimate</td>
<td>Standard Error</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.13781***</td>
<td>0.02434</td>
</tr>
<tr>
<td>heter</td>
<td>-0.19127***</td>
<td>0.05742</td>
</tr>
<tr>
<td>heter2</td>
<td>-0.08883*</td>
<td>0.04858</td>
</tr>
<tr>
<td>ratio</td>
<td>-0.77471***</td>
<td>0.06138</td>
</tr>
<tr>
<td>ratio2</td>
<td>0.73068***</td>
<td>0.05432</td>
</tr>
<tr>
<td>heter_ratio</td>
<td>0.05698</td>
<td>0.05500</td>
</tr>
<tr>
<td>R²</td>
<td>0.90</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>

Note: The confidence intervals in this plot are the confidence intervals for the
parameter from regression or for a given value of budget ratio in this case. The range between the point on the line and upper bound/lower bound represents the margin of error, which can be produced by SAS 9.3. The confidence level is 95%.

Figure 10 Prediction of percentage of error (%) in “first-best” selection

Compared to “first-worst” selection, we have negative error in the market in “first-best” selection. As budget ratio increases, the error is increasing, which is contrary to the trend in “first-worst” selection. Especially when heterogeneity is the largest, there will be 50% more abatement even if only 10% of abatement is traded in the market. We can make a conclusion that, if we are able to target projects, even uncertainty is large, we will have much more abatement than the expected just with a small expense or in a thin market. However, nutrient trading cannot reach at this ideal situation, as no one knows the “true” abatement information of projects.

3.3 Comparison with Targeting Strategies

We already know that the nutrient trading cannot achieve “first-best” solution in practice (at least without additional monitoring costs). However, the results are suggestive of further research: Are there any strategies close to “first-best” selection? How will these strategies perform under uncertainty? We will investigate two targeting methods: acreage targeting and benefit targeting.

First, we examine two-dimensional plots showing the relationship between the proportion of error and heterogeneity. In each of the following plot, there are ten points representing ten times of error draws at each level of heterogeneity. In acreage targeting (figure 11), generally, as heterogeneity increases, the range of error proportion would expand randomly. In benefit targeting (figure 12), when heterogeneity belongs to [0.1, 0.4], the proportion of error are around zero, and when heterogeneity equals to 0.5, the proportion of error reaches at largest value. But as
heterogeneity larger than 0.5, similar to “first-best” selection (figure 14), there is negative error, which means that the “true” abatement is larger than estimated results from Nutrient Net.

From this point of view, benefit targeting performs better than acreage targeting, because the results of benefit targeting is less random than those of acreage targeting. Furthermore, as the plots show, when heterogeneity is large, from 0.7 to 1, benefit targeting can produce more abatement than the estimation or have larger negative error than acreage targeting can do, which is similar to “first-best” selection.

Figure 11 Scatter plot of error/budget and heterogeneity in acreage targeting

Figure 12 Scatter plot of error/budget and heterogeneity in benefit targeting
Next, we will check the relationship between the proportion of error and budget ratio. First, for acreage targeting (figure 15), the smallest budget ratio may lead to largest range of error. Second, the range of error would be rather steady even when budget are increasing, so the budget ratio or the market thickness may not have a significant effects on the error in acreage targeting. By contrast, in benefit targeting, the range of error is quite large under small budget ratios, while when budget ratio exceeds 0.6, the range of error does not change much as budget ratio increases.
Thus, in this model, acreage targeting is more likely to produce larger error because the error will not be affected by budget. Benefit targeting produces small error when budget ratio is large.

Figure 15 Scatter plot of error/budget and budget ratio in acreage targeting

Figure 16 Scatter plot of error/budget and budget ratio in benefit targeting
Second, the surface plots for acreage targeting and benefit targeting in figures 19 and 20 show that there is no regular and clear pattern of the three-dimensional relationship in acreage targeting. For benefit targeting (figure 21 and figure 22), as heterogeneity increases, the total error (lbs) and proportion of error will both increase first and then go down.
Figure 19 Total error (lbs) in acreage targeting

Figure 20 The proportion of error in acreage targeting

Figure 21 Total error (lbs) in benefit targeting
Similarly, we construct regressions to examine the exact relationship among the proportion of error, heterogeneity and budget ratio.

Table 4 The estimations on error/budget in acreage targeting and benefit targeting

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Acreage targeting</th>
<th>Benefit targeting</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Parameter Estimate</td>
<td>Standard Error</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.00700</td>
<td>0.00537</td>
</tr>
<tr>
<td>heter</td>
<td>0.05524***</td>
<td>0.01599</td>
</tr>
<tr>
<td>heter2</td>
<td>-0.07635***</td>
<td>0.01381</td>
</tr>
<tr>
<td>ratio</td>
<td>0.00822**</td>
<td>0.02073</td>
</tr>
<tr>
<td>ratio2</td>
<td>-0.00545</td>
<td>0.01905</td>
</tr>
<tr>
<td>heter_ratio</td>
<td>-0.00790</td>
<td>0.01657</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.48</td>
<td>0.71</td>
</tr>
<tr>
<td>N</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

From the table, the model of acreage targeting does not fit well because the $R^2$-squared is just 0.48 and only heterogeneity and the quadratic term of heterogeneity are significant. The result is consistent with the pattern observed in the graphs. The regression of benefit targeting performs better, but still not as good as the models of “first-best” selection. We also display the predicted values of regression for acreage targeting and benefit targeting. As for acreage targeting, although the mean of the percentage of error is small, the large range of confidence interval indicates acreage
targeting may lead to more random results. When it comes to benefit targeting, we can see that if heterogeneity equals to 0.1, the percentage of error would decrease as budget ratio increases; while when heterogeneity belongs to [0.5, 1], the error would increase as budget ratio increases. However, even though the error is increasing, the largest percentage of error is just -3.81%, which means there are still more abatement than the estimation.

![Graph showing percentage of error in acreage targeting](image)

**Note:** The confidence intervals in this plot are the confidence intervals for the parameter from regression or for a given value of budget ratio in this case. The range between the point on the line and upper bound/lower bound represents the margin of error, which can be produced by SAS 9.3. The confidence level is 95%.

**Figure 23** Prediction of percentage of error (%) in acreage targeting
Note: The confidence intervals in this plot are the confidence intervals for the parameter from regression or for a given value of budget ratio in this case. The range between the point on the line and upper bound/lower bound represents the margin of error, which can be produced by SAS 9.3. The confidence level is 95%.

Figure 24 Prediction of Percentage of Error (%) in benefit targeting

From the above analysis, we can make a conclusion that benefit targeting performs better than acreage targeting in terms of error they may bring about and can be called as a next-best approximation. There are two reasons: (1) the results for acreage targeting are rather random, it is hard for researchers or policy makers to estimate or to control; and (2) acreage targeting is more likely to produce larger error, while benefit targeting produces small error or even “negative error”. With this selection, it is possible to produce positive error, the potential largest is less than 5%. So in this view, we can see that benefit targeting can be the next-best solution amongst the available options studied in this thesis. However, this result is under the constraint that the trading market is not mature enough and the abatement cost of potential participates is unknown.
Chapter 4

CONCLUSION

This study simulates systematic projects selection over an experimental design of 10 possible levels of abatement heterogeneity and 10 possible levels of budget or extent of market participation in performance-based nutrient trading program. The predicted percentages of error in total abatement are displayed in different scenarios, and the potential largest trading ratio is estimated. Besides, this research also introduces “first-best” selection mechanism, and evaluates the performance of two targeting strategies, acreage targeting and benefits targeting.

We find that in performance-based trading program, the largest potential percentage of error is 45.2%, assuming the scenario where 10% of total reductions are traded and the greatest level of abatement heterogeneity is presented. A trading ratio of 1.45:1 can be set up to offset the error. Our predictions provide a way to determine the values of trading ratio under different uncertainty and various market scenarios for policymakers. As long as policymakers have the following two types of information: the expectation of the level of uncertainty, and the amount of budget or the extent of market participation, they can pick up a trading ratio to offset the error in trading program.

Compared to the “first-worst” situation of trading, “first-best” selection is also simulated. The results show that under the largest level of abatement heterogeneity, and even only 10% of reductions are traded, there is 50% more abatement than the
estimates in the market. This means that if policymakers can target the projects whose abatement is underestimated, there will be more abatement even with a small amount of money or in a thin market. However, in practice the trading cannot achieve “first-best” solution due to asymmetric information.

Compared with “first-worst” and “first-best” selection strategies, benefit targeting can be a second-best solution with constraints in our study. The reasons are first, the results of acreage targeting are rather random, which is not easy to be estimated or to be controlled; secondly, benefit targeting is more likely to produce “negative error”, which is similar to “first-best” selection. Thus, in the cases where trading market is not mature enough, in addition that abatement cost of potential participants is unknown, benefit targeting is recommended to be adopted in order to avoid the nonadditional error.

Two of the most innovative contributions of this research are: first, systematic selection is simulated for four alternative strategies with the experimental design of 100 treatments; secondly, actual values of trading ratios are predicted under various scenarios of uncertainty and market thickness. As mentioned in literature review, there are multiple factors causing uncertainty. This study just simulates one of the factors, the uncertainty of estimation. So the trading ratios we give are actually “uncertainty ratios”, which account for the possible difference of estimation and “true” abatement. Further study is needed if more elements of uncertainty are desired to be simulated.
REFERENCES


   http://www.epa.gov/oaqps001/gr8water/xbrochure/chesapea.html