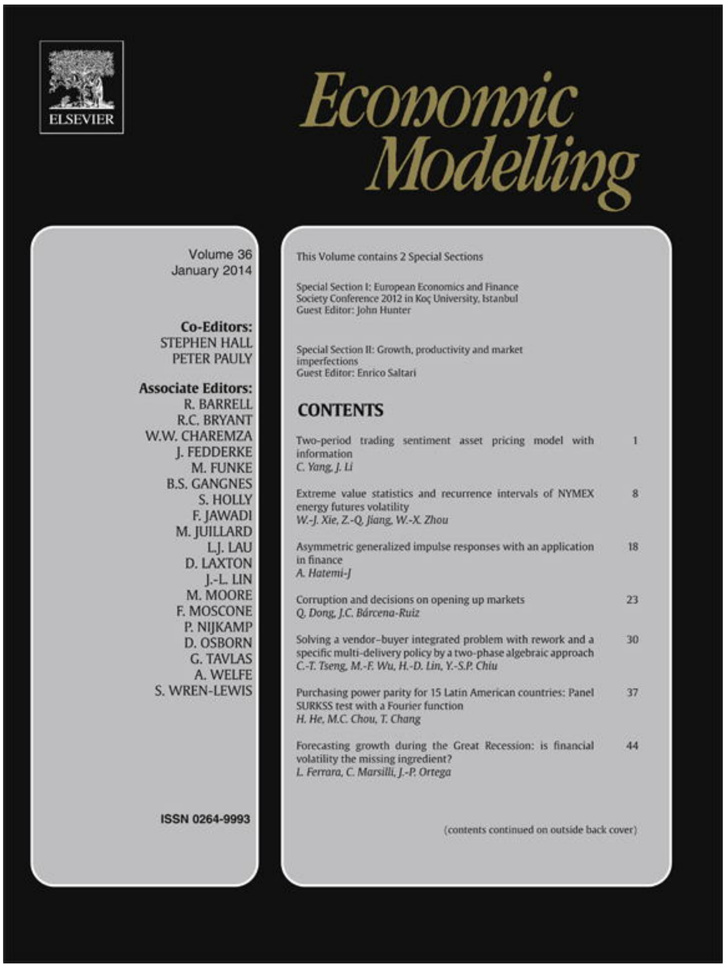

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Benchmarking an optimal pattern of pollution trading: The case of Cub River, Utah ☆

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ABSTRACT

This paper employs a recently developed, dynamic trading algorithm to establish a benchmark pattern of trade for a potential water quality trading (WQT) market in the Cub River sub-basin of Utah; a market that would ultimately include both point and nonpoint sources. The algorithm accounts for three complications that naturally arise in trading scenarios: (1) combinatorial matching of traders, (2) trader heterogeneity, and (3) discreteness in abatement technology. The algorithm establishes as detailed a reduced-cost benchmark as possible for the sub-basin by distinguishing a specific pattern of trade among would-be market participants. As such, the algorithm provides a benchmark against which an actual pollution market's performance could conceivably be compared. We find that a benchmarked trading pattern for a potential Cub River WQT market – where each source, point or nonpoint, would be required to reduce its pollution loadings – may entail some point sources selling abatement credits to nonpoint sources.

1. Introduction

The efficacies of pollution permit markets are typically evaluated along one of two lines — the degree of cost efficiency obtained through trading, or the extent of market liquidity, as reflected in trading volume and the time path of prices (Burtraw, 1996). While the market-liquidity approach is restricted to assessing the past performance of existing markets, the cost-efficiency approach is perhaps best used to establish benchmarks for future performance, e.g., by determining least- or reduced-cost allocations of the pollutant. In Sasaki and Caplan (2008), we have developed a trading algorithm that establishes detailed reduced-cost benchmarks for quantity-regulated markets (such as pollution trading with discrete abatement technology) by distinguishing specific patterns of trade among would-be market participants that would ultimately result in reduced-cost equilibria.[3]

The algorithm actually consists of two companion algorithms. The first, which we have labeled the "advancement algorithm," sequentially isolates least-cost trades starting from a pairing of the lowest- and highest-cost producers and then advancing forward to the next-least-cost pairing, accounting for each producer's average abatement cost and set of pairwise trading ratios at each step. The second, labeled the "retreat algorithm," then corrects for any surplus abatement resulting from these pairings by adjusting from the final pairing backward until all surpluses are eliminated (or reduced by as much as is technically feasible given the discrete nature of abatement technology). In this way, the algorithms provide a detailed trading-pattern benchmark (or normative construct) against which an actual pollution market's performance might ultimately be compared, i.e., the algorithms distinguish exactly who should trade with who, rather than just who is a potential seller and who is a potential buyer. Such added information is useful when it comes to establishing an optimal trading benchmark and measuring how well an actual market performs.

This paper uses the algorithm to establish a benchmark pattern of trade for a potential water quality trading (WQT) market in the Cub River sub-basin of Utah. The Cub River is well-suited for this kind of application due to the availability of both nutrient-loading and delivery-ratio estimates for the sub-basin's plethora of nonpoint sources.[4] By distinguishing all possible point-to-point, point-to-nonpoint, and nonpoint-to-nonpoint source trades, the algorithms are able to provide local water managers with as detailed a roadmap as possible of an optimal trading pattern within the sub-basin. We find that a benchmarked trading pattern for a potential Cub River WQT market – where each source, point or nonpoint, would be required to reduce its pollution loadings – may entail some point sources selling abatement credits to

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[3] Dales (1968) and Montgomery (1972) provide seminal discussions on the cost efficiencies associated with pollution trading. See the Appendix in Sasaki and Caplan (2008) for details on the distinction between reduced- and least-cost.

[4] For detailed information about how these estimates are derived see Neilson et al. (2009) and Caplan et al. (2009).

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nonpoint sources. This outcome runs counter to the way in which WQT markets generally work, where nonpoint sources are unregulated and therefore only provide offsets to regulated point sources (see Breetz et al., 2004; Environomics, 1999; Freeman, 2002; Hoag and Hughes-Popp, 1997; King, 2005; King and Kuch, 2003; U.S. Environmental Protection Agency, 2004 for further detail on the status of WQT markets nationwide).

As we have previously pointed out in Sasaki and Caplan (2008), by delineating a specific pattern of trade that would reduce aggregate abatement cost for discrete abatement technology the advancement and retreat algorithms differ markedly from the traditional simulation (e.g., linear programming) approach used in previous empirical studies. For example, McGartland and Oates (1985) simulate a least-cost benchmark for emissions in the Baltimore Air Quality Control Region based on estimates of integer-step abatement cost functions for over 400 polluters.[5] While their simulation approach can be used to compare source-specific emissions under the command-and-control (CAC) and least-cost regimes, the specific pattern of trade underscoring the comparison (which would conceivably result through trading) is not readily discernable. Rather, sources are solely identified as either potential buyers or sellers, with no specific linkages (which could be multilateral in nature) established between them. Therefore, policy makers have no way of effectively comparing actual trades with what would be a cost-effective trade pattern. Furthermore, McGartland and Oates's comparison of the CAC and least-cost outcomes is based on estimated marginal cost functions for each source (that are derived from the sources' actual discrete production costs), rather than directly on the discrete costs themselves. Thus, the more discrete the underlying abatement technology, the less reliable will be the McGartland and Oates 'smoothing' approach (i.e., there are essentially wider margins of error associated with representing what is inherently a discrete technology with a smooth one). The algorithms applied in this paper overcome these limitations.

As mentioned in Sasaki and Caplan (2008), similar algorithms are used to establish benchmarks in logistics optimization, where solutions to scheduling and routing problems have been developed on the basis of the heuristics for the traveling salesman problem. Algorithms have also been developed for solving problems in manufacturing, such as the printed-circuit-board-drilling problem (International Business Machines (IBM), 2007). For example, International Business Machines (IBM) (2007) has recently developed a vehicle routing planner (VRP) that finds optimal routes for delivery trucks on a given road network, where "optimal" in this sense means the minimum number of trucks required under capacity, time, and customer-demand constraints. Conceptually speaking, the companion trading algorithms used in this paper and the VRP algorithms are quite similar.

The next section presents a shortened version of our least-cost WQT model, as originally developed in Sasaki and Caplan (2008). Section 3 then describes how the companion algorithms work, first by reiterating Sasaki and Caplan (2008) basic intuition and then by building upon that paper's simple two-trader example. For readers mostly interested in this paper's results, Section 3 can be skipped without loss of continuity. Section 4 provides a brief description of the Cub River sub-basin, and Section 5 describes the sub-basin's environmental and economic data and discusses the results obtained from applying the companion trading algorithms to the data. Section 6 concludes.

2. A least-cost water quality trading model[6]

Consider a potential market for trading abatement credits among $i = \{1,2,\ldots,n\}$ would-be traders (a trader is referred to synonymously as a producer, a polluter, a seller, or a purchaser, depending upon the context). For future reference, the set of these would-be traders is denoted by N (we henceforth drop the descriptor "would-be" for expositional convenience). Further, let $R(i)$ represent the required abatement level for producer i set by regulation.

Each producer has his own abatement capability and associated cost structure related to a countable number of technology options, or steps. For example, a given producer's first-step technology might produce 100 units of abatement followed by 40 units in the second step, and so on. In this regard, let $S(i)$ represent the number of technology steps implemented by producer i (which for future reference defines the function $S: N \rightarrow \mathbb{N} \cup \{0\}$); let $A(i,k)$ represent the abatement level achieved by producer i in his kth technology step; and let $C(i,k)$ represent the corresponding abatement cost incurred by producer i in the kth technology step.[7]

With the above definitions, total abatement and associated total abatement cost incurred by producer i are given by $\sum_{k=1}^{S(i)} A(i,k)$ and $\sum_{k=1}^{S(i)} C(i,k)$, respectively. In the absence of trading, the authority's regulations are met only when $R(i) \leq \sum_{k=1}^{S(i)} A(i,k)$ for all i. However, trading would enable producer i to sell any extra abatement, i.e., abatement credits, $\sum_{k=1}^{S(i)} A(i,k) - R(i) > 0$, to other producers (who perhaps experience higher abatement costs). In this regard, let $P(i,j)$ represent the abatement credits that trader i would sell to trader j, which in turn defines the function $P: N \times N \rightarrow \mathbb{R}_+$. Note that because the purpose of this model is to demonstrate how *prospective* buyers and sellers of abatement credits are determined in a *potential* market, there is no need to determine a specific equilibrium price. Rather, the model is meant to lay the theoretical foundation for the trading algorithm, which in turn establishes a benchmark for the potential pattern of trade, irrespective of what an equilibrium price might ultimately be.

Heterogeneity (e.g., due to geographic spatiality) among producers complicates trading. For example, abatement of 100 kg by "upstream" polluter 1 may be equivalent to only abatement of 80 kg by "downstream" polluter 2 in terms of a given receptor point. As a result, 80 kg of abatement by polluter 2 could account for 100 kg of abatement for polluter 1 if abatement credits are exchangeable. Hence, all else equal, it would be preferable for "receptor-sensitive" polluters such as polluter 2 to abate excessively and sell their credits to "receptor-insensitive" polluters such as polluter 1.

We assume that trading ratios can be represented by a matrix T, where $T(i,j)$ is the trading ratio between seller i and purchaser j (note that trading ratios are themselves ratios of the purchaser's and seller's respective delivery ratios). Given T, $P(i,j)/T(i,j)$ equals the effective abatement credits that trader i sells to trader j. If $T(i,j) < 1$ (respectively, >1), then the quantity "swells" (respectively, "shrinks") when trader j purchases credits from trader i.

For example, suppose that polluter 1 is located upstream from polluter 2, and thus, due to spatial differences, 20% of pollutants from polluter 1 and 25% of pollutants from polluter 2 transmit to the receptor. In this case, abatement of 100 kg by polluter 1 translates to 20 kg at the receptor, which, in turn, is equivalent to abatement of 80 kg by polluter 2. Relatively speaking then, polluter 2's trading ratio with polluter 1 is $T(2,1) = 80/100$ and polluter 1's trading ratio with polluter 2 is $T(1,2) = 100/80$. The trading ratio matrix for this example is therefore

$$T = \begin{pmatrix} 1 & 5/4 \\ 4/5 & 1 \end{pmatrix}.$$

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[5] Atkinson and Lewis (1974) and Atkinson and Tietenberg (1982) use a similar approach for the St. Louis Air Quality Control Region, as do Seskin et al. (1983) for the Chicago Air Quality Control Region. See O'Ryan (1996) for application of this approach to air quality in Santiago, Chile. Alternatively, Kling (1994) uses regression analysis to estimate abatement cost functions for the control of hydrocarbon emissions from light-duty vehicles in California. More recent examples of this general approach include Keohane (2006) and Shadbegian et al. (2006).

[6] As mentioned in the previous section, this model is developed in more detail in our previous paper, Sasaki and Caplan (2008).

[7] See Caplan (2009) for a detailed discussion of the implications of discrete abatement.

Suppose further that the two polluters have the same constant marginal cost of abatement and that both polluters are required to abate $R(i) = 100$ kg each. Then, the optimal (i.e., least-cost) solution is that polluter 2 abates 180 kg and sells her credit of 80 kg to polluter 1, i.e., $P(2,1) = 80$. This fulfills the abatement requirement for polluter 1 as well since $P(2,1)/T(2,1) = 100 = R(1)$. In this case, polluter 1's abatement credits “swell” from 80 to 100 by trading with polluter 2.

The regulator's problem is to minimize total abatement cost among all producers. This problem is constrained by the achievement of a required abatement level by each producer, including net traded credits. Letting $\mathcal{S}$ and $\mathcal{P}$ denote the sets of all possible functions $S : N \to \mathbb{N} \cup \{0\}$ and $P : N \times N \to \mathbb{R}_+$, respectively, the regulator's problem is therefore expressed as

$$\min_{P \in \mathcal{P}, S \in \mathcal{S}} \sum_{i=1}^{n} \sum_{k=1}^{S(i)} C(i,k) \tag{1}$$

$$\text{subject to} \sum_{k=1}^{S(i)} A(i,k) + \sum_{j=1}^{n} P(j,i)/T(j,i) - \sum_{j=1}^{n} P(i,j) \geq R(i) \text{ for each } i \in N \tag{2}$$

$$\text{and } P(i,j) > 0 \Rightarrow P(j,i) = 0 \text{ for each pair } i, j \in N. \tag{3}$$

The left-hand side of (2) is producer i's own-abatement level plus effective credits purchased minus credits sold. Eq. (3) prohibits bidirectional trading. Also, (3) implies that the diagonal of P is zero.

For convenience define the functional $F : N \times \mathcal{S} \times \mathcal{P} \to \mathbb{R}$ by

$$F(i,S,P) = R(i) + \sum_{j=1}^{n} P(i,j) - \sum_{k=1}^{S(i)} A(i,k) - \sum_{j=1}^{n} P(j,i)/T(j,i).$$

Constraint (2) then reduces to

$$F(i,S,P) \leq 0 \text{ for each } i \in N. \tag{4}$$

When $F(i,S,P)$ is positive, producer i incurs an abatement deficit. Constraint (4) is thus equivalent to the elimination of an abatement deficit for each producer.

3. Basic intuition and a two-trader example

3.1. The basic intuition[8]

Begin, in iteration $m = 0$, with an initial state of no abatement (i.e., $S_0(i) = 0$ for all i N) and thus no trading (i.e., $P_0(i,j) = 0$ for all i,j N). The advancement algorithm iteratively updates S_m and P_m to S_{m+1} and P_{m+1}, respectively, such that exactly one producer “advances” her abatement step in each iteration, aiming to reduce abatement deficits $F(i,S_m,P_m)$. In other words, in the $(m + 1)$-st iteration, an increment occurs as $S_{m+1}(i) = S_m(i) + 1$ for exactly one i N. Producer i's resultant abatement may then be distributed to other producers through trading, and P is accordingly modified. The process is iterated so that S and P eventually fulfill constraint (4) while keeping the associated total cost (1) as small as possible. The algorithm ends at the M-th iteration where constraint (4) is first satisfied.

For each iteration, say, in the $(m + 1)$-st iteration, the primary task is to determine for which producer i should the abatement step $S_m(i)$ be advanced. If producer i advances, the resultant abatement level and associated cost are $A(i,S_m(i) + 1)$ and $C(i,S_m(i) + 1)$, respectively. It may be intuitively natural to advance the step of the trader i who has the least average abatement cost $C(i,S_m(i) + 1)/A(i,S_m(i) + 1)$. However, this idea is cursory; the denominator (or the quantity) may be further swelled (respectively, shrunk) via trading by the trading ratios, thus reducing (respectively, increasing) effective average abatement cost. Recall from Section 3 that the quantity of producer i's abatement swells greater as the trading ratio $T(i,j)$ is smaller. Thus, seller i should preferably assign the highest precedence of selling her abatement to prospective purchaser j who has the lowest trading ratio $T(i,j)$. As such, we need to queue the prospective purchasers of i's abatement in the order of increasing trading ratios, which Sasaki and Caplan (2008) call a “rearrangement”.

Since by the m-th iteration those who have fulfilled the constraint, $F(j,S_m,P_m) \leq 0$, are not included in the list of prospective purchasers of seller i' abatement and $\tilde{N}_m = \{j \in N | F(j,S_m,P_m) > 0\}$ is considered as the list of prospective purchasers. $\tilde{N}_m$ can include seller i herself, but the quantity that she sells to herself is necessarily reinterpreted as unsold production. Suppose that $j_1, j_2, \ldots$ is the rearranged list of the potential purchasers $\tilde{N}_m$. Hence, trader i assigns the highest precedence of selling her abatement to purchaser j_1, followed by j_2, and so on. There are three cases to consider in calculating trader i's effective average abatement cost:

Case 1. If trader i's next-step abatement $A(i,S_m(i) + 1)$ is not enough to meet purchaser j_1's abatement deficit (i.e., $A(i,S_m(i)1)/T(i,j_1) < F(j_1,S_m,P_m)$), then the resultant swelled quantity is $A(i,S_m(i) + 1)/T(i,j_1)$. Hence, trader i's effective average abatement cost is

$$\frac{C(i,S_m(i)+1)}{A(i,S_m(i)+1)/T(i,j_1)}. \tag{5}$$

Case 2. If trader i, in her next step, is able to abate an amount sufficient to fulfill the sum of *all* prospective purchasers' abatement deficits, then the swelled/shrunk quantity as a result of trading is $\sum_{j \in \tilde{N}_m} F(j,S_m,P_m)$. (Note that $F(j,S_m,P_m)$ is already in purchaser j's quantity scale, thus there is no need to divide it by $T(i,j)$). If we denote the number of purchasers by $\tilde{n} = |\tilde{N}_m|$, then this swelled/shrunk quantity is rewritten as $\sum_{\alpha=1}^{\tilde{n}} F(j_\alpha,S_m,P_m)$, and trader i's effective average abatement cost is

$$\frac{C(i,S_m(i)+1)}{\sum_{\alpha=1}^{\tilde{n}} F(j_\alpha,S_m,P_m)}. \tag{6}$$

Case 3. If the situation is neither Case 1 nor Case 2, then trader i is able to fulfill at least one prospective purchaser j_1's abatement deficit, but cannot fulfill that of everyone. Thus, let $\alpha^* (1 \leq \alpha^* < \tilde{n})$ be the number of purchasers (possibly including herself) whose deficits can be fulfilled as a result of trader i's selling her next-step abatement. Then, the fulfillment amounts to the swelled/shrunk quantity $\sum_{\alpha=1}^{\alpha^*} F(j_\alpha,S_m,P_m)$. Yet, this swelled/shrunk quantity is not all the benefits of trader i's abatement. She may still have remnant $A(i,S_m(i)+1) - \sum_{\alpha=1}^{\alpha^*} F(j_\alpha,S_m,P_m) T(i,j_\alpha)$ even after fulfilling α^* purchasers' deficits. Even though she cannot completely fulfill the deficit of the $(\alpha^* + 1)$-st purchaser (by definition of α^*), she can still sell this remnant to prospective purchaser j_{α^*+1}, the swelled/shrunk quantity of which is

$$\frac{A(i,S_m(i)+1) - \sum_{\alpha=1}^{\alpha^*} F(j_\alpha,S_m,P_m) T(i,j_\alpha)}{T(i,j_{\alpha^*+1})}.$$

In total, the swelled/shrunk quantity as a result of trader i's abatement is

$$\Omega := \sum_{\alpha=1}^{\alpha^*} F(j_\alpha,S_m,P_m) + \frac{A(i,S_m(i)+1) - \sum_{\alpha=1}^{\alpha^*} F(j_\alpha,S_m,P_m) T(i,j_\alpha)}{T(i,j_{\alpha^*+1})},$$

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[8] Similar to the WQT model itself, the basic intuition presented in this section is developed in more detail in our previous paper, Sasaki and Caplan (2008).

and trader i's effective average abatement cost is

$$C(i, S_m(i)+1)/\Omega. \tag{7}$$

Recall that the purpose of calculating these effective average abatement costs was to select a trader who, in the next step, has the least effective average cost. The algorithm lets this trader i^* advance her step, thus $S_{m+1}(i^*) = S_m(i^*) + 1$ whereas $S_{m+1}(i) = S_m(i)$ for all $i \neq i^*$. The abatement level $A(i^*,S_{m+1}(i^*))$ will be distributed (i.e., sold) to successive traders in seller i^*'s rearrangement, $j_1,j_2,\ldots,j_{\tilde{n}}$. If seller i^* can fulfill trader j_α's current abatement deficit, then the net amount $P(i^*, j_\alpha)$ sold by trader i^* to trader j_α increments by $F(j_\alpha,S_m,P_m)T(i^*,j_\alpha)$. If Case 3 holds, the remnant sold by trader i^* to the $(\alpha^* + 1)$-st purchaser is $A(i^*, S_{m+1}(i^*)) - \sum_{\alpha=1}^{\alpha^*} F(j_\alpha, S_m, P_m)T(i^*, j_\alpha)$, by which $P(i^*, j_{\alpha^*+1})$ increments.

In the course of repeated iterations, it is possible that a trader who acted as a net seller in earlier iterations of the algorithm turns out to be a net purchaser in later iterations (or vice-versa). This can occur, for example, if a trader in her first step has a low effective average abatement cost but incomparably high effective average cost in her second step. To comply with (3), the algorithm at the end of each iteration modifies P so that only net sellers have positive values.

Further, as we have shown in Sasaki and Caplan (2008), the advancement algorithm can fall short of the strict optimality associated with the regulator's problem in Section 2 due to redundancy in the producers' abatement steps. This possibility is best shown by force of example.

3.2. An example

The first part of this example provides a case where the advancement algorithm alone solves the cost-minimization problem presented in Section 2. The second part of the example then demonstrates how the advancement algorithm alone can fail to solve the cost-minimization problem, and how the retreat algorithm can be used to further reduce total abatement cost.[9]

Consider a two-polluter community $N = \{1,2\}$ where both polluters are supposed to abate $R(1) = R(2) = 100$ kg. As in Section 2, let the trading ratios be $T(1,2) = 5/4$ and $T(2,1) = 4/5$. Suppose that polluter 1 has only one abatement step whose attributes are $A(1,1) = 100$ and $C(1,1) = 100$, and polluter 2 has two abatement steps whose attributes are $A(2,1) = 90$, $C(2,1) = 90$, $A(2,2) = 90$, and $C(2,2) = 100$.

Iteration 1. Currently, $S_0(1) = S_0(2) = 0$, $P_0(1,2) = P_0(2,1) = 0$, and $F(1,S_0,P_0) = F(2,S_0,P_0) = 100$. First, for the possible seller $i = 1$, the rearranged list of possible purchasers is $\{1,2\}$ and $\alpha^* = 1$. By (5)–(7), trader 1's effective average abatement cost is

$$\mathrm{EAC}(1, S_0(1)+1) = \frac{C(1, S_0(1)+1)}{F(1, S_0, P_0) + \frac{A(1,S_0(1)+1) - F(1,S_0,P_0)T(1,1)}{T(1,2)}}$$

$$= \frac{100}{100 + \frac{100-100\cdot 1}{5/4}} = 1.$$

Second, for the possible seller $i = 2$, the rearranged list of possible purchasers is also $\{1,2\}$ and $\alpha^* = 1$. Again by (5)–(7), trader 2's effective average abatement cost is

$$\mathrm{EAC}(2, S_0(2)+1) = \frac{C(2, S_0(1)+1)}{F(1, S_0, P_0) + \frac{A(2,S_0(2)+1) - F(1,S_0,P_0)T(2,1)}{T(2,2)}}$$

$$= \frac{90}{100 + \frac{90-100\cdot(4/5)}{1}} = \frac{9}{11}.$$

Since $\mathrm{EAC}(1,S_0(1)) > \mathrm{EAC}(2,S_0(2) + 1)$, we choose $i^* = 2$ and advance her step as $S_1(2) = S_0(2) + 1 = 1$. But we retain $S_1(1) = S_0(1) = 0$. Since $\alpha^* = 1$ and the rearranged list of purchasers is $\{1,2\}$ for seller $i^* = 2$, trading fulfills purchaser 1's abatement deficit. For this, the seller $i^* = 2$ sells $F(1,S_0,P_0)T(2,1) = 100 \cdot (4/5) = 80$ to purchaser 1, and sells its remnant $A(2,S_1(2)) - F(1,S_0,P_0)T(2,1) = 90 - 80 = 10$ to herself.

Iteration 2. Currently, $S_1(1) = 0$, $S_1(2) = 1$, $P_1(1,2) = 0$, $P_1(2,1) = 80$, $F(1,S_1,P_1) = 0$, and $F(2,S_1,P_1) = 90$. First, for the possible seller $i = 1$, the rearranged list of possible purchasers is $\{2\}$ and $\alpha^* = 0$. Trader 1's effective average cost is

$$\mathrm{EAC}(1, S_1(1)+1) = \frac{C(1, S_1(1)+1)}{A(1, S_1(1)+1)/T(1,2)} = \frac{100}{100/(5/4)} = \frac{5}{4}.$$

Second, for the possible seller $i = 2$, the rearranged list of possible purchasers is also $\{2\}$ and $\alpha^* = 1$. Trader 2's effective average cost is

$$\mathrm{EAC}(2, S_1(2)+1) = \frac{C(2, S_1(2)+1)}{F(2, S_1, P_1)} = \frac{100}{90} = \frac{10}{9}.$$

Since $\mathrm{EAC}(1,S_1(1) + 1) > \mathrm{EAC}(2,S_1(2) + 1)$, we choose $i^* = 2$ again, and advance her steps as $S_2(2) = S_1(2) + 1 = 2$. But we retain $S_2(1) = S_1(1) = 0$. Since $\alpha^* = 1$ and the rearranged list of purchasers is $\{2\}$ for the seller $i^* = 2$, trading fulfills the purchaser 2's own abatement deficit. For this, the seller $i^* = 2$ sells $F(2,S_1,P_1)T(2,2) = 90 \cdot 1 = 90$ to herself. Currently, $S_2(1) = 0$, $S_2(2) = 2$, $P_2(1,2) = 0$, $P_2(2,1) = 80$, $F(1,S_2,P_2) = 0$, and $F(2,S_2,P_2) = 0$. Since constraint (4) is satisfied, we have terminated the iterations.

The final policy is, therefore, $S(1) = 0$, $S(2) = 2$, $P(1,2) = 0$, and $P(2,1) = 80$. In other words, polluter 1 abates nothing while polluter 2 abates $\sum_{k=1}^{S(2)} A(2,k) = 180$ kg, out of which $P(2,1) = 80$ kg is sold to polluter 1, which actually amounts to $P(2,1)/T(2,1) = 100$ kg of swelled quantity equaling the required abatement $R(1) = 100$ for polluter 1. Comparing this result with the example presented in Section 3, the resultant total cost is $\sum_{i=1}^{2} \sum_{k=1}^{S(i)} C(i,k) = C(2,1) + C(2,2) = 190$, which is lower than the total cost of 290 that would arise in the absence of trading. In this example, it is also easy to see that the advancement algorithm solves the cost-minimization problem (1)–(4). Thus, there is no need for retreat.

We can alter the above example in a simple way to show when retreat would be necessary. Continue to assume that both polluters are initially required to abate $R(1) = R(2) = 100$ kg, and that the trading ratios are $T(1,2) = 2/4$ and $T(2,1) = 4/5$. Now polluter 1 has two abatement steps. His first step retains the attributes $A(1,1) = 100$ and $C(1,1 = 100)$ and his second step has attributes $A(1,2) = 150$ and $C(1,2) = 200$. Polluter 2 continues to have two abatement steps available. However, her first step now has attributes $A(2,1) = 900$ and $C(2,1) = 900$ and her second step has attributes $A(2,2) = 100$, and $C(2,2) = 1000$. As we will see in the next section, this disparity in abatement levels and costs between polluters 1 and 2, respectively, reflects the actual disparities found for nonpoint and point sources in the Cub River sub-basin.

Iteration 1. As in the previous example, $S_0(1) = S_0(2) = 0$, $P_0(1,2) = P_0(2,1) = 0$, and $F(1,S_0,P_0) = F(2,S_0,P_0) = 100$. Again by (5)–(7), polluter 1's effective average abatement cost is $\mathrm{EAC}(1,S_0(1) + 1)$. However, polluter 2's effective average abatement cost is now

$$\mathrm{EAC}(2, S_0(2)+1) = \frac{C(2, S_0(1)+1)}{F(1, S_0, P_0) + \frac{A(2,S_0(2)+1) - F(1,S_0,P_0)T(2,1)}{T(2,2)}}$$

$$= \frac{900}{100 + \frac{900-100\cdot(4/5)}{1}} = \frac{45}{46}.$$

In this case, seller $i^* = 2$ again sells $F(1,S_0,P_0)T(2,1) = 100 \cdot (4/5) = 80$ to purchaser 1, and this time sells remnant $A(2,S_1(2)) - F(1,

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[9] In Sasaki and Caplan (2008) we discuss the general conditions under which the advancement and retreat algorithms together solve the cost-minimization problem.

S_0,P_0)$T(2,1) = 900 - 80 = 820$ to herself. As a result, seller $i^* = 2$ now has an abatement surplus of $820 - 100 = 720$. The advancement algorithm's iterations end here, resulting in a total abatement cost of 900, which is only slightly lower than the total cost of $C(1,1) + C(2,1) = 1000$ that would arise in this new scenario in the absence of trading. A need of retreat is therefore apparent given polluter 2's large abatement surplus and the relatively small overall cost savings.

To begin the retreat process, consider the alternative of polluter 1 taking the first abatement step in the first iteration, rather than polluter 2. In this first step, $A(1,1) = 100$ shrinks to $F(2,S_0,P_0)/T(1,2) = 100 \cdot (4/5) = 80$ if polluter 1 sells to polluter 2. No remnant remains for polluter 1. Without loss of generality, we can assume that this is what polluters 1 and 2 agree to in the first iteration.

Now in the second iteration, it is clear that if polluter 2 abates (using what would be her first abatement step) a large surplus will again result. Thus, consider polluter 1's second abatement step $A(1,2) = 150$ at cost $C(1,2) = 200$. Of the 150 kg abated, polluter 1 can sell 25 to polluter 2, which shrinks to $F(2,S_1,P_1)/T(1,2) = 25 \cdot (4/5) = 20$. This satisfies constraint (4) with equality for polluter 2 and leaves $150 - 25 = 125$ for polluter 1, which satisfies (4) with inequality, i.e., with a 25 kg surplus. Given the discreteness of the problem, this is the lowest surplus possible.

Therefore, using the retreat algorithm polluter 2 abates nothing while polluter 1 abates $\sum_{k=1}^{S(2)} A(1,k) = 250$ kg. The resultant total cost is $\sum_{i=1}^{2} \sum_{k=1}^{S(i)} C(i,k) = C(1,1) + C(1,2) = 300$, which is much lower than the total cost of 1000 that would arise in the absence of trading, as well as the total cost of 900 that would arise using solely the advancement algorithm.

4. The Cub River

The Cub River sub-basin (to which the companion algorithms described in Section 3.2 will now be applied) is located in the Bear River Basin, Utah, which comprises 19,000 km^2 of mountain and valley lands located in northeastern Utah (44% of watershed), southeastern Idaho

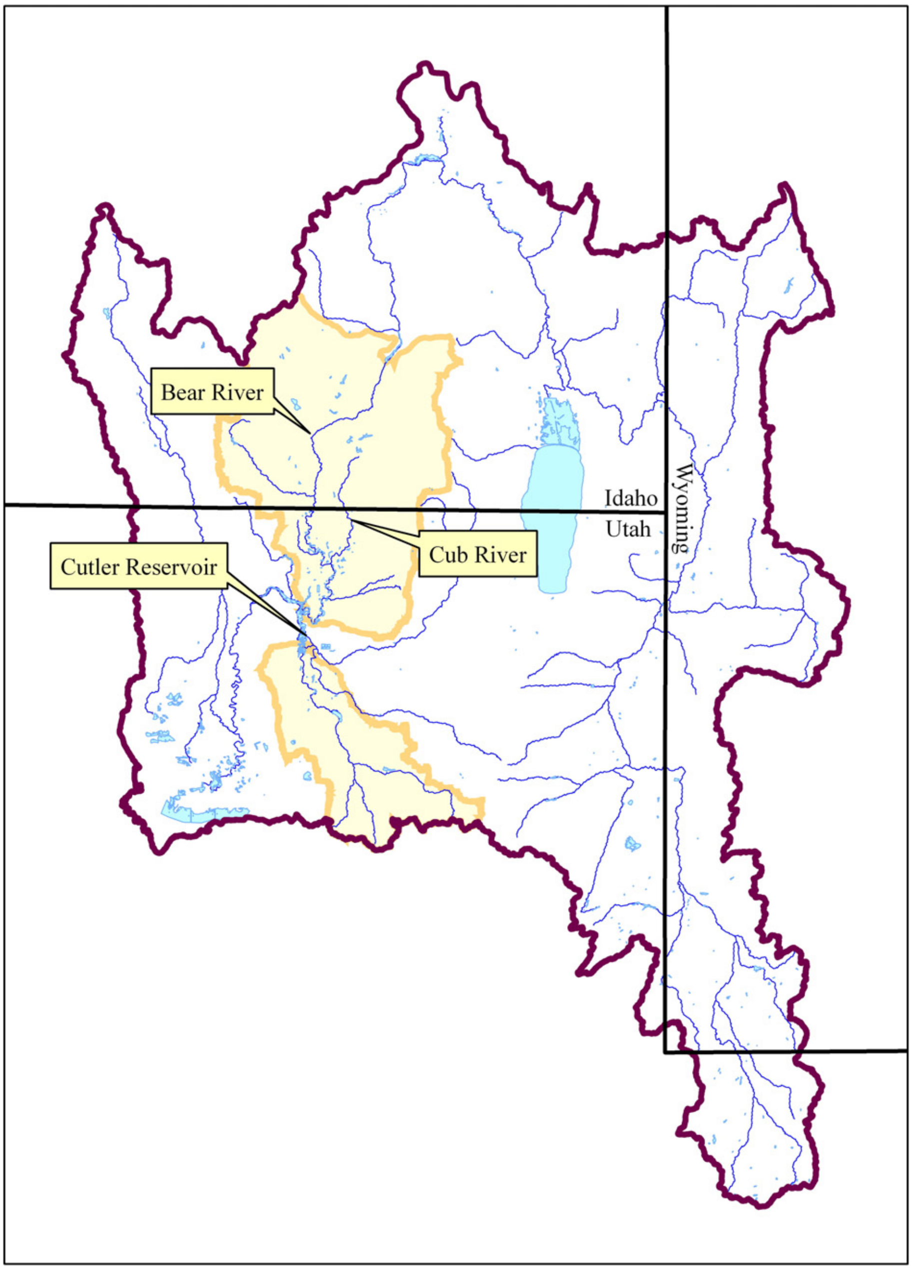

Fig. 1. The Bear River basin.

(36%), and southwestern Wyoming (20%) — see Fig. 1. The basin ranges in elevation from 1283 m to over 3962 m and is entirely enclosed by mountains. Agricultural lands throughout the basin, as well as urban areas, are located in valleys along the main stem of the Bear River and its tributaries. Common crops include dryland and irrigated pasture, hay, alfalfa, and corn, which are used locally to feed cattle and dairy cows. Total population in the basin is roughly 100,000 United States Census Bureau (2009).[10]

Currently, several water bodies in the basin are on the Clean Water Act's 303(d) list of impaired waters in each of the three states. One of these 303(d)-listed water bodies – the Cub River – forms the focus area for this study (see Fig. 2, which identifies receptor points for both the Cub River's confluence with the Bear River and Cutler Reservoir). The Cub River is included on the 303(d) list because of dissolved oxygen depletion during summer months due primarily to excessive total phosphorus (TP) loadings from point and nonpoint sources. A TMDL is currently being developed for the Cub River, and WQT has been identified as one potential solution to the TP problem.

From its point of entry in Utah, the Bear River and most of its tributaries flow through agricultural lands. As a result, major anthropogenic sources of TP loadings in the basin are nonpoint sources. The Cub River sub-basin is comprised of approximately 1300 farms, four city-owned wastewater treatment plants (WWTPs), and one ice cream manufacturer. According to Utah Department of Environmental Quality (Utah DEQ) (2008), loadings from animal feeding operations (both confined and unconfined) are already (or are in the process of becoming) adequately controlled through a variety of state- and federally funded programs. We therefore ignore loadings from these sources for the purposes of this study. In the end, aggregate annual delivered loads to the Cub River receptor point from point and nonpoint sources are estimated to be roughly 4500 and 1700 kg, respectively.

5. An application of the trading algorithms

To apply the advancement and retreat algorithms to the Cub River sub-basin, and thereby establish a reduced-cost trading benchmark, field-level data for nonpoint sources and source-level data for point sources were obtained for current loads (of total phosphorus), as well as $R(i)$, $A(i,k)$, $C(i,k)$, and $T(i,j)$, for each i,j N and each k for each respective i (described in further detail below). The field-level data for nonpoint sources was then aggregated to the farm-level. This information was then fed to the algorithms to generate values for $P(i,j)$ and $F(i,S,P)$.

Total phosphorus (TP) load estimates for each nonpoint source located in the sub-basin were obtained from a hydrologic model developed by Neilson et al. (2009). The Neilson et al. (2009) framework utilizes (i) the TOPNET hydrology model Bandaragoda et al. (2004), (ii) variable source area (VSA) calculations to resolve spatial areas contributing surface runoff Lyon et al. (2004), (iii) a sub-basin loading model component based on the VSA calculations, event mean concentrations (EMCs), and spatially distributed land-use information, and (iv) a water body response component that incorporates the QUAL2E model to determine delivery ratios Brown and Barnwell (1987). This combination of models provides for a representation of the physical hydrology at the watershed scale and the associated in-stream response at a daily time step. The approach also results in a representation of the spatial variability of daily loadings at the field scale and daily delivery ratios to receptor points of interest.[11]

The Neilson et al. (2009) model generated current annual nonpoint-source TP loads ranging from approximately 52 to 0.002 kg per field, and corresponding trading ratios $T(i,j)$ for both point and nonpoint sources in the sub-basin ranging from 0.9 to 1.37. Point-source TP load estimates were obtained from those reported in Caplan et al. (2009). Annual loads range from approximately 1700 kg (for a WWTP) to 0.001 kg (for the ice cream manufacturer). For the purposes of this study, it is assumed that the target load for each nonpoint source is 30% of its current load, implying that $R(i)$ for all nonpoint sources is 70% of current loads. For all point sources, the associated $R(i)$ is 80% of current loads. These percentages are in line with the preliminary Total Maximum Daily Load (TMDL) for the Cub River published by Utah Department of Environmental Quality (Utah DEQ) (2008). For simplicity we assume uniform required reductions across all nonpoint and point sources, respectively.

Estimates for best-management-practice (BMP) effectiveness and per-acre costs for nonpoint sources were also taken from Caplan et al. (2009) (see the references therein). Two types of BMPs were considered in that study – conservation tillage and nutrient management – both of which are deemed relevant by local authorities for the Cub River sub-basin. As discussed in Caplan et al. (2009), conservation tillage ranges in percent effectiveness from 60 to 80% and nutrient management from 40 to 50%, and per-acre costs of these BMPs range from approximately \$3 for conservation tillage to as much as \$17 for nutrient management (which in our study translates into an average cost for nonpoint sources of \$0.45 per kilogram of TP abated). Because no BMP field studies have (yet) been performed in the Mountain West region of the US, we must randomly assign draws from the respective ranges of these estimates to each of the nonpoint sources in our population according to a set of pre-determined proportions, or probabilities. We therefore acknowledge that the benchmark established by the trading algorithm is contingent upon the random assignment of these estimates, and in this way is only illustrative of what an actual benchmark might be should the BMP data limitations be overcome in the future. In the meantime, however, the benchmark we establish in this paper is based upon the current (and foreseeable) information realities faced by regulators of the Cub River sub-basin.

The values for BMP effectiveness (denoted as E), cost per-acre cost (denoted C/L), and associated probabilities for E and C/L, denoted π_E and π_{CL}, respectively, are taken from Caplan et al. (2009) and included in Table 1. In relation to our previous use of notation, E multiplied by current load equals to a nonpoint source's abatement level ($A(i,k)$), where $k = 1$ for all i. The numerator in C/L is $C(i,k)$, again with $k = 1$ for all i. L is the corresponding number of acres. Unlike for E and C/L, empirical estimates of π_E and π_{CL} do not exist in the literature.

For example, each nonpoint source in our population had a 20% chance of being assigned a C/L of 3 and a 20% chance of being assigned an E of 60%. In all, there were $3 \times 3 = 9$ possible combinations of C/L and E (with associated joint probabilities) for each nonpoint source.

Estimates for abatement levels and associated total costs for the sub-basin's point sources were also taken from Caplan et al. (2009). These estimates correspond to two "tiers" of abatement technology for each source. For Tier 1 technology, annual abatement levels (i.e., $A(i,1)$) range from 827 to 0.0003 kg; similarly for Tier 2 technology. Associated Tier 1 abatement costs (i.e., $C(i,1)$) range from \$344,000 to \$6500, and Tier 2 costs (i.e., $C(i,2)$) range from \$362,000 to\$26,400.[12] For our study, these costs translate into average costs for the sub-basin's WWTPs of \$0.74 and \$0.79 per kilogram abated for Tier 1 and 2 technologies, respectively.[13]

Similar to the second part of the example presented in Section 3.2, where large differences in abatement levels and costs exist between the polluters, retreat was necessary to reduce both the sub-basin's abatement surpluses (i.e., the $F(i,S,P)s$) and its overall abatement costs to their lowest possible levels. In this respect, the sub-basin's nonpoint

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[10] Utah Department of Environmental Quality (Utah DEQ) (2008) provides a detailed description of the basin's physical, biological, and socioeconomic characteristics.

[11] See Caplan et al. (2009), and associated references therein, for a discussion of alternative hydrologic models that have previously been developed to support assessments of WQT in other river basins.

[12] See U.S. Environmental Protection Agency (2003) for a detailed discussion of abatement technology for point sources.

[13] We acknowledge that these average costs are generally lower than those reported in Lee and Jones (1998), U.S. Environmental Protection Agency (2003), and Keplinger et al. (2004). Again, the particular trading benchmark established in this paper, which in turn is based on our underlying assumptions about abatement costs, is only illustrative of what an actual benchmark would be if alternative cost estimates are used.

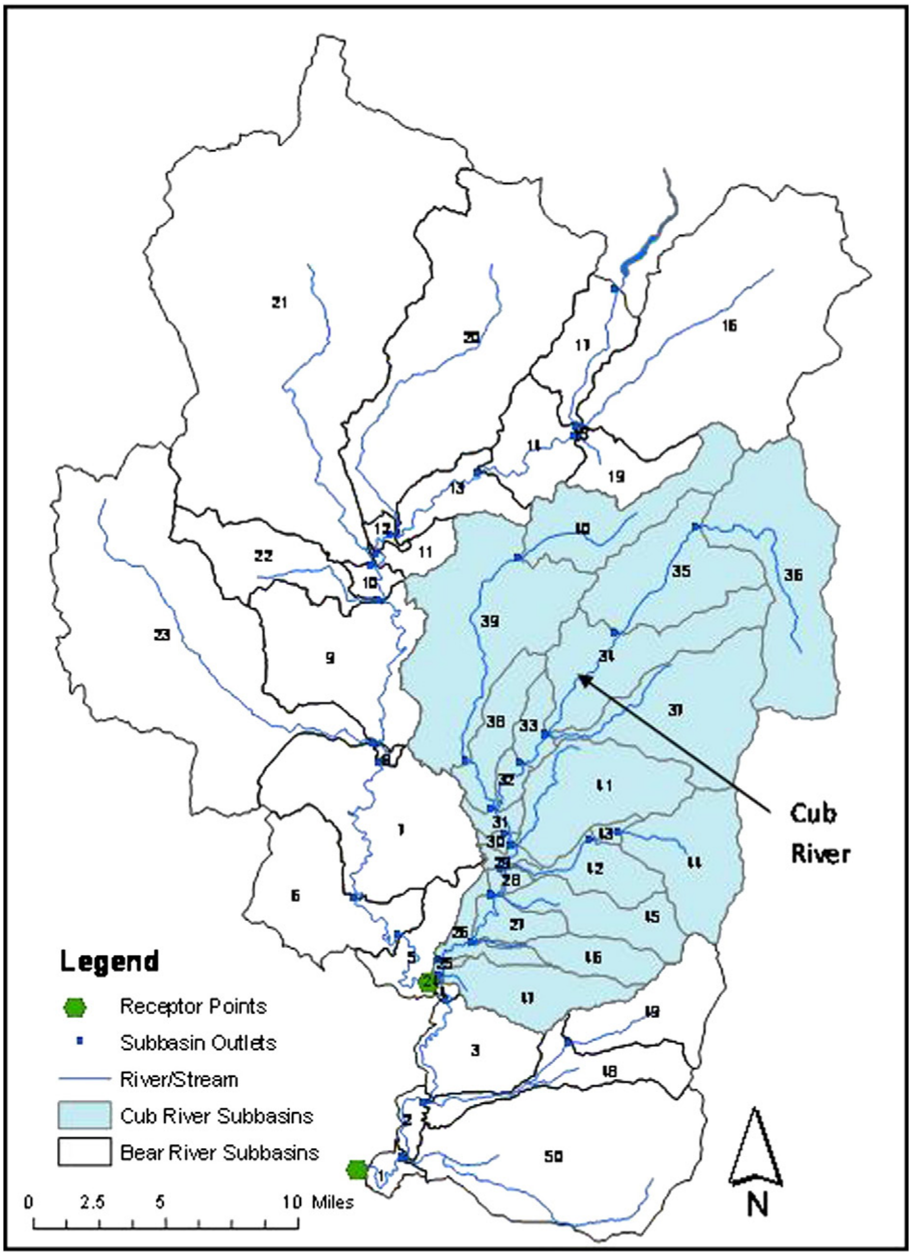

Fig. 2. The Cub River sub-basin.

(point) sources are reminiscent of polluter 1 (2) in the second part of the example in Section 3.2.

Due to the sheer number of the sub-basin's point and nonpoint sources involved in the benchmark trading exercise (as mentioned in Section 4 there are 1300 nonpoint sources and five point sources), we are precluded from presenting final results for the advancement and retreat algorithms for each source (i.e., the trade pattern for the entire sub-basin). These results are available online at http://www.bearriverinfo.org/library/object.aspx?id=203. Nevertheless, to get a flavor of the sub-basin wide results, we highlight the results for two nonpoint sources (the two largest nonpoint polluters in the sub-basin) and two point sources (both WWTPs) that were involved in trades with each other as well as with other sources in the benchmark solution. In concert with the sub-basin wide cost savings associated with the advancement and retreat algorithms (reported further below), these results demonstrate our main finding — that in the benchmark solution, where both point and nonpoint sources are regulated, it can be cheaper for point sources to sell abatement credits to nonpoint sources as part of an overall WQT market outcome.

Profiles of the two point and two nonpoint sources are provided in Table 2. The profiles include estimates of current and target loads, required abatement ($R(i)$), abatement levels ($A(i,k)$), and total abatement costs ($C(i,k)$) for each source. With respect to required abatement, we do not account for any additional restrictions the Clean Water Act may impose on point sources, such as WWTPs, which would otherwise cause the point sources' $R(i)$ levels to be larger than those reported in a future TMDL (or a TMDL that is subsequently adjusted to reflect added restrictions in the point sources' NPDES permits). For each of

Table 1
BMP effectiveness and per-acre cost information.

C/L	π_{CL}	E	π_E
3	0.20	0.60	0.20
7	0.60	0.75	0.60
17	0.20	0.90	0.20

Table 2
Profiles of two nonpoint sources and two point sources.

Source (i)	Current load (kg)	Target load (kg)	$R(i)$ (kg)	$A(i,1)$ (kg)	$C(i,1)$ ($)	$A(i,2)$ (kg)	$C(i,2)$ ($)
NPS_1	52.1	15.6	36.5	39.1	8530	–	–
NPS_2	38.6	11.6	27.0	28.9	2692	–	–
PS_1	1719.7	337.5	1350.0	810.0	343,846	810.0	361,514
PS_3	1722.1	344.4	1377.7	826.6	303,385	826.6	303,473

the two nonpoint sources (NPS and NPS_2), only one abatement step (and associated cost) is assumed available, while for each of the point sources (PS_1 and PS_3) two abatement steps are assumed available.

As a result of running the trade algorithms on the entire sub-basin dataset, we obtain the following results for these four sources. In the benchmark solution, NPS_1 abates nothing and instead purchases 39 credits (measured in kilograms) from PS_1 and 0.001 credits from another nonpoint source (classified as NPS_{85} in our dataset). Adjusting these credits via the corresponding trading ratios for these respective sources results in NPS_1 satisfying constraint (4) of Section 2 with equality, i.e., NPS_1 carries neither an abatement surplus nor deficit. In contrast, NPS_2 abates its full amount and sells *all* of its abatement – not just what would be its available credits if it retained enough of its abatement to satisfy constraint (4) – to PS_3. To meet its required reduction, NPS_2 then purchases enough credits (29 kg worth) from PS_1 to satisfy its constraint (4) with equality.

As for the two point sources, PS_1 abates its full amount (using both of its abatement steps) and sells all of its abatement to a large proportion of the sub-basin's nonpoint sources. To meet its required reduction, PS_1 then purchases 651 credits from another point source (classified as PS_2 in our dataset), 409 credits from PS_3, and the remainder from a host of nonpoint sources. In the end, PS_1 carries a negligible credit surplus. Similar to PS_1, PS_3 also chooses to abate its full amount (using both of its abatement steps). However, PS_3 sells its abatement to far fewer nonpoint sources than does PS_1, choosing instead to sell 409 and 356 credits to PS_1 and PS_2, respectively. PS_3 then purchases enough credits from a host of nonpoint sources to meet its own required-abatement constraint with equality.

Total annual abatement cost for the sub-basin to meet required TMDL load reductions under a no-trading scenario amounts to roughly $2,706,000. In this no-trade scenario, approximately 80% of the nonpoint sources are able to meet their required reductions through their individual abatement efforts, and thus have surplus abatement available to cover the deficit resulting from the remaining 20% that are unable to meet their requirements on their own. The net surplus amounts to 79.3 kg. Point sources would each need to implement both of their technology tiers to meet their required TP reductions. Similar to the nonpoint sources, this results in an abatement surplus. The surplus for point sources amounts to 740.7 kg. Thus, the total annual abatement surplus in the no-trading scenario amounts to approximately 820 kg.

In contrast, use of the advancement and retreat algorithms results in a benchmarked total annual abatement cost for the sub-basin of roughly $1,780,000, i.e., a $926,000 savings relative to the no-trading scenario. Further, the abatement surplus for the entire sub-basin is a negligible amount. Therefore, in sum, the trading algorithms result in a substantial cost and abatement savings for the sub-basin by encouraging the widest possible gamut of trading opportunities — point-to-point, nonpoint-to-nonpoint, and bi-directional nonpoint-to-point.

6. Concluding remarks

This paper has employed Sasaki and Caplan (2008) trading algorithm (the companion advancement and retreat algorithms) to derive a benchmark pattern-of-trade for a potential water quality trading (WQT) market located in the Cub River sub-basin of Utah; a potential market with both point and nonpoint sources. By accounting for all possible point-to-point, nonpoint-to-nonpoint, and bi-directional point-to-nonpoint source trades, the algorithms have provided a reduced-cost benchmark against which a potential market's performance could conceivably be compared.

We find that a benchmarked trade pattern for a potential Cub River WQT market – where each source, point or nonpoint, is required to reduce its pollution loadings – may entail some point sources selling abatement credits to nonpoint sources. This result – which is contingent upon both our hydrologic and cost assumptions – occurs because although point sources do face relatively high total costs of abatement, on an average- or marginal-cost basis (which is the basis upon which potential trading is ultimately made) some point sources face relatively low average costs once the levels at which these sources are capable of abating are taken into account. Further, the abatement levels achieved by some of our point sources (and thus the potential for these sources to generate abatement credits) far exceed what disparate nonpoint sources are capable of achieving on their own. Although the literature on point sources provides evidence of relatively high total abatement costs (see Keplinger et al., 2004; Lee and Jones, 1998; U.S. Environmental Protection Agency, 2003), to our knowledge this literature has not investigated to the same extent how these total costs, once translated into average and marginal abatement costs, compare with small, disparate nonpoint-source costs. Our results suggest that, to the extent that their technologies can abate large enough quantities of pollutants, at least some point sources may be capable of achieving concomitantly low average abatement costs relative to nonpoint sources.

The trading algorithm can be used to derive benchmarked trade patterns – both at the watershed and individual-source levels – for a wide variety of potential WQT markets. In turn, the benchmarks can then be used to guide actual trades among sources that would occur in an actual market, and to assess the optimality of market outcomes over time. One obvious deficiency of the current paper is that it represents a single application of the trading algorithms to a single sub-basin in a single state. A welcomed extension would therefore be additional applications to a wide variety of potential WQT markets in other areas of the country. A second deficiency concerns wider access to the same type of load and delivery-ratio estimates generated by the Neilson et al. (2009) model. Neilson et al. (2009) modeling approach is admittedly in its infancy, and is therefore not widely available for use in other watersheds. Application of the trading algorithm requires both hydrologic and economic information, which can be difficult to obtain for certain watersheds.

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