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Key Point:

- Allowing trading reduces the total costs of complying with the Clean Water Act

Supporting Information:

- Readme
- Trading-ratios vs. one-for-one trading
- Description of the genetic algorithm used
- Characteristics of WWTPs

Correspondence to:
M. W. Doyle,
martin.doyle@duke.edu

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Optimizing the scale of markets for water quality trading

Martin W. Doyle[1], Lauren A. Patterson[2], Yanyou Chen[3], Kurt E. Schnier[4], and Andrew J. Yates[5]

[1]Nicholas School of the Environment, Duke University, Durham, North Carolina, USA, [2]Nicholas Institute for Environmental Policy Solutions, Durham, North Carolina, USA, [3]Department of Economics, Duke University, Durham, North Carolina, USA, [4]Department of Economics, University of California, Merced, California, USA, [5]Department of Economics and Curriculum for the Environment and Ecology, University of North Carolina, Chapel Hill, North Carolina, USA

Abstract Applying market approaches to environmental regulations requires establishing a spatial scale for trading. Spatially large markets usually increase opportunities for abatement cost savings but increase the potential for pollution damages (hot spots), vice versa for spatially small markets. We develop a coupled hydrologic-economic modeling approach for application to point source emissions trading by a large number of sources and apply this approach to the wastewater treatment plants (WWTPs) within the watershed of the second largest estuary in the U.S. We consider two different administrative structures that govern the trade of emission permits: one-for-one trading (the number of permits required for each unit of emission is the same for every WWTP) and trading ratios (the number of permits required for each unit of emissions varies across WWTP). Results show that water quality regulators should allow trading to occur at the river basin scale as an appropriate first-step policy, as is being done in a limited number of cases via compliance associations. Larger spatial scales may be needed under conditions of increased abatement costs. The optimal scale of the market is generally the same regardless of whether one-for-one trading or trading ratios are employed.

1. Introduction

1.1. Scale of Environmental Markets

The use of market-like mechanisms in environmental regulation (hereafter "environmental markets") is now well established, and environmental markets span atmospheric emissions, fishing quotas, endangered species habitat, and aquatic ecosystems [*Boyd et al.*, 2003]. Yet there is great variability in how such markets are implemented, particularly in the spatial scale over which these markets are allowed to operate. For example, the SO_2 market—originally designed to consist of two spatial areas of trades—became a single conterminous U.S. market [*Burtraw et al.* 2005], and aquatic ecosystem service markets adopt a range of watershed scales [*Womble and Doyle*, 2012]. Setting a spatial scale is a decision that must be made a priori in establishing an environmental market, and thus is a key policy decision.

The scale of an environmental market can be thought of as being defined by the number of trading areas (zones) within a larger market domain. As the spatial scale of the market increases, the number of zones decreases, and correspondingly the number of pollution sources in a given zone increases. For any environmental market, there exists an optimal scale that reflects the trade-off between two competing factors. On one hand, increasing the scale of the market usually decreases the cost to the market participants of complying with pollution reduction simply by increasing the number of trading options. On the other hand, increasing the scale of the market opens the possibility of increases in environmental damages through the resulting spatial pattern of emissions; one large zone allows trades to potentially concentrate pollution into a particular area, i.e., a pollution hot spot [*Boyd et al.*, 2003]. The notable exception, however, is the set of pollutants whose effects are not spatially dependent, e.g., chlorofluorocarbons and greenhouse gasses such as CO_2 that are uniformly mixed in the atmosphere. In such cases, the optimal-scale problem is trivial, as there are no hot spots, and so there should only be one trading zone.

There is a growing interest in determining the optimal scale of environmental markets [e.g., *Williams*, 2003; *Krysiak and Schweitzer*, 2010; *Yates et al.*, 2013]. These papers discuss and utilize theoretical models to examine the trade-off between compliance costs and hot spots. However, there are two critical gaps in this literature. First, there is little in the way of guidance for regulators about how to actually determine the optimal scale for an environmental market. *Yates et al*. [2013] present an example in which they determine the optimal scale of a market, but their procedure is impractical for markets with more than about 10 sources of pollution. Second, the extant literature on optimal scale generally assumes that permits trade within zones on a one-for-one basis. This means that each source is required to hold one pollution permit to emit one unit of emissions. If a source reduces emissions by one unit, then it can sell a permit to another source and that source may increase emissions by one unit. Thus, emissions trade one-for-one. Although one-for-one trading is frequently used in actual permit markets, water quality trading programs are increasingly applying a different type of trading in which a given source is required to hold a source-specific quantity of permits for each unit of emissions. As explained in detail below, these requirements determine the rate at which emissions exchange through trade, and hence are called trading ratios. In this paper, we seek to develop two practical algorithms for determining the optimal scale of a water quality market and compare the performance of a market when optimized for scale using one-for-one trading to the performance of a market optimized for scale using trading ratios.

1.2. Water Quality Trading Programs

Water quality trading programs are a particular application of environmental market principles that has received considerable theoretical, policy, and rhetorical attention in the water resources and environmental economics literature [e.g., *Dales*, 1968; *Montgomery*, 1972; *Eheart*, 1980; *Eheart et al*., 1980; *Lence et al*., 1988; *Riggs*, 1999; *Hung and Shaw*, 2005; *Morgan and Wolverton*, 2005; *Wainger*, 2012]. Water quality markets are often advocated as a means to reduce the costs of achieving goals of the Clean Water Act, particularly nutrient control requirements [*Sado et al*., 2010]. Nutrient pollution is regulated by several statutes, the most relevant of which is the National Pollutant Discharge Elimination System (NPDES, 40 CFR 122) through which the Environmental Protection Agency (EPA) issues a permit that authorizes a regulated point source (e.g., wastewater treatment plant, WWTP) to discharge some maximum allowable amount of a pollutant. If the NPDES system fails to meet ambient water quality standards in a given water body, then an additional regulation of total maximum daily loads (TMDLs) is developed. This procedure sets measurable criteria for each water body and based on these criteria, constrains the load of a pollutant that can be emitted under the NPDES. The maximum loads are based on the ability of the aquatic system (channel network and receiving water body) to assimilate that pollutant and sustain the intended purpose.

Pollutants discharged into water bodies that fall under TMDLs can be derived from point sources (PSs) or from nonpoint sources (NPSs), such as agricultural or urban runoff, although the latter are notoriously difficult to monitor and regulate [*Stephenson and Shabman*, 2011]. Here we focus on PS-PS trade, and in particular, the promise of specific permitting strategies that have allowed market-like conditions to emerge, one of which has been developed in North Carolina. This approach is undertaken via a group compliance permit: within a watershed, PSs subject to NPDES permitting requirements are grouped and assigned individual source limits, the sum of which defines a cap for the NPDES permit holders. Individual NPDES limits are waived so long as the overall sum of discharges from the compliance group stays below the cap. Group compliance participants are able to trade pollutant allowances with others in the group, thus creating market-like conditions. This approach has been applied to the Neuse River basin in North Carolina through the Neuse River Compliance Association (NRCA), which was formed in 2002.

A key issue that emerges in any water quality trading program, and particularly in the North Carolina examples, is the spatial scale over which such group compliance approaches might be allowed to operate and how increasing or decreasing spatial scale of these markets may affect their efficacy. The Neuse River and Tar River are adjacent and both flow into the same estuary—the Albemarle-Pamlico Sound. Thus, what might be the economic and water quality implications of allowing interbasin trades between the Neuse and Tar? Moreover, three other river basins (the Roanoke, Chowan, and Pasquotank) flow into the same estuary as the Neuse and the Tar; should these five different basins be combined into one larger trading association? That is, at what scale should this water quality market be set to optimize the trade-off between compliance costs and damages?

1.3. Goal, Analysis Approach, and Overview

Our first goal is to develop techniques for determining the optimal scale of water quality markets and of environmental markets generally. There are several previous papers that analyze issues of scale for water quality markets. *Sado et al*. [2010] analyze PS trades in the Passaic River (New Jersey) to quantify the potential benefits

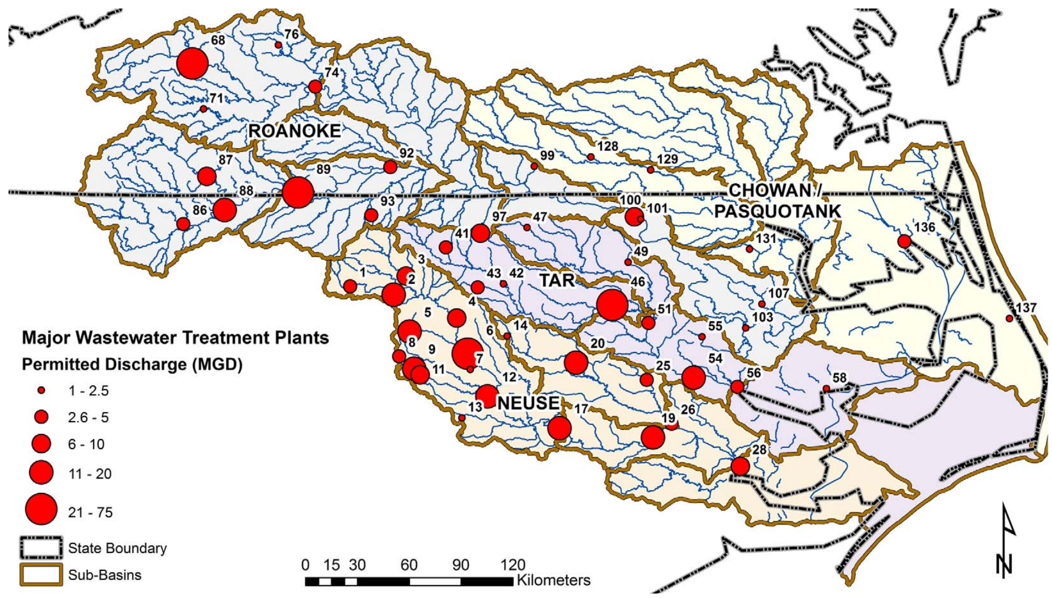

Figure 1. Albemarle-Pamlico Sound Estuary drainage basin. Each WWTP numbered corresponds to the database of WWTPs listed in supporting information 3. The river basins correspond to HUC-6 watersheds, although the Chowan/Pasquotank are often combined because a major river does not pass through the Pasquotank, although the Chowan River drains into the estuary separate from any streams in the other basins. The Chowan drains $\sim$13,000 km^2 and the Pasquotank $\sim$9400 km^2.

of allowing trading amongst the largest 22 WWTPs. They allow for the possibility of trading in zones, but they only considered compliance costs, not the trade-off between compliance costs and damages from hot spots. *Yates et al*. [2013] analyze the optimal scale of trading in the Neuse River basin, but are limited in their ability to analyze any cases beyond 10 WWTPs. Building on this foundation, we seek to determine the optimal scale for a market with a large number of WWTPs. The novelty of our work is the application and evaluation of two approaches to address the "curse of dimensionality" that occurs in optimal-scale problems: as the number of WWTPs increases, the number of ways that these WWTPs can be organized into markets (the set of feasible market designs) increases superexponentially. Our first approach uses a genetic algorithm to efficiently search over the feasible set. The second approach exploits the existence of multiple hierarchical hydrologic (i.e., watershed) scales to define a simple search algorithm that greatly reduces the number of market designs evaluated.

Our second goal is to extend the theory of optimal scale to include trading ratios and then compare the performance of trading ratios to one-for-one trading. Starting with *Montgomery* [1972], trading ratios have been proposed for permit markets in which the emissions of pollution have spatial heterogeneity. Simple intuition suggests that, because trading ratios can be selected to account for these spatial differences, they should lead to lower total costs than one-for-one trading [*Muller and Mendelsohn*, 2009; *Henry et al*., 2011]. As discussed below, however, our model features an information asymmetry. We assume that sources of pollution have better information about their abatement costs than the regulator. In such a model, trading ratios may actually lead to higher costs than one-for-one trading [*Fowlie and Muller*, 2013; *Holland and Yates*, 2014]. We investigate this issue in conjunction with an optimal-scale analysis.

Our specific application is point source to point source (PS-PS) water quality trading among major NPDES permittees within the entire drainage basin of the Albemarle-Pamlico Sound. The approach developed here is generalizable to other environmental impact-market scenarios in which there are discrete pollution emitters that can trade within a spatial area, and the emissions are mixed via environmental processes that cause spatially distributed damages that may be exacerbated by the trading program itself (i.e., damages via hot spots).

2. Methods

2.1. Study System

The Albemarle-Pamlico sound (Figure 1) is the second largest estuary in the U.S. with a contributing watershed area of 74,936 km^2 (28,922 square miles). Land use in the region is a mixture of agricultural, forest, and

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growing urban/suburban land cover, with a population of over 4.5 million people in 2010. Water quality in the estuary has declined for decades due to high nitrogen loads (along with other nutrients, including phosphorus) derived from agricultural runoff and point sources of industrial and municipal wastewater, all contributing to estuarine eutrophication [*Paerl et al*., 2006]. The corresponding decline in water quality imposes significant damages on society [*Poor et al*., 2007; *Walsh et al*., 2011]. The watershed draining into the estuary is comprised of five major river basins: Neuse, Tar, Roanoke, Chowan, and Pasquotank. There are also smaller watersheds that contribute directly into the estuary. The bulk of the drainage area is within the state of North Carolina, but a significant portion of the Roanoke and Chowan basins are located within Virginia, which contributes 80% of the permitted nitrogen loading from the Roanoke basin and 75% from the Chowan.

Within the watershed at the time of analysis, there are 103 NPDES permitted WWTPs spread throughout 13,633 km of river channel network. WWTPs are given permits for the quantity of Total Nitrogen (TN) that can be emitted, where TN is the sum of Kjeldahl Nitrogen (ammonia nitrogen + organic nitrogen), nitrite (NO_2), and nitrate (NO_3). The permitted discharges from WWTPs in the study area range from 0.67 to 3290 L/s (0.015 million gallons per day (MGD) to 75 MGD). Of these, 97.2% (7089 of 7295 kg/d; 15,628 of 16,082 lb/d) of the permitted TN emissions are derived from 51 WWTPs that have permitted discharges >3290 L/s; EPA classifies WWTPs with discharges >3290 L/s (1 MGD) as "major." We limit our analysis to these major emitters.

2.2. Model

The basic building block of our model is a market design formed by assigning WWTPs into trading zones. There is a distinct permit market in each zone, and there is no trading across zones; the more zones, the smaller the scale of the market. For each market design, we quantify the total costs (compliance costs and damages). The optimal scale of the market is defined by the particular market design that leads to the lowest total costs. The basic theory underlying this calculation has been developed previously assuming that trading within a zone is one-for-one [*Williams*, 2003; *Krysiak and Schweitzer*, 2010; *Yates et al*., 2013; *Malueg and Yates*, 2009]. We adapt this work to allow trade according to a set of arbitrary trading ratios.

There are two salient features to our model. First, we assume that the WWTP operators have better information about the costs of abating pollution than the regulator. If this is not the case, then there is no need to implement a permit market as the regulator can simply assign each WWTP the optimal emissions of pollution. Second, we assume that water quality matters throughout the river system, not just within the estuary. This implies that the optimal-scale problem occurs regardless of whether we use one-for-one trading or trading ratios. By way of contrast, if we only cared about damages at the estuary, then selecting trading ratios equal to the transfer coefficients (percentage of load to reach the estuary) would keep damages constant for any market design, and we would simply want one large market to minimize abatement costs.

There are m WWTPs that generate emissions of pollution. This pollution causes damages, which are quantified at n measurement sites. Both the WWTPs and the measurement sites are spatially distributed along the river network system. We use specific functional forms to capture the costs and damages. Following *Weitzman* [1974], the literature frequently employs quadratic forms because of their tractability. Although quadratic forms may be inaccurate at very high levels of abatement, we do not expect to be in that range for this study. The costs to WWTP i of abating pollution is

$$C_i(\theta_i, e_i) = \frac{\lambda}{2}\left(\frac{\theta_i}{\lambda} - e_i\right)^2 \tag{1}$$

where e_i are the emissions of pollution, θ_i is a cost parameter known by the WWTP i but not known to the regulator, and λ is the second derivative of the cost function with respect to emissions (the slope of the marginal abatement cost function). The regulator views θ_i as a random variable with expected value $\bar{\theta}_i$ and variance σ_i^2.

Turning to damages, consider the vectors x and y, where x_j is the pollution at site j (mass of total nitrogen per year) due to the activity of the WWTPs and y_j is due to other exogenous sources of pollution (e.g., agricultural runoff). The flow of pollution through the river system is determined by the $m \times n$ transfer matrix $\mathbf{A}$ that maps emissions from the sources to the measurement sites. If we let e be a vector of emissions, then $x = e\mathbf{A}$. The damage function is

$$D(x+y)=\frac{1}{2}(x+y)\boldsymbol{B}(x+y)^{\boldsymbol{t}}=\frac{1}{2}(e\boldsymbol{A}+y)\boldsymbol{B}(e\boldsymbol{A}+y)^{t} \tag{2}$$

where **B** is a diagonal matrix with all entries equal to b, and t denotes the transpose of a matrix. We interpret b as the slope of the marginal damage function at a measurement site. Total costs are the sums of the C_i and D.

Each WWTP is given an endowment of permits w_i. From this starting point, they may increase or decrease emissions of pollution by buying or selling permits with other WWTPs in their trading zone. In mathematical terms, the set of feasible market designs is simply the collection of all partitions of the set {1,2,3, . . . , m}, where each number identifies a specific WWTP. For example, the market design {1,2,4}, {3,5,6, . . . , m} defines two trading zones. WWTPs 1, 2, and 4 comprise the first zone, and the rest comprise the second zone. Notice that each WWTP is in only one trading zone. At one extreme, corresponding to the trivial market design {1,2,3, . . . , m}, there is a single zone. All WWTPs trade with each other and so we call this the unconstrained full trading market design; this is the largest scale of a trading program. At the other extreme, corresponding to the market design {1}, {2}, . . . {m}, there are m zones, which precludes any trading, so we call this the no-trading market design; this is effectively the smallest scale.

A market design may include a small number of WWTPs, so there may be concern that WWTPs will manipulate the price in the market to their advantage. Previous theoretical research shows that a given WWTP's ability to manipulate the price depends on their abatement cost function and permit endowment relative to the average abatement cost function and average permit endowment [*Yates et al*., 2013]. This research also shows, however, that the effects of this price manipulation on abatement costs and damages tend to cancel out [*Yates et al*., 2013], and preliminary experimental evidence supports these theoretical predictions [*Schnier et al*., 2014]. Thus, as far as total costs are concerned, we can assume that the individual markets in a zone are approximately competitive, and thereby analyze them with standard methods [e.g., *Montgomery*, 1972].

We consider two different administrative structures that govern the trade of permits within a zone. The first is one-for-one trading. If WWTP i reduces emissions by one unit, then it can sell a permit unit to WWTP j, and so WWTP j may increase emissions by one unit. We also consider trading ratios. Here each WWTP i faces a requirement to hold r_i pollution permits to emit one unit of pollution. If WWTP reduces emissions by one unit, then it may trade r_i permits to WWTP j, which may then increase emissions by r_i/r_j. Thus, the r_i determine the rate at which emissions exchange through trade. We describe the choice of the trading ratios below.

In supporting information 1, we describe the equilibrium emissions of pollution (e_i^{eq}) as a function of the permit price, the trading ratios, and the market design. Substituting the values for e_i^{eq} into the abatement cost and damage function gives the expected total costs W for a given market design

$$W=\sum_{i=1}^{m}E\left[C_i\left(\theta_i,e_i^{eq}\right)\right]+E[D(e^{eq})] \tag{3}$$

In theory, to determine the optimal scale of the market, one evaluates all possible market designs using this expression and then selects the market design with the lowest expected total costs. The optimal market design specifies the optimal number of zones and the optimal assignment of WWTPs into these zones.

In practice, an exhaustive search of the feasible set of market designs is impractical when there are more than about 10 WWTPs [*Yates et al*., 2013]. The number of market designs for a given value of m is known as the Bell number B_m and can be found by repeated application of the formula (starting with $B_0=1$)

$$B_{m+1}=\sum_{k=0}^{m}\binom{m}{k}B_k \tag{4}$$

In our case, with $m=51$, there are 3×10^{48} possible market designs. Accordingly, we develop two algorithms to obtain low cost, but not necessarily optimal market designs. The first is a genetic algorithm. Genetic algorithms are applied to a wide variety of scientific, engineering, and economic problems [e.g., *Holland*, 1975; *Hartmann*, 1998; *Morris et al*., 1998]. They work particularly well in situations such as ours in which one must search over a large and discrete space for near-optimal solutions (In our model, the search space is equal to the set of market designs. This set is large because there are many possible designs according to the formula above. It is discrete because the set of market designs cannot be mapped using a continuous mathematical function.). The key toward obtaining good performance of a genetic algorithm is in the rules for mating, offspring, and mutations. We describe the details of our implementation and accuracy testing of a genetic algorithm in supporting information 2. We refer to those market designs identified by the genetic algorithm as the "optimal" market designs, while acknowledging that they may not be truly optimal due to the limitations of the search algorithm. It is important to note that optimal market designs need not follow geographical or political constraints. They may instead group into a trading zone very geographically disparate WWTPs in different basins; they may combine some WWTPs from the Roanoke with the Neuse, or allow all but one WWTPs to trade in a particular watershed. Because of this tendency, regulators may be reluctant to implement the market designs identified by the genetic algorithm. It is therefore desirable to develop a second algorithm that generates more intuitively structured market designs.

The second algorithm is a simple search algorithm that exploits the natural hierarchy of river basins and subbasins. Here we consider four "full trading" market designs and the default no-trading market design. In the first full trading design, there is one zone (i.e., the unconstrained full trading design), so that all WWTPs may trade with each other. The other market designs retain the full trading idea, but impose various constraints on the scale of trading. In the second design, we have full trading constrained by river basins. In this design, there are five zones, one for each river basin (HUC-6), and all WWTPs in a given basin can trade with each other, but there is no trade across basins. In the third design, we have full trading constrained by subbasins. In this design, there are 13 zones, one for each subbasin, which correspond to HUC-8 scale subbasins. All WWTPs in a given subbasin can trade with each other, but there is no trade across subbasins.

The final market design is included to acknowledge that political jurisdictions may not overlap with geographic distinctions. The study area is divided by the political boundary between North Carolina and Virginia. Many water quality regulations are initiated and administered by the states rather than the federal government; the Neuse River Compliance Association, for example, is established by North Carolina legislature [*NCDENR* (*North Carolina Department of Natural Resources*), 2001]. The closest entity for multistate water quality management is the Roanoke River Basin Bi-State Commission, which like many interstate river basin commissions is a coordinating but nonregulatory entity (Virginia State Code § 62.1–69.37). Interstate trading of water quality may then pose difficulties to establish, and a realistic scenario may be that water quality permits are allowed to be traded within a single state but not between states. As a practical example, the Chesapeake Bay TMDL establishes water quality trading programs in three separate states, but as of yet there is no trading across states. Accordingly, our fourth market design corresponds to full trading constrained by states. In this market design, all of the WWTPs in North Carolina are in one zone and all of the WWTPs in Virginia are in another zone. Given these four constrained full trading designs (none, state, river basin, and subbasin) and the no-trading design, the second algorithm simply calculates the total cost of each design and then selects the design with the lowest cost.

We run both algorithms on two different regulatory systems. The first has one-for-one trading and the other has trading ratios set according to the procedure described below.

2.3. Model Parameters

The values for the parameters defining the cost functions and damage function are determined by following the procedure in *Yates et al*. [2013]. The expected value of the cost parameter $\bar{\theta}_i$ is assumed to be proportional to the size of WWTP *i* and, in turn, the variance, σ_i, to be proportional to the expected value such that each random variable has a constant coefficient of variation. In particular, we define

$$\sigma_i = \left(\frac{\eta}{100}\right)\left(\frac{\bar{\theta}_i}{2}\right) \tag{5}$$

The constant of proportionality η can be interpreted as the "percent error" in the random variables. It captures the intuitive notion that it is quite likely that the outcome of a random variable is within two standard deviations of the expected value. For example, for a normal random variable, there is a 95% chance that the random variable takes on a value that is within η percent of the expected value.

With this construction, the trade-off between compliance costs and damages is summarized by the values of the percent error η and the damage parameter, *b* (recall from (2) that *b* is the slope of marginal damage).

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As η increases, the regulator becomes more uncertain about compliance costs and hence seeks to increase the scale of the market. We use the terminology "increases the severity of compliance costs" to describe this change. As b increases, the severity of damages increases, and hence the regulator seeks to decrease the scale of the market. Analyzing the effects of a change in b is consistent with a long tradition in the environmental economics literature, starting with *Weitzman* [1974], of examining the ratio of slope of marginal damage to the slope of marginal abatement cost. Here we vary b and keep λ constant. We consider 15 parameter combinations from within the bounds determined by *Yates et al*. [2013]: 3 for η (5, 10, and 20% error) and 5 for b (US \$30,000 (mg/L)^2, US \$48,750 (mg/L)^2, US \$67,500 (mg/L)^2, US \$86,250 (mg/L)^2, and US \$105,000 (mg/L)^2). The permit endowment w_i is simply set equal to the emissions level that minimizes expected total costs of the no-trading market design. In this way, the no-trading market design can be thought of as the optimal command-and-control regulation.

The next set of model parameters are the elements of the transfer matrix $\boldsymbol{A}$ and the vector of exogenous emissions of total nitrogen y, which is the permitted parameter from WWTPs through the NPDES program. Each WWTP emits pollution, which is then transferred through the river network to the estuary. We focus here on nitrogen, although other pollutants could be modeled using similar approaches. The first step is to determine the location of the emissions and monitoring sites. Each WWTP is treated as a location of emissions and also a location of a monitoring site. We also treat tributary junctions containing WWTPs as additional monitoring sites and include monitoring sites in the estuary at the mouth of each river basin. This gives us 96 monitoring sites.

As pollutants are transferred downstream through a river network, there is natural attenuation and retention, as well as addition of pollutants from other sources (e.g., NPS) that affect natural attenuation. Similar to our approach of developing a generalizable economic model, to quantify transfer coefficients and spatially explicit water quality in the river network, we use a widely available nitrogen transfer model: SPARROW—Spatially-Referenced Regression on Watershed Attributes. The SPARROW model is a nonlinear regression, which uses spatially referenced watershed and stream channel characteristics to predict in-stream nutrient loads. The SPARROW model is widely used in studies of watershed-scale water quality patterns, including the entire Mississippi River basin [*Alexander et al*., 2000]. One of the utilities of SPARROW here was that the U.S. Geological Survey has developed the model for much of the Southeastern U.S., including the entire Albemarle-Pamlico Sound contributing drainage areas [*Hoos and McMahon*, 2009]. We thus use the SPARROW results to determine the elements of the transfer matrix, $\boldsymbol{A}$. Given this and the emissions of pollution at each WWTP, we then quantify the amount of nitrogen contributed by a specific WWTP at each of the measurement sites.

Geospatial discharge locations for each WWTP are obtained from EPA's Enforcement and Compliance History Online (ECHO). Discharge locations were linked to the nearest stream reach available in the U.S. Geological Survey's SPARROW model (SPARROW) for the Southeastern U.S. [*Hoos and McMahon*, 2009]. There are eight WWTPs that did not discharge to a SPARROW identified stream reach. In these cases, the nearest downstream SPARROW reach is selected to serve as the receiving stream reach. For each stream reach that is connected to a wastewater treatment plant, we obtain SPARROW model predictions of streamflow, TN load (from point and nonpoint sources, the latter providing the vector y), and the transfer coefficient t_i [*Hoos and McMahon*, 2009]. These data are then used to calculate the spatially explicit pollution (i.e., TN) loads throughout the river network, which provides the information necessary to determine the values in matrix $\boldsymbol{A}$ (the database of WWTPs is given in supporting information 3).

The final set of parameters is the set of trading ratios. For this analysis, we consider a particular set of trading ratios that is consistent with the CWA and TMDL regulation. Suppose the unit of analysis is the estuary. Let $r_i = t_i$. This implies that the trading ratios are equal to the transfer coefficients to the estuary. Trade between any two WWTPs will keep the total nitrogen load (in mass) at the estuary equal to a constant. Thus, *any* market design with these trading ratios will meet a TMDL set for the estuary. This gives us a realistic benchmark from which to compare trading ratios with one-for-one trading. However, one-for-one trading may violate the TMDL at the estuary.

2.4. Scenarios Analyzed

We use the coupled hydrologic-economic model to assess alternative scenarios related to policy implementation, specifically the issue of scale at which the regulatory policy would be implemented. For a given

Table 1. Total Costs (in Millions of Dollars per Year) Using the Genetic Algorithm to Find Optimal Market Designs and Full Trading With Different Scale Constraints[a]

b	η	Trading Rule	No Trading	Genetic Algorithm for Optimal Trading	Full Trading, No Constraints	Full Trading, State Constraints	Full Trading, Basin Constraints	Full Trading, Subbasin Constraints
30,000	5	One-for-one	10.664	9.818 (8%)	9.871 (7%)	9.882 (7%)	9.842* (8%)	9.948 (7%)
		Trading ratio		9.817 (8%)	9.864 (8%)	9.864 (8%)	9.830* (8%)	9.918 (7%)
	10	One-for-one	13.343	9.912 (26%)	9.925* (26%)	10.010 (25%)	10.002 (25%)	10.437 (22%)
		Trading ratio		9.897 (26%)	9.912* (26%)	9.936 (26%)	9.963 (25%)	10.324 (23%)
	20	One-for-one	24.061	10.136 (58%)	10.141* (58%)	10.519 (56%)	10.639 (56%)	12.394 (48%)
		Trading ratio		10.105 (58%)	10.107* (58%)	10.226 (57%)	10.497 (56%)	11.946 (50%)
48,750	5	One-for-one	16.614	15.778 (5%)	15.952 (4%)	15.942 (4%)	15.821* (5%)	15.920 (4%)
		Trading ratio		15.764 (5%)	15.936 (4%)	15.924 (4%)	15.803* (5%)	15.888 (4%)
	10	One-for-one	19.293	15.964 (17%)	16.007* (17%)	16.070 (17%)	15.980 (17%)	16.410 (15%)
		Trading ratio		15.938 (17%)	15.985* (17%)	15.997 (17%)	15.937 (17%)	16.294 (16%)
	20	One-for-one	30.010	16.197 (46%)	16.226* (46%)	16.583 (45%)	16.620 (45%)	18.368 (39%)
		Trading ratio		16.158 (46%)	16.182* (46%)	16.289 (46%)	16.472 (45%)	17.918 (40%)
67,500	5	One-for-one	22.448	21.618 (4%)	21.975 (2%)	21.934 (2%)	21.696* (3%)	21.786 (3%)
		Trading ratio		21.6013 (4%)	21.945 (2%)	21.917 (2%)	21.671* (3%)	21.751 (3%)
	10	One-for-one	25.128	21.773 (13%)	22.031 (12%)	22.064 (12%)	21.856* (13%)	22.276 (11%)
		Trading ratio		21.714 (14%)	22.000 (12%)	21.990 (12%)	21.805* (13%)	22.157 (12%)
	20	One-for-one	35.845	22.188 (38%)	22.254* (38%)	22.579 (37%)	22.497 (37%)	24.237 (32%)
		Trading ratio		22.130 (38%)	22.196* (38%)	22.285 (38%)	22.341 (38%)	23.782 (34%)
86,250	5	One-for-one	28.172	27.352 (3%)	27.941 (1%)	27.861 (1%)	27.471* (2%)	27.549 (2%)
		Trading ratio		27.328 (3%)	27.893 (1%)	27.843 (1%)	27.437* (3%)	27.510 (2%)
	10	One-for-one	30.851	27.479 (11%)	27.998 (9%)	27.990 (9%)	27.631* (10%)	28.040 (9%)
		Trading ratio		27.448 (11%)	27.944 (9%)	27.917 (10%)	27.571* (11%)	27.917 (10%)
	20	One-for-one	41.569	27.969 (33%)	28.224* (32%)	28.509 (31%)	28.274 (32%)	30.003 (28%)
		Trading ratio		28.012 (33%)	28.148 (32%)	28.214 (32%)	28.109* (32%)	29.544 (29%)
105,000	5	One-for-one	33.788	32.974 (2%)	33.851 (0%)	33.722 (0%)	33.149* (2%)	33.212 (2%)
		Trading ratio		32.948 (2%)	33.782 (0%)	33.704 (0%)	33.104* (2%)	33.169 (2%)
	10	One-for-one	36.468	33.110 (9%)	33.909 (7%)	33.852 (7%)	33.391* (9%)	33.704 (8%)
		Trading ratio		33.070 (9%)	33.833 (7%)	33.779 (7%)	33.238* (9%)	33.576 (8%)
	20	One-for-one	47.185	33.692 (29%)	34.139 (28%)	34.374 (27%)	33.954* (28%)	35.669 (24%)
		Trading ratio		33.548 (29%)	34.039 (28%)	34.079 (28%)	33.778* (28%)	35.204 (25%)

[a]Numbers in parentheses show the savings relative to the no-trading case. One-for-one trading and trading ratios. Asterisks indicates row minimum of constrained trading.

combination of the parameters b and η, we quantify the total costs (damages plus abatement costs) of six different scenarios for two different policy systems (one-for-one and trading ratios). The first scenario uses the genetic algorithm to determine the optimal trading design. The remaining five scenarios correspond to the market designs analyzed by the simple search algorithm. First is the no-trading baseline. Here there is no trading, so WWTPs have to expend the costs necessary to reduce their own emissions to the endowment w_i. This also corresponds to the smallest scale for the market. This scenario mimics the total costs that we would expect under the no-trading implementation of the CWA. Next are the four constrained full trading scenarios (none, state, river basin, and subbasin). The unconstrained full trading scenario corresponds to the largest scale for the market; all WWTPs are together in one single market.

3. Results

3.1. Effect of Political Boundary

Limiting trading to within-state boundaries always has higher costs than at least one of the other full trading cases (Table 1). This suggests that states may wish to take a cooperative approach to developing water quality trading systems. Because the state constraint is never optimal, and it does not nest within the other constraints, we do not include it in any subsequent analysis.

3.2. One-For-One Versus Trading Ratios

Holding scale constant, for all parameter values we consider, trading ratios lead to lower costs than one-for-one trading (Table 1 and Figure 2), but the differences between the two trading rules are small. In addition, the second algorithm identifies the same optimal scale for trading under both trading rules, with only one exception ($b = 86{,}250$, $\eta = 20$). One-for-one trading at the optimal scale often leads to lower expected total

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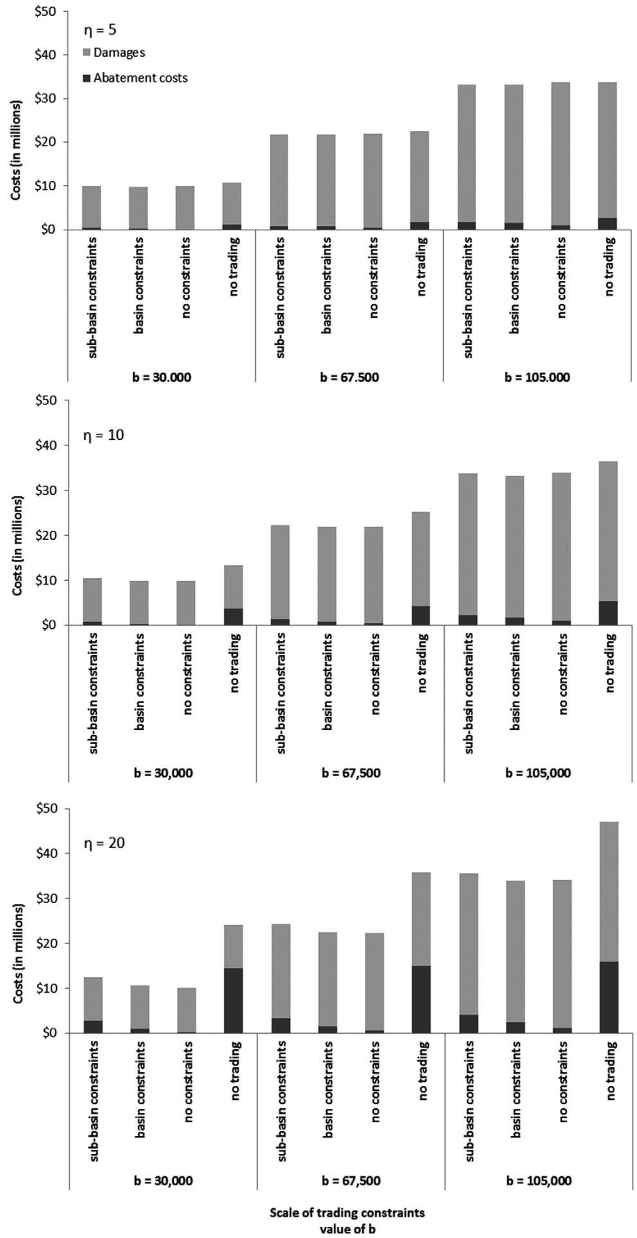

Figure 2. Damages and abatement costs as a function of b, η, and spatial scale of market under one-for-one trading rule.

costs than using trading ratios at full scale (see for example $b = 30{,}000$, $\eta = 5$). The genetic algorithm generally identifies slightly different optimal market designs for one-for-one trading versus the trading ratios (Figures 3 and 4).

3.3. Constrained Full Trading Versus No Trading

Moving from no trading to any of the constrained full trading outcomes decreased expected total costs (Table 1 and Figure 2). It is of interest to break down this decrease in expected total cost into its component parts. Consider one-for-one trading. In the most restrictive trading case of within-subbasin trading compared to no trading, the reductions in abatement costs are several times the increases in damages. For the model parameters that value damages the most ($b = 105{,}000$) and minimize abatement cost effects ($\eta = 5$), going from no trading to within-subbasin trading increases damages by $0.3 million, but decreases abatement costs by $0.9 million. In all other cases, this effect is more pronounced. For example, in the moderate case ($\eta = 10$; $b = 67{,}500$), going from no trading to within-subbasin trading increases damages by $0.1 million but reduces abatement costs by $3.0 million.

3.4. Savings With Scale: The Simple Search Algorithm

For the simple search algorithm, we determine which market design leads to the lowest total cost (Table 1 and Figure 2). For example, consider the moderate parameters ($\eta = 10$, $b = 67{,}500$) and one-for-one trading. Here total costs for the within-basin trading case ($21.9 million) are lower than total costs for the unconstrained design ($22.0 million) and the within-subbasin trading case ($22.3 million). For one-for-one trading, out of the 15 parameter value sets, the simple search algorithm identifies the within-basin trading design as optimal for nine of those sets, and the unconstrained design as optimal for six sets. For trading ratios, the simple search algorithm identifies the within-basin trading design as optimal for 10 sets, and the unconstrained design as optimal for five sets. Generally speaking, as the abatement cost parameter increases, the differences in total costs across market designs increase, so that identifying the proper scale for trading becomes more important.

3.5. Performance of the Simple Search Algorithm and the Genetic Algorithm

Surprisingly, the optimal market design identified by the genetic algorithm generated only modest additional cost savings compared to the design identified by the simple search algorithm using watershed-scale

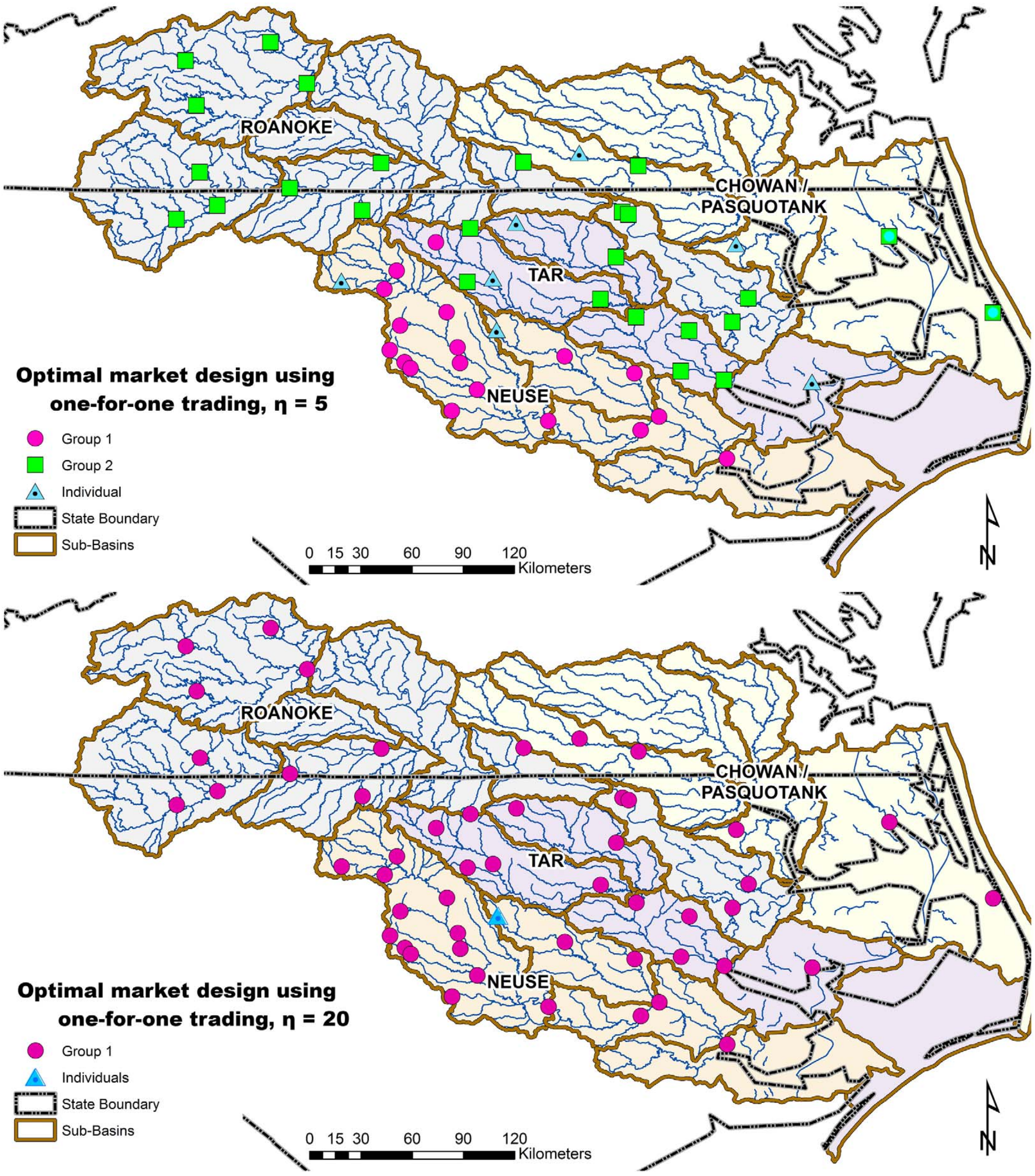

Figure 3. Market designs using genetic algorithm to find the optimal market designs assuming $b = 67{,}500$ and (top) $\eta = 5$ and (bottom) $\eta = 20$ and one-for-one trading. Note that the market designs developed under optimal trading can be nonintuitive; there are individual WWTPs that are not allowed to trade with any other WWTPs, including those in their basin.

constraints, at most saving \$0.26 million (Table 1). In other words, the simple procedure of selecting the lowest cost one of the four constrained full trading scenarios compared favorably to the low cost market design identified by the genetic algorithm that evaluated between 250,000 and 500,000 distinct market designs. In addition, the genetic algorithm often creates nonintuitive trading zones. For example, in the case of $b = 67{,}500$, $\eta = 5$ and one-for-one trading (Figure 3), the optimal trading result makes several individual WWTPs unable to trade with others in the same basin. For the same parameters but using trading ratios instead, the optimal trading result calls for a small zone in which WWTP from the Neuse basin are paired with WWTP from the Tar Basin (Figure 4). Whether or not such nonintuitive groupings would be readily adopted by regulatory agencies or accepted by the particular WWTP excluded from trading is questionable. For the conditions analyzed here, identifying the optimal design by employing the genetic algorithm may not be justified as a regulatory alternative due to these limited cost savings and greater computational and administrative complexity. Rather it may be better to use the simple search algorithm to identify the best constrained full trading market design.

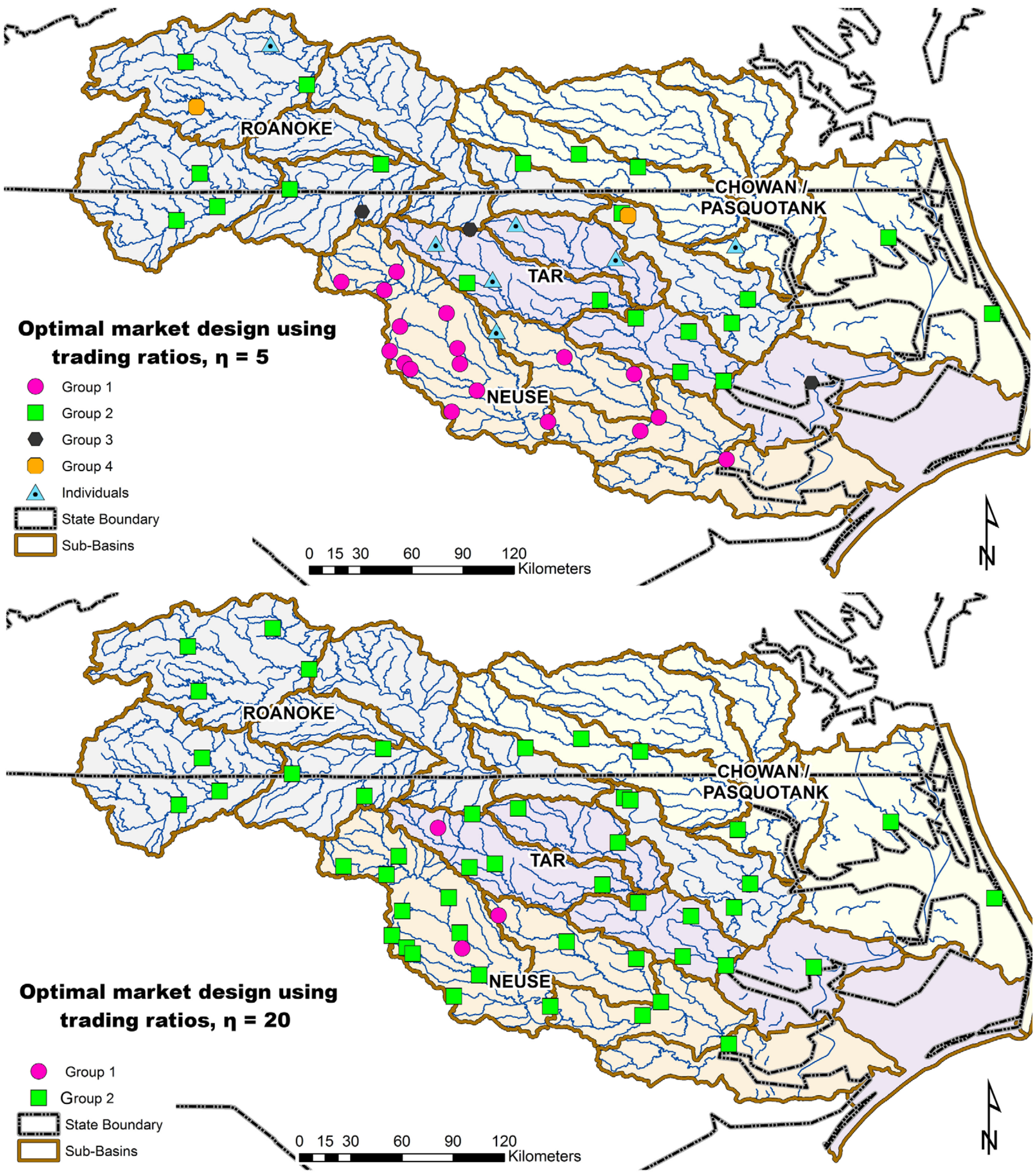

Figure 4. Market designs using genetic algorithm to find the optimal market designs assuming $b = 67{,}500$ and (top) $\eta = 5$ and (bottom) $\eta = 20$ and trading ratios. Note that the market designs developed under optimal trading can be nonintuitive; there is a small grouping of WWTPs in the Neuse and Tar that are allowed to trade.

3.6. Pareto Frontier

Up to this point, we have illustrated our results by varying the parameters of the model and identifying the resulting changes in the optimal market designs. A complementary procedure is to vary the objective function itself, rather than the model parameters. In our case, this means that rather than using the standard economic objective function equal to the simple sum of abatement costs and damages, we use an objective function that is equal to the weighted sum of abatement costs and damages. The cost minimization procedure is done repeatedly for a variety of the values of the weights. Plotting the various combinations of costs and damages that result from this procedure gives the Pareto Frontier. We create the Pareto Frontier for both trading ratios and one-for-one trading by varying the weight on abatement costs from 0 to 1 in steps of 0.1 (Figure 5).

There is a region of high curvature in the frontier around the points at which approximately equal weight is placed on abatement costs and damages. If the weights vary much from these central values, the optimal solution tends toward either full trading (when there is greater weight on abatement costs) or no trading

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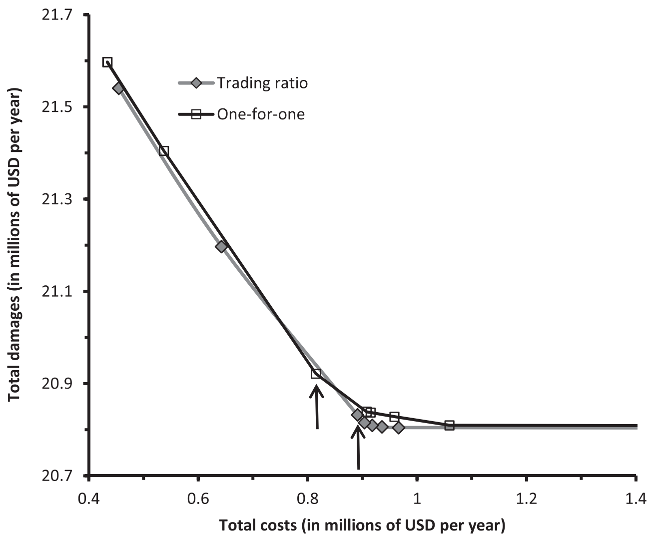

Figure 5. Pareto Frontier (with $b = 67{,}500$ and $\eta = 10$ for both trading ratios and one-for-one trading). Arrows indicate outcomes for equal weights on damages and costs.

(when there is greater weight on damages). As the weight on abatement costs approaches one, the objective function essentially disregards damages, so the optimal solution has full trading, which will ensure the lowest abatement costs. Conversely, as the weight on damages approaches one, the objective function essentially disregards abatement costs. Damages are lowest when there is no trading, so this is the optimal market design. This corresponds to the solution under the traditional application of the Clean Water Act, which implicitly places a weight of one on damages.

Notice that the frontier corresponding to one-for-one trading is very close to the frontier corresponding to trading ratios. The reason for this is as follows. When we move from one-for-one trading to trading ratios (keeping a fixed weight), we are implicitly placing a bit more emphasis on damages and a bit less emphasis on abatement costs. Another way of making a change like this would be to keep the type of trading fixed at one-for-one, but increase the weight on damages slightly. So, as can be seen in Figure 5, given a point on the trading ratio frontier, there is a point on the one-for-one frontier that is quite close, but corresponds to a greater weight on damages.

4. Discussion, Limitations, and Further Work

We analyze a feasible and realistic water quality trading program. In addition, we utilize a water quality model—SPARROW—that is empirically based and widely used for policy and management, allowing applications of our techniques to other basins. Our previous work has shown theoretically [*Yates et al*., 2013] and experimentally [*Schnier et al*., 2014] that small markets such as those that emerge here (i.e., limited number of participants) perform reasonably well compared to a competitive benchmark. Putting these regulatory, hydrologic, and economic developments together produces a combined approach to generate policies and analyses that were not previously available.

Our results show very clearly that allowing trading reduces total costs, often substantially, from a baseline case of no trading. Beyond the gains from allowing trading, our analysis also shows that the gains by increasing the scale of trading are modest compared with the gains made by simply allowing at least subbasin trading and that the basin scale for a water quality market is perhaps the most straightforward starting point for trading programs; the size of these basins ranged from 4700 km^2 in the Pasquotank to 25,400 km^2 in the Roanoke, with an average size of 14,000 km^2. The exception to this rule-of-thumb is when abatement costs were quite large (simulated here by increasing values of η). If regulations on WWTPs are made more stringent (e.g., further reduction in total nitrogen permitted to be emitted), then abatement costs will inevitably rise, and the gains to be made from adjusting the scale of water quality markets would be more significant. The Pareto Frontier shows that when unequal weights are applied to abatement costs and damages, the solution is generally an extreme market design in which there is either full trading or no trading.

We consider one-for-one trading as well as trading ratios defined such that the total nitrogen load in the estuary remains constant. Generally, we find only small differences between the two types of trading. Given that the trading ratios that we utilize here satisfy TMDL regulation under the CWA, they are a natural focus for current regulation. It may be possible, however, to find other ways to define the trading ratios that lead to even lower total costs, albeit by risking violating TMDL water quality constraints. These trading ratios would account for damages along the entire river network, not just at the estuary.

We do not explicitly include transactions costs in the analysis. *Stavins* [1995] presents a model of transactions costs in a single permit market. In his model, transactions costs are paid by WWTPs and they are an increasing function of the volume of trade. In our model, there are many markets. As the number of markets increases, the volume of trade will decrease, which in turn will decrease the transactions costs paid by the WWTPs. But the increase in the number of markets may increase the transactions costs paid by the regulators that oversee the markets. Thus, the net effect of transactions costs on the optimal scale of the market may be ambiguous—it may increase or decrease the optimal scale depending on which effect dominates.

Our results are predicated on the assumptions that WWTPs are willing and able to minimize the cost of complying with water quality regulation and that they fulfill this objective by exploiting the opportunities to trade in the market. There is some evidence that these assumption will not necessarily hold in actual programs [*Netusil and Braden*, 2001; *Hamstead and BenDor*, 2010; *Ribaudo and Gottieb*, 2011; *Nguyen et al*., 2013]. To the extent that this is true, it would suggest that the optimal scale of the market should shift toward fewer markets. This would help the WWTPs to reduce the compliance costs by providing greater scope for trading.

Our procedures should be directly applicable to cap-and-trade programs to address water pollution issues in other geographical regions. In particular, our simple search algorithm—selecting the optimal scale by evaluating a small number of constrained full trading scenarios—is relatively straightforward to implement and yields market designs that are consistent with river basin geography. The data from SPARROW are available for all of the watersheds in the Southeast U.S. By simply adapting our parameters to these watersheds, it is possible to determine the optimal scale of water quality markets in this entire geographic region. More generally, one could also apply our approach to air pollution. Here it is perhaps less obvious how to implement the simple search algorithm, as airsheds may not have the hierarchical structure found in most watersheds. In this case, the genetic algorithm may provide more value than we found in our study, and the sensitivity to scale may be much greater. Moreover, fewer market designs generated by the genetic algorithm would seem illogical because of the approximate nature of airshed boundaries.

In sum, our analysis provides a generalizable approach to quantifying the effect of different spatial constraints on environmental markets when emissions are mixed by environmental processes and there are corresponding spatially explicit damages. We find that allowing trading between WWTPs can reduce total costs, even when including damages, and that the current implementation of compliance associations as has been developed in North Carolina are appropriately scaled—river basins—to reduce abatement costs while constraining damages. Allowing trading to occur at the river basin scale is an appropriate policy first step, although there will need to be greater spatial scales allowed for trading as abatement costs increase.

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