Chapter 9
The Environmental Trading Problem

9.1 Introduction

The increasing stringency of environmental regulations and the global rise of concerns about the environmental impact of industrial production have led to an increased focus on waste management decisions as a component of industrial sustainability. Pollutant credit trading, an approach that provides economic incentives for reducing pollution, is one novel idea introduced in an attempt to reduce the financial burden of waste management [56] . Both the US Environmental Protection Agency (USEPA) and the US Department of Agriculture (USDA) seek to promote this type of market-based solution. However, industry-level decision making under a pollutant trading scheme faces many difficulties, especially in the presence of uncertainty. In this chapter, the L-shaped BONUS algorithm is applied to the pollutant trading problem to optimize such decisions. This chapter is based on the paper by Shastri and Diwekar [51].

9.2 Basics of Pollutant Trading

Pollutant trading is a market-based approach to pollution reduction based on the idea that different pollutant sources have different pollution control costs. Therefore, if the task of pollutant reduction can be assigned to the facilities with the lowest control costs, the total cost of pollution control across all pollutant sources is minimized. A market-based trade mechanism accomplishes this by efficiently allocating pollutant reduction efforts among sources. With such a system in place, a facility that would otherwise exceed its allowable pollutant discharge has two options for meeting its regulatory obligations: (1) reducing its pollutant level or (2) paying another facility to reduce *its* pollutant level by an equivalent amount. The pollutant trading system therefore allows the facility to choose the lower cost option, whereas in the absence of such a system, it would have to reduce its own pollutant level at any cost.

In the case of watershed based trading, the total amount of pollutants that may be released into a watershed over time, while allowing the watershed to still meet

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water quality standards, is evaluated by the state or federal authority. This amount, in combination with factors such as the existing discharge levels, the expected discharge from nonindustrial sources, and the relative size and economic contributions of each polluter, leads to the establishment of a regulation such as a total maximum daily load (TMDL) for each polluter. A polluter may then bring itself into compliance by applying waste treatment methods, incurring both capital and operating costs that depend on the type and amount of waste treated, the existing technology, and the level of reduction to be achieved. If this is found to be a high-cost proposition, the facility may instead buy "credits" from another polluter, allowing it to release an amount of discharge greater than its TMDL into the watershed. The polluter that has sold credits, meanwhile, must reduce its discharge an equivalent amount below its TMDL [57].

The credit trading market is affected by transaction costs, number of participants, availability of cost data, and uncertainties related to continued industry participation and data availability. Trading economics are also influenced by the trading ratio, how many units of pollutant reduction a source must purchase to receive credit for one unit of load reduction.

Among the participants in the trading market, each polluter is classified as a point source (PS) or a nonpoint source (NPS). Point sources are those that have direct and measurable emissions, such as industries, while nonpoint sources have diffused emissions that are more difficult to measure, such as agricultural runoffs. Because nonpoint sources are the primary polluters in most watersheds, from a volumetric perspective, and because pollution control costs are typically lower for nonpoint sources, trading between point and nonpoint sources has considerable potential for pollution reduction.

However, the nonpoint sources are difficult to measure at a reasonable cost, and the diffusion of the pollutants makes it difficult to estimate the effectiveness of pollution reduction strategies. Further, pollution from nonpoint sources is often dependent on stochastic factors such as rainfall and other weather conditions. These factors introduce a significant amount of uncertainty into the economics of trading between point and nonpoint sources. Thus, in the presence of multiple polluters in both point and nonpoint categories, heuristics-based decision making is likely to be suboptimal. A framework based on mathematical modeling concepts and making use of the BONUS method can have significant value to industries in analyzing their options.

9.3 Christina Watershed Nutrient Management

The Christina watershed is an important watershed in the Lower Delaware River (LDR), draining three states and providing up to 100 million gallons of public drinking water per day [48]. The LDR Basin has had ongoing problems with both point and nonpoint sources of pollution, consisting primarily of industrial discharges, urban runoff, and agriculture. This has led to concern over both sediment and nutrients released into the watershed. Sediment consists of loose sand, clay, and other soil particles caused primarily by soil erosion and decomposition of plants and animals, and can be greatly accelerated by human use of land. Nutrients consist of nitrogen and phosphorus that find their way into the watershed through agricultural, storm water, wastewater, household, and industrial runoff [24].

Various watersheds within the LDR basin have been declared “impaired,” having pollutant levels that exceed those allowable for maintenance of water quality. Thirty-nine segments of the basin have been declared impaired due to their low levels of dissolved oxygen (DO) and nutrient additions from various point and nonpoint sources, including industrial and municipal point sources, and agricultural, superfund, and hydromodification nonpoint sources are considered to be the major cause. Authorities have proposed two different TMDLs for the Christina watershed, a low-flow TMDL focusing on the impact of nitrogen and phosphorus additions from the point sources, and a high-flow TMDL accounting for the nonpoint source additions of bacteria and sediment. Trading has been proposed as a viable option to achieve reductions in phosphorus, total nitrogen, ammonia nitrogen, and carbonaceous biochemical oxygen demand (CBOD), allowing the point source load allocations to meet the low-flow TMDL targets.

The simplest trading mechanism would involve trading among the various point sources. However, opportunities for pollutant reduction in this manner are limited by similar treatment costs throughout the watershed. A more effective trading mechanism would instead leverage trading between point and nonpoint sources, as nonpoint sources offer significant opportunity to reduce pollution by converting existing agricultural land to forest or implementing best management practices (BMP) on the cultivated lands. Therefore, this chapter proposes a trading mechanism by which land is allocated to a particular point source and the point source is responsible for management of the nonpoint source to offset nutrient discharges from the point source facility.

9.4 Trading Problem Formulation

A general trading problem applicable to any watershed is formulated, and subsequently applied to the Christina watershed case study. Because of the uncertainity associated with the nonpoint sources, a stochastic programming problem is required. The problem considers trading between a set of point sources and a single nonpoint source, assumed to be a farm. All sources discharge pollutants into a common body of water, such as a lake. The maximum amount of discharge per day into the body of water is statutorily regulated. The model does not consider regulations on nonpoint source emissions, a simplification that reflects actual regulations that exclude nonpoint sources due to the impossibility of accurately measuring their emissions. The development of TMDL results, therefore, in specific load allocations for each point source that becomes the baseline for trading between the point source and the nonpoint source. Note that the reduction techniques for the nonpoint source are nonlinearly dependent on the type and quantity of pollutant being treated.

Uncertainties in both inputs and outputs to the sources necessitate that the problem be formulated as a stochastic program. Let $i = 1, ..., P$ represent the set of point source and $j = 1, ..., M$ represent the chemicals that are regulated. Assume that the current pollutant discharge levels and the discharge reduction cost are known for each chemical at every point source.

Additional parameters characterizing each point source are:

- $D(i)$, the total volumetric discharge from point source i, expressed as volume/time
- $e_{p0}(i, j)$, the pretreatment discharge quantity of chemical j from point source i, expressed as mass/volume
- $c_p(i, j)$, the cost of treating chemical j at point source i, expressed as dollars/mass.

Some point sources have uncertainties in the measurement of their discharge quality and quantity, typically introduced when a point source treats incoming wastewater from a variety of sources, and resulting in both inputs and outputs that vary within certain limits. For example, a publicly owned water treatment plant (POWT) may treat sewage waste as well as water runoffs, the latter having a variable quantity and content. Therefore, only $c_p(i, j)$ is a deterministic parameter for all i and j; both $D(i)$ and $e_{p0}(i, j)$ contain uncertainty.

The nonpoint source is assumed to have a fixed amount of available land that can be divided among all point sources to implement treatment technologies (BMP). The nonpoint source is characterized by:

- L_{max}, the maximum amount of nonpoint source land available for trading, expressed as area
- e_{n0}, the pretreatment discharge quantity of chemical j from the nonpoint source, expressed as mass·area/time
- $c_n(j)$, the cost for the nonpoint source discharge reduction of chemical j, expressed as dollars/area
- $b_{NPS}(j)$, the nonpoint source abatement efficiency of chemical j
- $q_n(j) = e_{n0}(j)b_{NPS}(j)$, the abatement in nonpoint source discharge of chemical j, expressed as mass·area/time.

As previously mentioned, there are difficulties in measuring both the emissions and the reduction efficiencies for a particular technology at a nonpoint source, thus the actual reductions achieved by BMP are not precisely known. Therefore, e_{no} and b_{NPS} (and thus $q_n(j)$) contain uncertainty, while other parameters are assumed to be known for all i and j.

In addition to the waste load allocation for each point source, there are regulatory restrictions on the maximum amount of any chemical that can be discharged into the water body at a particular location. Enforcing this limit ensures that the implementation of pollutant trading does not result in the creation of localized points of high pollutant concentration known as "hot spots." Accordingly, the model includes $z_{red}(ij)$ representing the targeted reduction in discharge of chemical j by point source i (expressed as mass/time) and $z_{allowed}(j)$ representing the maximum permitted discharge of chemical j at any single location (expressed as mass/time).

Two decisions are to be made, with the goal of achieving the reduction targets at the lowest *total* cost:

1. How much end-of-pipe treatment reduction should be achieved at each point source?

2. How much land (NPS) should be allocated to each point source to achieve further reductions?

Accordingly, the decision variables in the model are $q_p(i, j)$, the discharge abatement of chemical j at point source i (expressed as mass/volume), and $L(i, j)$, the land allocated for trading by point source i to treat chemical j. The objective function is therefore

$$Min f_1(c_n, L) + E[f_2(D, c_p, q_p)], \tag{9.1}$$

where E is the expectation operator over the uncertain parameters and f_1 and f_2 are nonlinear functions of the respective variables. The first term in the objective represents the cost incurred due to trading through the allocation of land for each point source from the nonpoint source, while the second term represents the expected value of the total end-of-pipe treatment cost incurred by the point source to satisfy the regulations in the presence of uncertainty.

A feasible solution to this problem must meet the following constraints :

$$\sum_{i,j} L(i, j) \leq L_{max} \tag{9.2}$$

$$E\left[D(i, j)q_p(i, j) + L(i, j)q_n(j)\right] \geq z_{red}(i, j) \qquad \forall\,(i, j) \tag{9.3}$$

$$E\left[D(i, j)\left(e_{p0}(i, j) - q_p(i, j)\right)\right] \leq z_{allowed}(j) \qquad \forall\,(i, j) \tag{9.4}$$

$$0 \leq q_p(i, j) \leq e_{p0}(i, j) \qquad \forall\,(i, j) \tag{9.5}$$

$$q_n(j) = e_{n0}(j)b_{NPS}(j) \qquad \forall\,(i, j) \tag{9.6}$$

The first constraint (9.2) ensures that the total land allocated to all point sources does not exceed the amount of land available at the nonpoint sources. The second set of constraints (9.3) ensures that each point source achieves its individual reduction target for each chemical, with or without trading, while the third set (9.4) ensures that the emission of pollutant j at any location does not exceed the maximum allowable amount. The reduction of each chemical at each point source is restricted to values between zero and the initial concentration by the fourth set of constraints (9.5). Finally, the fifth set of constraints (9.6) models the effect of uncertainty on the problem by relating the pollutant reduction by the nonpoint source ($q_n(j)$) to the uncertain parameters $e_{n0}(j)$ and $b_{NPS}(j)$.

The problem can be made more tractable by converting it into a two-stage stochastic programming problem with recourse. The first-stage decisions are land allocations (the trading itself) between the point source and the nonpoint source, $L(i, j)$, and the second-stage decisions are the amounts of point source abatement, $q_p(i, j)$, achieved by end-of-pipe treatment. The two-stage formulation, including specific definitions of functions f_1 and f_2, is given as

$$First - stage\ problem \tag{9.7}$$

$$Min \sum_{i=1}^{P}\sum_{j=1}^{M} c_n(i, j)L(i, j)^{\alpha_j} + E\left[R(L, q_p, q_n, D)\right] \tag{9.8}$$

Table 9.1 Point source details for Christina River Basin

Point source	Total discharge (MGD[a])	Current discharge (kg/day)		Targeted (% reduction)		Treatment (cost, $/kg)	
		N	P	N	P	N	P
1	0.4	30.30	30.30	0	13	15.6	5.2
2	1.028	233.63	38.94	26	26	14	4.9
3	7.5	568.18	568.18	25	0	10.9	3.8
4	3.85	291.66	299.76	0	68	12.7	4.2
5	0.6	68.18	45.45	10	10	15.4	5.1
6	1.1	125.0	313.72	34	83	14.4	5
7	0.72	5.45	5.45	5	5	18.3	5.4
8	0.7	171.06	26.51	69	0	15.4	5.12

[a] *MGD* Millions of gallons per day

$$subject\ to:$$

$$\sum_{i=1}^{P}\sum_{j=1}^{M} L(i,j) \le L_{max}, \tag{9.9}$$

where R is the recourse function. The term α_j is a constant for chemical j that represents the nonlinear relationship between land allocation and pollutant reduction.

$$Second - stage\ problem \tag{9.10}$$

$$Min\ E\left[R(L, q_p, q_n, D)\right] = \sum_{n=1}^{N_{samp}}\sum_{i=1}^{P}\sum_{j=1}^{M} D(i,j,n)c_p(i,j)q_p(i,j,n) \tag{9.11}$$

$$subject\ to:$$

$$D(i,j,n)q_p(i,j) + L(i,j)q_n(j,n) \ge z_{red}(i,j,n) \qquad \forall\,(i,j,n) \tag{9.12}$$

$$D(i,j,n)\left[e_{p0}(i,j) - q_p(i,j,n)\right] \le z_{allowed}(j) \qquad \forall\,(i,j,n) \tag{9.13}$$

$$0 \le q_p(i,j) \le e_{p0}(i,j) \qquad \forall\,(i,j) \tag{9.14}$$

$$q_n(j,n) = e_{n0}(j)b_{NPS}(j,n) \qquad \forall\,(j,n), \tag{9.15}$$

where N_{samp} is the sample size used to represent the uncertain space in the optimization algorithm, and n is a particular sample from that space.

For the Christina watershed, the authorities have recommended 8 point sources for trading, out of a total of 104 point sources. Two of the eight are private industries, while the other are municipal polluters. Two nutrients, nitrogen and phosphorus, are considered tradable commodities, and both have known TMDL-generated reduction targets at each point source. The total volumetric discharge, current discharge levels, and reduction targets for both pollutants are given in Table 9.1, along with the mean values for the cost of end-of-pipe treatment at each point source. Various parameters

Table 9.2 Point source details of NPS emission and treatment

	Nitrogen	Phosphorus
Mean value of emission quantity (kg per unit area per day)	20.2	30.5
Standard deviation in emission quantity	2.0	2.0
BMP cost ($ per unit area)	17.18	17.18
BMP nutrient reduction efficiency	0.50	0.39
Standard deviation in reduction efficiency	0.02	0.02

BMP best management practice

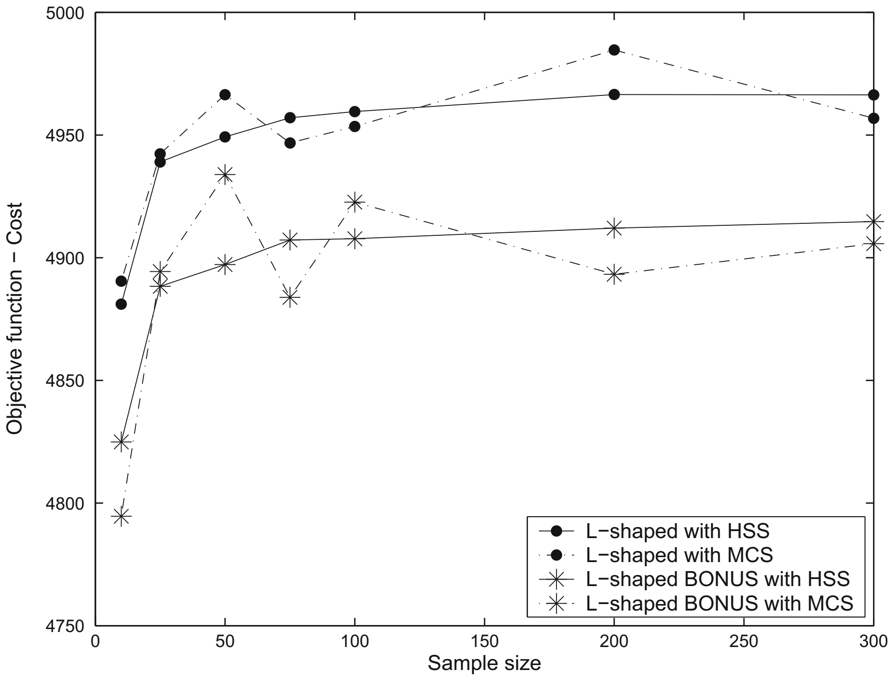

Fig. 9.1 Variation of the objective function result with sample size

of the BMPs along with the average pretrading discharges of both nutrients for the nonpoint source are given in Table 9.2. The maximum allowed concentrations at a discharge point ($z_{allowed}$) are 450 and 570 kg/day for nitrogen and phosphorus, respectively. The total quantity of land available for trading (L_{max}) is 500 units.

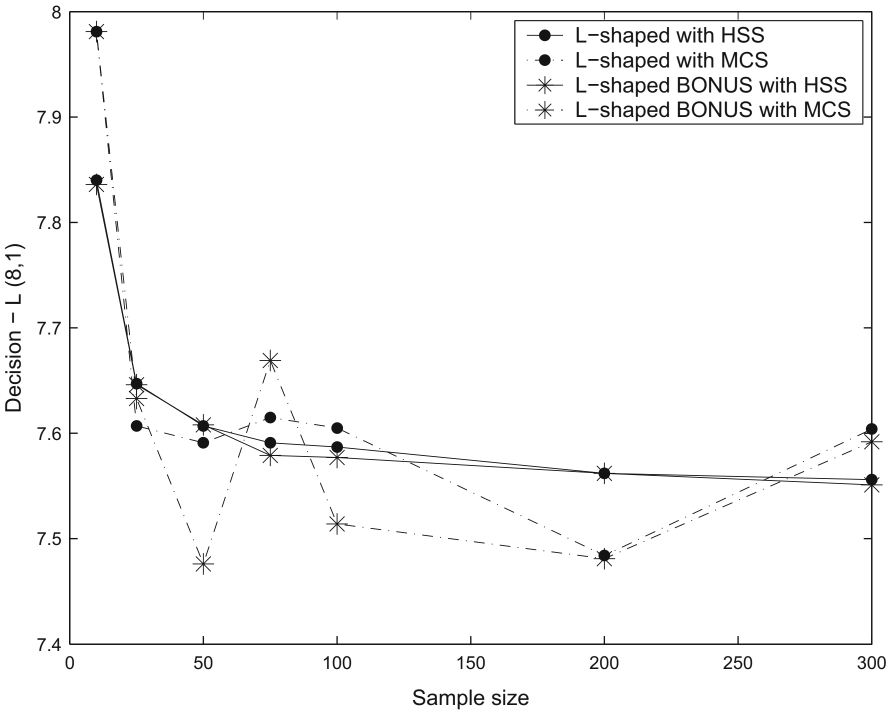

Fig. 9.2 Variation of decision variable L(8,1) with sample size

9.5 Results

To show the efficacy of the L-shaped BONUS method algorithm compared to the standard L-shaped method, and to ensure the benefits of the L-shaped BONUS method are independent of the sampling technique used, the problem was solved in four ways:

- Standard L-shaped method with Hammersley sequence sampling (HSS) technique
- Standard L-shaped method with Monte Carlo sampling (MCS) technique
- L-shaped BONUS method with HSS technique
- L-shaped BONUS method with MCS technique.

For each methodology, the value of the objective function (total cost) is shown as a function of sample size in Fig. 9.1. The value of land allocated by point source 8 toward nitrogen pollution trading ($L(8, 1)$), a representative decision variable, is shown in Fig. 9.2. While it can be seen that the optimization method has a larger effect on the value of the objective function than the sampling technique, the variation among all four methodologies is just larger than 1 %, well within acceptable tolerance limits for the solution of a stochastic nonlinear program. The plot for the decision variable shows an even smaller average difference between the standard L-shaped

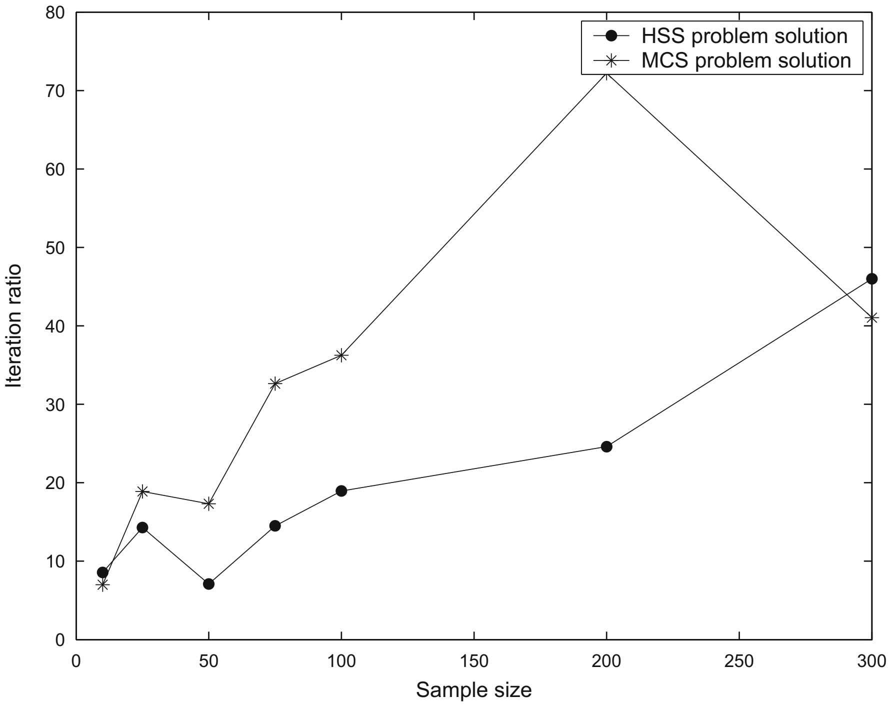

Fig. 9.3 Variation of computational time with sample size

method and the L-shaped BONUS method (0.05 % for HSS and 0.26 % for MCS). This indicates that the reweighting approximation used in L-shaped BONUS method does not sacrifice accuracy in calculating results.

Figure 9.3 shows the iteration ratio, the number of iterations required for the standard L-shaped method divided by the number of iterations required for the L-shaped BONUS method, as a function of sample size. The iteration ratio generally increases as the sample size gets larger; thus, the larger the sample size, the greater the computational savings using the BONUS method. Because Figs. 9.1 and 9.2 show that the value of both the objective function and the representative decision variable reaches a steady-state value as the sample size is increased, indicating that a large sample size is needed for accurate results, it can therefore be concluded that the L-shaped BONUS method is of significant utility in reducing the computational cost of the environmental trading problem.

The solution to the trading problem is qualitatively similar under all four solution methods: to minimize the total cost, every point source needs to achieve part of its required reductions through trading with the nonpoint source. Such a decision is unlikely to result when each point source makes an independent decision, without consideration of the overall cost of reductions. Therefore, the results strongly suggest that a rigorous method and systematic mathematical analysis should be performed to achieve environmental benefits at the lowest possible cost.

9.6 Summary

In this chapter, because the environmental trading problem that seeks to manage nutrient pollution in the Christina River Basin of the LDR is formulated as a two-stage stochastic programming problem, the use of a specialized stochastic programming solution method, such as the L-shaped method, is appropriate for finding its solution. The L-shaped BONUS algorithm, combining the standard L-shaped method with the BONUS reweighting scheme, provides results within 2 % of those provided by the standard L-shaped method while reducing iterations by a factor of more than 20 for large sample sizes. Therefore, it is concluded that the L-shaped BONUS method provides both accurate results and a significant reduction in computational cost.

Notations

$b_{NPS}(j)$	nonpoint source abatement efficiency of chemical j
$c_n(j)$	cost for the nonpoint source discharge reduction of chemical j, expressed as dollars/area
$c_p(i, j)$	cost of treating chemical j at point source i, expressed as dollars/mass
$D(i)$	total volumetric discharge from point source i, expressed as volume/time
$e_{p0}(i, j)$	pretreatment discharge quantity of chemical j from point source i, expressed as mass/volume
e_{n0}	pretreatment discharge quantity of chemical j from the nonpoint source, expressed as mass·area/time
$L(i, j)$	land allocated for trading by point source i to treat chemical j
L_{max}	maximum amount of nonpoint source land available for trading, expressed as area
M	number of regulated chemicals
n	a particular sample from the uncertain space
N_{samp}	the sample size used to represent the uncertain space in the optimization algorithm
P	number of point sources
$q_n(j) = e_{n0}(j)$ $b_{NPS}(j)$	abatement in nonpoint source discharge of chemical j, expressed as mass·area/time
$q_p(i, j)$	discharge abatement of chemical j at PS i (expressed as mass/volume)
R	recourse function
$z_{red}(ij)$	targeted reduction in discharge of chemical j by point source i (expressed as mass/time)
$z_{allowed}(j)$	maximum permitted discharge of chemical j at any single location (expressed as mass/time)
Greek letters	
α_j	cost exponent