Controlling Ozone and Fine Particulates: Cost Benefit Analysis with Meteorological Variability

Jhih-Shyang Shih, S. Michelle Bergin, Alan J. Krupnick, and Armistead G. Russell

November 2003 • Discussion Paper 03–55

Resources for the Future
1616 P Street, NW
Washington, D.C. 20036
Telephone: 202–328–5000
Fax: 202–939–3460
Internet: http://www.rff.org

Controlling Ozone and Fine Particulates: Cost Benefit Analysis with Meteorological Variability

Jihih-Shyang Shih, S. Michelle Bergin, Alan J. Krupnick, and Armistead G. Russell

Abstract

In this paper, we develop an integrated cost-benefit analysis framework for ozone and fine particulate control, accounting for variability and uncertainty. The framework includes air quality simulation, sensitivity analysis, stochastic multi-objective air quality management, and stochastic cost-benefit analysis. This paper has two major contributions. The first is the development of stochastic source-receptor (S-R) coefficient matrices for ozone and fine particulate matter using an advanced air quality simulation model (URM-1ATM) and an efficient sensitivity algorithm (DDM-3D). The second is a demonstration of this framework for alternative ozone and $PM_{2.5}$ reduction policies. Alternative objectives of the stochastic air quality management model include optimization of the net social benefits and maximization of the reliability of satisfying certain air quality goals. We also examine the effect of accounting for distributional concerns.

Key Words: ambient air, ozone, particulate matter, risk management, public policy, cost-benefit analysis, variability and uncertainty, stochastic simulation, stochastic multi-objective programming, decisionmaking, National Ambient Air Quality Standards

JEL Classification Numbers: C6, Q2, Q25, Q28

Contents

Controlling Ozone and Fine Particulates: Cost Benefit Analysis with Meteorological Variability

Jihh-Shyang Shih, S. Michelle Bergin, Alan J. Krupnick, and Armistead G. Russell*

1. Introduction

The process of developing strategies for meeting National Ambient Air Quality Standards (NAAQS) for ozone and fine particulates has been a subject of considerable debate among the states and between them and the U.S. Environmental Protection Agency, as well as in the research community. In formulating standards and demonstrating attainment, policymakers obliquely take into account some uncertainties and variability, but these issues are generally not directly or quantitatively addressed. Other issues include less than optimal emphasis on and incentives for finding cost-effective approaches to meeting standards and a lack of recognition that different control policies affect environmental endpoints differently. Currently, a framework to integrate uncertain scientific information with policy analysis to inform decisionmakers and to develop control strategies is lacking.

The objective of this paper is to present an integrated cost-benefit analysis framework for ozone and fine particulate control, accounting for meteorological variability and uncertainty. The framework includes an air quality simulation model, sensitivity analysis, stochastic multi-objective air quality management, and stochastic cost-benefit analysis.

This paper has two major contributions. The first is the development of stochastic source-receptor (S-R) coefficient matrices for ozone and fine particulate matter using an advanced air quality simulation model (URM-1ATM) (Kumar et al., 1994; Boylan et al., 2002) and an efficient sensitivity algorithm (DDM-3D) (Yang et al., 1997). The second is the demonstration

* Jhih-Shyang Shih and Alan J. Krupnick are Fellow and Senior Fellow, respectively, at Resources for the Future. S. Michelle Bergin and Armistead G. Russell are Ph.D. candidate and Professor, respectively, at Georgia Institute of Technology. We would like to thank Yueh-Jiun Yang, Jim Wilkinson, Jim Boylan, and Dick Morgenstern for valuable duscussions and technical support; Mike Batz, Lisa Crooks, and Meghan McGuinness for excellent research assistance. We would like to give our special thanks to Dr. Allen Basala for his constant encouragement and valuable comments. Financial support of this research from EPA and the National Science Foundation is very much appreciated.

of how to conduct analyses of alternative ozone and $PM_{2.5}$ reduction policies using this modeling approach. Alternative objective functions utilized include optimization of the net social benefits and maximization of the reliability of satisfying certain air quality goals.

In this paper, we present the framework and preliminary results of a few such cases, such as optimizing expected net benefit, incorporating equity criteria in developing control strategies, and making trade-offs between expected net benefits and reliability levels required to meet air quality goals.

This framework has the potential for seven major uses: (1) to develop federal rules regarding transport and to develop state implementation plan (SIP) control strategies; (2) to evaluate interstate transfer of pollutants and emissions; (3) to study trading across states/regions and/or pollutants; (4) to conduct cost-benefit analysis and risk management analysis; (5) to help set air quality standards; (6) to investigate the importance of uncertainty and conduct value of information analysis; and (7) to set research priorities.

2. Air Quality Model, Performance Evaluation, and Sensitivity Analysis

Ozone and $PM_{2.5}$ share common sources and formation routes in the atmosphere. Ozone, a gas, is formed secondarily in the atmosphere by reactions between nitrogen oxides (NO_x) and volatile organic compounds (VOCs) in the presence of sunlight. Fine particulate matter is composed of many different chemical species, including (but not limited to) ammonium sulfate, ammonium nitrate, and organic and elemental carbon. Depending on the chemical composition, $PM_{2.5}$ can be directly emitted—e.g., from diesel vehicles, dust, and biomass burning, and/or formed secondarily from reactions of sulfur dioxide (SO_2), NO_x, ammonia (NH_3), and VOCs. Controls placed to reduce one form of particulate may affect concentrations of the other, though not necessarily proportionally or even in the same direction.

Previous studies have explored the responses of both ozone and $PM_{2.5}$ to various controls (Krupnick et al., 2000), but have based their results on out-of-date air quality models. Control strategies exist that lower both $PM_{2.5}$ and ozone concurrently, or lower one or the other. Thus, from an air quality management perspective, it is desirable to understand the relative efficacy of NO_x and SO_2 emissions reductions in controlling these air pollutants.

Air Quality Model

URM-1ATM is applied to two well-studied, high-pollution meteorological episodes occurring July 9-19, 1995 and May 22-29, 1995. These base episodes were selected because high-quality and complete data were available, they were previously modeled using a different multi-scale grid definition but with the same simulation system, and they cover large meteorological variation with moderate to high pollution formation. Meteorological information is developed using the Regional Atmospheric Modeling System (RAMS) (Pielke et al., 1992) in a nonhydrostatic mode, including cloud and rain microphysics.

Emissions were generated using the Emissions Modeling System (EMS-95) (Wilkinson et al., 1994). Day-specific emissions for the year 2010 are estimated under conditions that are anticipated with changes in population growth, vehicle turnover, emissions control technologies, and anticipated emissions regulations, including the NO_x SIP call. Given nonattainment designations in 2004 or 2005, many designated ozone and PM nonattainment areas would design implementation plans to meet a 2010 attainment date. Meteorological and initial and boundary conditions are hour- and day-specific, and are held constant for base and future years.

URM Model Performance

The July and May 1995 base case episodes have been used to evaluate URM performance against ambient measurements. Excluding model ramp-up days, eight and five days of simulation are available for evaluation of the July and May episodes, respectively. Data from the EPA's Aerometric Information Retrieval System (AIRS) (U.S. EPA, 2001) is used to evaluate model performance. EPA guidelines for urban scale ozone modeling are +/- 15% for Normalized Mean Bias (NMB), and +/- 35% for Normalized Mean Error (NME). This regional scale application resulted in an average NMB for ozone of –4.4% for the May episode and of 3.1% for the July episode, and the NME was 17% for May and 22.3% for July, all well within the stated guidelines. These values are calculated from measurements at sites coinciding with either $24km^2$ or $48km^2$ cells. Data were available for over 400 sites for each episode.

The Interagency Monitoring of Protected Visual Environments (IMPROVE) (NPS, 2000) network provides 24-hour averaged speciated aerosol data taken on Wednesday and Saturday of each week in our episodes, and these data are used to evaluate model performance for aerosols. Three days of data were available during the July episode (July 12, 15, and 19), with measurements from 18 sites in total, 12 of which coincided with $24km^2$ or $48km^2$ cells. These sites resulted in an average NMB for $PM_{2.5}$ of –9.34% and an average NME of 22.34%. Two days of data were available for the May episode (May 24 and 27), with measurements from 17 sites in total, 11 of which coincided with $24km^2$ or $48km^2$ cells. These sites resulted in an average NMB for $PM_{2.5}$ of 9.77% and an average NME of 28.64%. There are no EPA guidelines to indicate acceptable model performance for aerosols.

Sensitivity Analysis

The Direct Decoupled Method in Three Dimensions (DDM-3D) model (Yang et al., 1997) is employed to calculate the local sensitivities of specified model outputs simultaneously with concentrations. It is an alternative to the brute force method, where multiple simulation runs are needed. Instead, the DDM-3D solves differential sensitivity auxiliary equations simultaneously to calculate the sensitivity fields (temporal and spatial). The result of this method is the partial derivative of species concentrations with respect to minute changes in emissions. The major difference between the conventional brute force sensitivity approach and DDM-3D sensitivity analysis is the computational efficiency of the latter. The use of DDM-3D could potentially eliminate the need for a large number of individual perturbation runs. This feature of the research is important because the time between nonattainment designation and implementation plan development is limited and should be no more than three years.[1]

3. Source-Receptor (S-R) Matrices

The methods developed in this research yield the first regional set of S-R matrices derived from a unified air quality chemistry model.

The receptor states/regions of interest typically cover multiple simulation grid cells. Therefore, to derive source-receptor matrices (S-Rs), we aggregated individual grid cell sensitivity values to a single receptor site value. The sensitivity used for aggregation is the change of pollutant concentration at the peak of the specified time scale (one-hour or 8-hour daily maximum for ozone, and 24-hour average for $PM_{2.5}$). This receptor aggregation is performed on both a population-weighted and an area-weighted basis. Population-weighted S-Rs are needed for estimating health benefits from application of source controls and also give a better proxy for health effects than do area-weighted measures. The sensitivities are normalized as the change of pollutant concentration over a specific time scale per 1,000 tons of a precursor emissions reduction by state and by source type. These sensitivity values represent the marginal reduction of emissions from the source region to ozone or $PM_{2.5}$ reduction at a receptor site.

---

[1] Part D, Subpart 1 of the Clean Air Act. http://www.epa.gov/oar/caa/caa172.txt

The ozone sensitivity results are comparable with others in the literature based on simpler models (Rao et al., 1999). The PM sensitivity coefficients, however, are smaller (Krupnick et al., 2000). This result may be due, in part, to the episodes chosen for study.

Here, we present stochastic S-R matrices for ozone and $PM_{2.5}$ based on their sensitivities with respect to elevated point source NO_x reductions found in two different meteorological episodes. We used an emissions inventory projected to the year 2010 as baseline emissions (Pechan, 2002). This inventory assumes that all existing mandated and expected federal controls on emissions have been implemented, so the NO_x emissions are in general low.

We consider two different categories of sensitivity matrices: single cell S-R matrices and population-weighted S-R matrices. A single cell S-R coefficient is the sensitivity of the peak concentration at a single cell within the receptor state/region, calculated without spatial and population weighting. Use of this matrix is most appropriate for considerations of compliance with air quality standards and assumes that every grid cell within the receptor state/region has a monitoring station. The state/region is in compliance as long as the concentration at any single grid cell is greater than or equal to the air quality standard. On the other hand, we need to aggregate population-weighted sensitivity coefficients for every grid cell within the receptor state/region to obtain the S-R coefficient for use in benefit calculations. The benefit is calculated as concentration change multiplied by population. If the high pollutant concentration change happens in a rural area, it will receive a smaller weight relative to that of a concentration change in an urban area.

Quantify Uncertainty and Variability of Source-Receptor Coefficients

Air quality simulation models have been and will continue to be used for developing air quality control strategies. There are many sources of uncertainty in the air quality simulations. Composite uncertainty combines effects of several types of uncertainty, including models, parameters, emissions inputs, and meteorology. Alcamo and Bartnicki (1990) investigate the uncertainty of S-R relationship for sulfur deposition in Europe. Hanna et al. (2001) study the uncertainties in predicted ozone concentrations (not sensitivity) for the Ozone Transport Assessment Group (OTAG) region. In this research, we are interested in the uncertainty and variability of S-R coefficients (sensitivity) for both ozone and $PM_{2.5}$ for the entire northeast of the United States. Although our modeling framework is robust and allows us to study various sources of uncertainty, due to limited resources, we only investigate the uncertainty and variability of the S-R coefficient caused by meteorological variability. The purpose of this research is to demonstrate the concept and the framework. The effects of other sources of uncertainty are left for future work.

As we mentioned earlier, July 9-19, 1995 and May 22-29, 1995 meteorological episodes are used in this study. Excluding the ramp-up days, we have eight 24-hour simulations available for the July episode (one for every day) and five for the May episode. We pool these 13-day samples together to quantify the variability of sensitivities from different meteorological variations. To quantify the variability, we fit normal distributions to every element of the S-R matrices and assume there is no correlation among elements within individual S-R matrices. The Kolmogorov-Smirnov test is used to conduct a "goodness-of-fit" test of the proposed distribution (Ang and Tang, 1975). Table 1 provides a summary of the percentage of elements in the above four different S-R matrices that pass the normality test with 5% significance level. As these percentages are very high, we accept the assumption of normality.

Table 1. Summary of Normality Test

Matrix	**1 hour daily maximum ozone**	**24 hour daily average $PM_{2.5}$**
Single cell S-R matrices	83.1%	93.6%
Population-weighted S-R matrices	89.8%	96.1%

Correlation Between Ozone and $PM_{2.5}$ Sensitivities

NO_x is a precursor of both ozone and $PM_{2.5}$. Reducing NO_x will have impacts on ozone and $PM_{2.5}$ concentrations, so ozone and $PM_{2.5}$ sensitivities with respect to NO_x reductions are correlated. However, the relationship is imbedded in a complicated chemical reaction mechanism and may not be linear. Therefore, we also investigate the correlation between ozone and $PM_{2.5}$ sensitivities with respect to NO_x reduction. In Table 2, we report the results of our investigation on the correlation of ozone and $PM_{2.5}$ sensitivities for both non-population-weighted single cell and population-weighted S-R matrices.

Table 2. Correlation Between Ozone and $PM_{2.5}$ Sensitivity

Summary Statistics	Single Cell S-R Matrices	Population Weighted S-R Matrices
Average	0.47	0.60
Std dev	0.35	0.38
Min	-0.87	-0.98
Max	1.00	1.00

For single cell S-R matrices, the average correlation between ozone and $PM_{2.5}$ sensitivities is about 0.47. For population-weighted S-R matrices, the average correlation is about 0.60. These correlations are not trivial, and should be considered when developing control strategies. Otherwise, one would either underestimate or overestimate the cost of control, depending on whether the correlation is positive or negative. We hope to investigate this kind of inter-pollutant correlation in detail in the future. In this research, for simplicity, we treat ozone and $PM_{2.5}$ sensitivities as independent for both types of S-R matrices.

4. State Cost Function Development

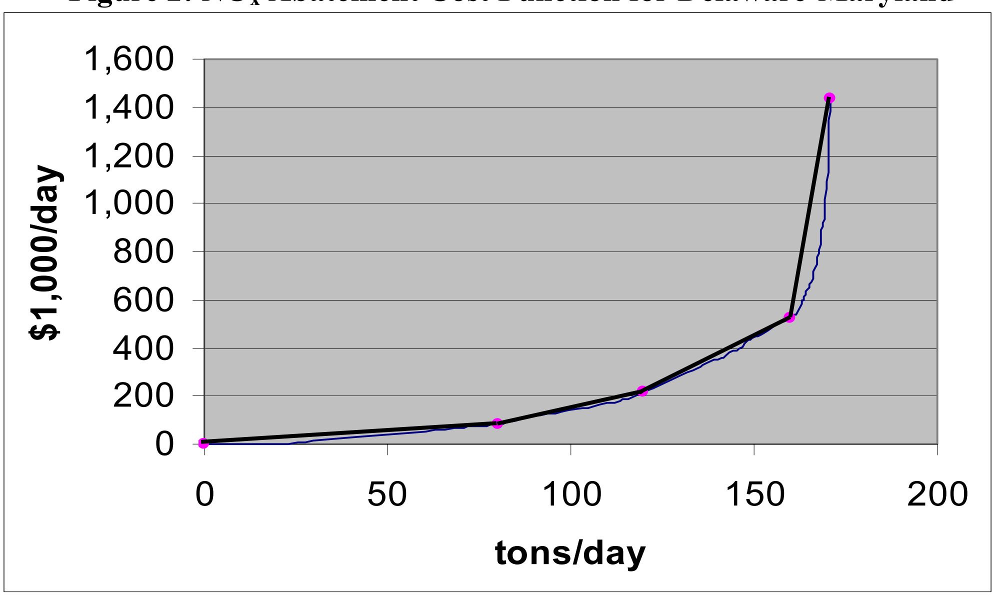
In this section, we discuss the development of a NO_x control cost function for each state. We use the control cost data from earlier research (Krupnick, 2000). The original raw cost data is from a model run by E.H. Pechan and Associates for EPA, called the Emission Reduction and Cost Analysis Model for Oxides of Nitrogen (ERCAM-NO*x*) (Pechan 1997). For each utility boiler, we identify five different NO_x control technologies. For each of these technologies at an individual boiler, we develop the marginal costs for an individual control technology and the marginal NO_x reduction achievable using this single technology. Costs for each control technology are expressed in total control costs (in 2000 dollars) divided by the tons of NO_x emissions reductions. A total of 925 utility boilers were considered in the study domain. For each boiler, we consider as many as five different control technologies. These five different NO_x control technologies include low excess air (LEA), over fire air (OFA), low-NO_x burners (LNB), selective noncatalytic reduction (SNCR), and selective catalytic reduction (SCR).

To develop state NO_x control cost envelope functions, we pool the marginal costs and associated NO_x reductions of these five technologies for all utility boilers (some boilers are not assigned all five technologies). We then rank the marginal costs from the smallest to the largest and the associated NO_x reductions. Based on this marginal cost envelope, we then construct the total cost function for every state.

Using the above approach, we obtain total costs of NO_x control for 19 states. The general observation is that total cost increases moderately when NO_x reduction is small. As NO_x reductions increase, the total cost increases dramatically. For mathematical programming purposes, we need to develop a mathematical function to describe the observed total costs. We use a piecewise linear approximation approach to describe the total cost data points.

The following Figure 2 shows the linear approximation of the nonlinear total cost function for NO_x reduction in DEMD.

Figure 2: NO_x Abatement Cost Function for Delaware-Maryland



5. The Development of Stochastic Benefit Coefficients

Coefficients relating changes in ozone concentrations and $PM_{2.5}$ concentrations to health benefits were developed from an updated version of the Tracking and Analysis Framework (Bloyd et al., 1996; Krupnick et al., 2000). TAF incorporates concentration-health response functions, population data, and valuation functions, along with standard errors on any estimated coefficients. In the following Table 3, we present low, medium, and high estimates of these "unit" benefit values in 2000 dollars per day per ppb (or μg/m^3) per person.[2]

Table 3. Benefit Coefficients

	Ozone (dollars per day per ppb per person)	**$PM_{2.5}$** (dollars per day per μg/m^3 per person)
Low	0.0018	0.047
Medium	0.0043	0.338
High	0.0170	0.864

in $2000
Source: (Bloyd et al., 1996)

6. Stochastic Multi-Objective Air Quality Management Model

A wide variety of mathematical programming models have appeared in the air pollution management and operations research/management science literature. For example, Greenberg (1995) and Cooper et al. (1996) have done excellent surveys and evaluations of these models, which include both deterministic (Morrison and Rubin, 1985) and stochastic models (Ellis et al., 1985; Watanabe and Ellis, 1993; Sullivan, 1997). These models generally use a linear cost function (applied to SO_2 reductions) and use a Lagrangian model to develop S-R coefficients. In this research, we develop a stochastic multi-objective air quality management model, which is different from previous research in several ways. First, we use an Eulerian-type air quality simulation model and a very efficient DDM-3D sensitivity algorithm to develop the S-R coefficients and to quantify the S-R coefficient distribution due to meteorological variability for both ozone and $PM_{2.5}$. Second, we consider net benefit as an objective function rather than only applying a cost function. The model is formulated to optimize expected net benefits subject to air quality at a specific state/region, satisfying air quality requirements with specified reliability.

[2] We did not consider nonhealth effects, such as visibility for $PM_{2.5}$ and material damage and vegetative effects for ozone in this research.

Third, the model also allows decisionmakers to take various equity criteria into account when developing control strategies. In the following section, we present the stochastic multi-objective chance constrained programming model developed in this research.

Stochastic Multi-Objective Chance Constrained Programming (CCP) Model

$$\text{Maximize} \quad E[\sum_r TBD_r - \sum_s TCD_s]$$

s.t.

$$x_s \le d_s, \qquad \forall s \qquad (1)$$

$$\Pr[PEAKO3_r - \sum_s (O3_{sr} * x_s) \le GO3_r] \ge \alpha_{O3,r}, \qquad \forall r \qquad (2)$$

$$\Pr[PEAKPM_r - \sum_s (PM_{sr} * x_s) \le GPM_r] \ge \alpha_{PM,r}, \qquad \forall r \qquad (3)$$

$$O3BD_r = \sum_s (O3_{sr}^w * x_s) * ub_{o3} * p_r, \qquad \forall r \qquad (4)$$

$$PMBD_r = \sum_s (PM_{sr}^w * x_s) * ub_{pm} * p_r, \qquad \forall r \qquad (5)$$

$$TBD_r = O3BD_r + PMBD_r, \qquad \forall r \qquad (6)$$

$$x_s = \sum_n z_{s,n} * b_{s,n} \qquad \forall s \qquad (7)$$

$$TCD_s = \sum_n z_{s,n} * bf_{s,n} \qquad \forall s \qquad (8)$$

$$\sum_{n=1}^{5} z_{s,n} = 1 \qquad \forall s \tag{9}$$

$$\sum_{n=1}^{4} y_{s,n} = 1 \qquad \forall s \tag{10}$$

$$z_{s,1} \le y_{s,1} \qquad \forall s \tag{11}$$

$$z_{s,2} \le y_{s,1} + y_{s,2} \qquad \forall s \tag{12}$$

$$z_{s,3} \le y_{s,2} + y_{s,3} \qquad \forall s \tag{13}$$

$$z_{s,4} \le y_{s,3} + y_{s,4} \qquad \forall s \tag{14}$$

$$z_{s,5} \le y_{s,4} \qquad \forall s \tag{15}$$

$$y_{s,n} = 0,1 \qquad \forall s, n = 1, \cdots, N-1 \tag{16}$$

$$z_{s,n} \ge 0 \qquad \forall s, n = 1, \cdots, N \tag{17}$$

The objective function of the above optimization problem is to maximize the expected value of net benefits (total benefits, TBD, at all the receptors minus total costs, TCD, at all the sources) to the entire study domain. The first constraint means that NO_x reductions from an individual state cannot be greater than the total emissions in the state. The second constraint says that peak ozone concentration at receptor *r* after control (which equals the peak ozone concentration before control, $PEAKO3_r$, minus the total control effects, $\sum_s (O3_{sr} * x_s)$, which equals the summation of single cell S-R coefficients, $O3_{sr}$, multiplied by emissions reductions, x_s, from all the sources) should be less than the ambient ozone concentration goal, G_{O3}, with a given reliability, $\alpha_{O,r}$. Because of meteorological variability, the impact at a receptor due to control from a source state/region ($O3_{sr}$) is a random variable. So there is always a possibility that a specified ambient air quality goal at a receptor state/region will not be satisfied 100% of the time. Realizing this, the constraint allows for violation of the air quality goal at the receptor, but air quality must reach a specified reliability level. The third constraint is that the peak $PM_{2.5}$ concentration at receptor *r* after control (which equals the ozone concentration before control, $PEAKPM_r$, minus the total control effects, $\sum_s (PM_{sr} * x_s)$, which equals the summation of single cell S-R coefficients, PM_{sr}, multiplied by emissions reductions, x_s, from all the sources) should be less than the air quality PM goal, G_{PM}, with reliability $\alpha_{PM,r}$. The reliability level can be a given input parameter. The overall problem is to find a control strategy such that the air quality goal is satisfied with the appropriate reliability level and net benefits are also maximized. One can also treat the reliability as an unknown decision variable and move it to the objective function, which means that, given the air quality goal, one can find the maximum reliability achievable.

The fourth equation is the daily ozone control benefit for a specific state/receptor, *r*. It is equal to the "population-weighted" S-R coefficients, $O3^{w}_{sr}$, multiplied by emissions reduction from all sources times the unit ozone benefit, ub_{o3}, times total population, p_r, of this receptor state/region. The fifth equation is the daily $PM_{2.5}$ control benefit for a specific state/region, *r*. Equation 6 is the summation of equations 4 and 5 above.

Note that equations 4 and 5 include the multiplication of two random variables, namely S-R coefficients and unit ozone and unit $PM_{2.5}$ benefit coefficients. This multiplication complicates the solution because there is no easy way to approximate the probability distribution of the multiplication of two random variables analytically. To simplify the complexity in the stochastic air quality management model, we use the deterministic median of the benefit coefficients rather than treating the benefit coefficients as random variables. So the implicit assumption is that the benefit coefficients are linear functions. In that case, the right hand side of equations 4 and 5 are just the summation of stochastic ozone and $PM_{2.5}$ population-weighted source-receptor coefficients multiplied by a deterministic variable and a parameter, making them normally distributed random variables. The expected benefits then are equal to the summation of source-receptor mean coefficients multiplied by a deterministic variable and parameter. The sixth equation is the total daily benefit from NO_x control at receptor *r*.

Equations 7–17 are linear approximations of the nonlinear total cost functions for individual source states. For each nonlinear total cost function, we use five break points to construct the piecewise linear function, which is made of four straight line segments. The functional values at these break points, bf_n, are given. Then we use a linear combination of known functional values at these break points to approximate values between these break points. The solution can only fall in one of the four segments. Every break point is assigned a weighting variable, z_n, with a value between 0 and 1 and a 0-1 binary interval indicator variable, y_n. If a solution, *x*, falls within the interval (b_n, b_{n+1}), then *x* can be represented as a linear combination as

$$x = z_n b_n + (1 - z_n) b_{n+1} \tag{18}$$

Since the function *f*(*x*) is linear for $b_n \le x \le b_{n+1}$, we may write

$$f(x) = z_n bf_n + (1 - z_n) bf_{n+1} \tag{19}$$

When $y_n = 1$, which means *x* falls in the interval *n*, then only z_n and z_{n+1} may be positive, but all other z_n's must equal 0. On the other hand, z_n is bounded above by the summation of neighboring integer interval variables, $y_{n-1} + y_n$. Finally we have all weighting variables at break points sum equal to 1 and interval indicator variables sum equal to 1. For a detailed discussion of this technique, please see Winston (1995).

7. Stochastic Simulation

There are two major purposes for developing our stochastic simulation model. The first purpose is to use this module to estimate benefit distribution for the control strategy obtained in the stochastic air quality management model (in which we use deterministic benefit coefficients).

The second purpose is to verify the air quality chance constraint—that is, if the variability distributions of source-receptor coefficients are not normally distributed as in our assumptions.

In the stochastic air quality management model, we use normal distributions to approximate the variability of ozone and $PM_{2.5}$ S-R coefficients, but use constant median value for benefit coefficients although they are actually random variables. In the first stage, we make sure that the chance constraints are satisfied. In the second stage, we conduct the stochastic simulation using results from the stochastic air quality management model to quantify the distribution of net benefits. In the second stage, we then can explicitly incorporate the uncertainty of the benefit coefficients. We can also use the stochastic simulation model to verify the air quality chance constraints.

8. Data

In this section, we provide some input information needed in the stochastic multi-objective air quality management model, including state baseline concentrations for ozone and $PM_{2.5}$ and state population data.

Baseline pollutant concentrations for ozone and $PM_{2.5}$, $PEAKO_r$ and $PEAKPM_r$, are based on the URM-1ATM model prediction using July and May episodes of 1995. In the following Table 4, we list the peak of one-hour and eight-hour daily maximum ozone concentrations and 24-hour daily average $PM_{2.5}$ concentrations for 19 states/regions in the study domain. These are the concentration levels that need to be reduced in the stochastic air quality management model.

Table 4. State Baseline Concentrations for Ozone and $PM_{2.5}$*

Benchmark Concentration	Ozone[1] (ppb)	Ozone[2] (ppb)	$PM_{2.5}$[3] ($\mu g/m^3$)
AL	82.58	77.65	44.11
DEMD	96.26	92.68	68.33
GA	81.77	74.58	53.42
IL	89.50	85.70	50.60
IN	104.25	96.85	40.77
KY	92.35	85.32	107.45
MACTRI	98.50	89.34	77.64
MI	111.80	102.54	33.76
MO	81.06	76.75	37.25
NC	76.49	72.51	47.79
NJ	97.74	88.77	108.62
NY	101.73	96.84	108.62
OH	99.48	95.44	44.88
PA	95.44	89.63	55.50
SC	77.15	70.84	39.76
TN	85.19	78.64	36.56
VA	93.38	88.43	59.38
WI	93.19	87.65	18.01
WV	92.36	87.47	43.70

*Unweighted maximum concentration from single grid cell.
[1] The peak of one-hour daily maximum from July and May episodes.
[2] The peak of eight-hour daily maximum from July and May episodes.
[3] The peak of 24-hour daily average maximum from July and May episodes.

In the model development section, state population data, p_r, are from the 2000 census database. The census data were actually at the census block level, which are typically sub-grid cell level units. The census block population and housing counts are aggregated to a grid cell level. Census blocks that occupy one or more grid cells have their population and housing counts apportioned to a grid cell by their area percentage in a grid cell. The 2000 census population data is listed in the following Table 5:

Table 5. 2000 State/Region Population

State Region	Population (1,000)
AL	4,447
DEMD	6,080
GA	8,186
IL	12,419
IN	6,080
KY	4,042
MACTRI	10,803
MI	9,938
MO	5,595
NC	8,049
NJ	8,414
NY	18,976
OH	11,353
PA	12,281
SC	4,012
TN	5,689
VA	7,079
WI	5,364
WV	1,808
Total	150,615

Source: http://www.census.gov/statab/ranks/rank01.txt

9. Results

At the beginning of this paper, we mentioned that our framework has several uses. In this section, we illustrate some of them. The first use discussed below is to derive the socially optimal control strategy. The second use builds on the first, taking equity and distributional issues into account. The last is to demonstrate how the framework can be applied in a novel risk management context to derive the trade-off between the risk of violating the air quality goal and the net benefits of control.

Case 1. Optimize Expected Net Benefits Without an Air Quality Constraint

In this first case, we examine the allocation of emissions reductions that maximizes net benefits for the entire study domain, without an air quality requirement for any state. In the result Table 6, the cost column gives the NO_x control cost for the individual states. The three benefit columns (ozone, PM, and ozone & PM benefit) in Table 6 show the total benefits occurring at a receptor state because of the NO_x reductions over the entire study domain. Negative net benefits indicate states where emissions reductions benefit other states, but aggregated reductions do not benefit these states enough to offset the state's control costs (IN, TN, and WV). This could occur for a number of reasons, such as the state's location near the upwind modeling domain boundary (IN, TN), low population levels (WV) or low pollution levels in that state, and/or high baseline emissions and therefore high control costs (IN, WV). Because emissions reductions in those states are found to contribute to net benefits overall, one implication of these results is that states benefiting from these reductions should share the costs of emissions reductions in the upwind states as part of their own air quality plans.

The results show that the optimal NO_x reduction is about 20% of the baseline, and that net benefits are about \$1 million per day. Ozone-based health benefits are \$0.3 million per day, while $PM_{2.5}$ benefits are about seven times this amount. On a per-ton-reduced basis, benefits are \$250/ton of NO_x reduced as it affects ozone and \$1,700/ton reduced as NO_x affects $PM_{2.5}$. Costs are just over \$1.4 million per day, or \$1,100/ton of NO_x reduced. The largest net benefits are experienced in New York, which is not surprising given the weather patterns, which cause New York to gain many benefits from reductions in emissions from other states, and the relatively low costs of control in New York. The latter occurs because relatively few tons are reduced in the optimal case (only 43 percent of baseline) and at a relatively low cost per ton (only around \$700/ton reduced).

Table 6. Optimize Expected Net Benefit Without an Air Quality Constraint

Objective Value $997,928

	NO_x Reduction (tons/day)	Reduction Fraction	Cost ($1,000 /day)	Ozone Benefit ($1,000 /day)	PM Benefit ($1,000 /day)	Ozone & PM Benefit ($1,000 /day)	Net Benefit ($1,000 /day)
AL	0	0	$0	$4	$19	$23	$23
DEMD	80	0.47	$84	$23	$147	$170	$86
GA	0	0	$0	$13	$55	$67	$67
IL	0	0	$0	$6	$48	$54	$54
IN	250	0.6	$406	$11	$69	$80	($326)
KY	62	0.21	$57	$13	$95	$108	$51
MACTRI	50	0.43	$45	$22	$176	$198	$152
MI	0	0	$0	$9	$29	$37	$37
MO	0	0	$0	$2	$2	$3	$3
NC	115	0.42	$63	$27	$123	$150	$87
NJ	34	0.55	$19	$29	$170	$199	$180
NY	84	0.43	$57	$43	$401	$444	$387
OH	107	0.22	$84	$18	$157	$176	$92
PA	200	0.37	$170	$30	$294	$324	$154
SC	0	0	$0	$8	$28	$36	$36
TN	141	0.71	$211	$15	$77	$92	($119)
VA	63	0.39	$95	$29	$150	$178	$83
WI	0	0	$0	$1	$6	$7	$7
WV	56	0.27	$99	$6	$34	$40	($59)
Total	1,242		$1,390	$310	$2,078	$2,388	$998

Case 2. Every State Net Benefit Is Non-Negative

In Case 1, the net benefits across states vary widely. Some states have large positive benefits and some states have negative benefits. In our research, we discuss four different methods to incorporate equity criteria in developing control strategies. Here, we only show one example. In Case 2, we model a scenario in which the expected net benefit for each state is constrained to be non-negative.

For this case, we just add a constraint for every state/region that says the net benefit at an individual state has to be greater than zero. The results are in the following table:

Table 7. Every State Net Benefit Is Non-Negative

Objective Value $864,359

	NO_x Reduction (tons/day)	Reduction Fraction	Cost ($1,000/day)	Ozone Benefit ($1,000/day)	PM Benefit ($1,000/day)	Ozone & PM Benefit ($1,000 /day)	Net Benefit ($1,000 /day)
AL	15	0.04	$22	$4	$18	$22	$0
DEMD	80	0.47	$84	$19	$120	$138	$55
GA	53	0.22	$70	$13	$57	$70	$0
IL	7	0.03	$12	$3	$9	$12	$0
IN	11	0.03	$19	$3	$16	$19	$0
KY	53	0.18	$49	$6	$43	$49	$0
MACTRI	50	0.43	$45	$19	$160	$179	$134
MI	19	0.06	$15	$5	$11	$15	$0
MO	0	0	$0	$1	$1	$2	$2
NC	115	0.42	$63	$24	$107	$131	$68
NJ	34	0.55	$19	$26	$149	$174	$155
NY	84	0.43	$57	$37	$340	$378	$321
OH	94	0.19	$74	$9	$65	$74	$0
PA	200	0.37	$170	$25	$232	$257	$87
SC	24	0.12	$38	$8	$29	$38	$0
TN	69	0.35	$57	$9	$47	$57	$0
VA	63	0.39	$95	$23	$115	$138	$43
WI	3	0.02	$3	$1	$2	$3	$0
WV	13	0.06	$23	$4	$20	$23	$0
Total	987		$914	$238	$1,541	$1,779	$864

In comparing results in this table with results for Case 1, total net benefits are reduced from $1 million per day in the optimal case to $0.86 million per day. States that have negative net benefit in Case 1 cut back their emissions control to reduce their control costs. This difference is fairly minor because few states are in the negative net benefit category. Although the net benefits gain from those four states is about $0.5 million per day, other states/regions in the entire study domain encounter a loss of $0.6 million per day, which results in a net benefit loss of $0.1 million per day for the entire domain. Some states may encounter bigger losses than others. For example, OH, PA, and GA show large losses of $92 thousand per day, $67 thousand per day, and $67 thousand per day, respectively. The other states encounter smaller net benefit losses.

Case 3. Trade-Off Between Expected Net Benefits and Reliability Level Required to Reduce DEMD Peak Ozone Concentration from 96.3 ppb (Baseline Concentration) to 93.5, 94, 94.5 ppb

In this case, we investigate the trade-off between net benefits for the entire study domain and, as an example, the reliability level of DEMD meeting an ozone reduction from the predicted baseline concentration of 96.3 ppb to goals of 93.5, 94, and 94.5 ppb. The selection of DEMD and these ozone goals are for illustrative purposes only. If one selects an upwind state instead or a more stringent air quality goal, it is likely that there will be no feasible solutions because of the small S-R coefficients toward the upwind state and/or the very low baseline emissions.[3]

Because of meteorological variability, we expect that the reliability-net benefits curve would slope downward. More emissions would need to be reduced in order to meet the air quality goal with a higher reliability requirement. Because the benefit function is linear, and marginal costs increase with greater emissions reductions, net benefits fall as reliability increases.

The results in Figure 3 bear out this expectation. Indeed, the net benefit can go from positive to negative as the reliability requirement gets higher and higher. Furthermore, meeting a given air quality goal can even become infeasible for reliability requirements above a certain level. In this illustrative case, the maximum reliability for DEMD to meet air quality goals of 93.5, 94, and 94.5 ppb is 67%, 83%, and 93%, respectively. This solution is found by treating the reliability parameter as an unknown variable, moving it to the objective function, and maximizing it.

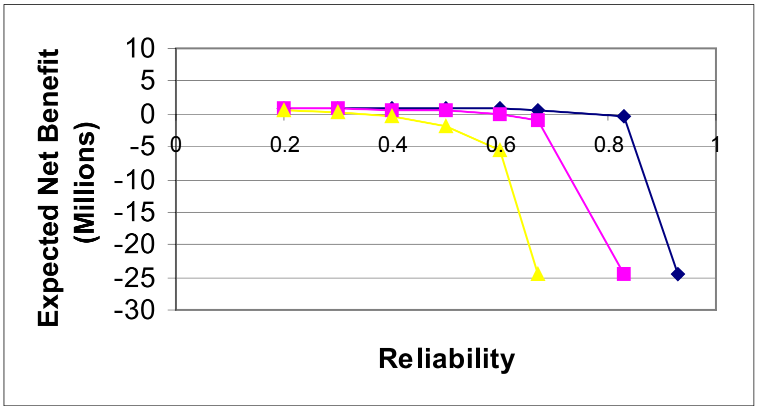
---

[3] Instead of selecting a single state for this analysis, it is theoretically possible to select all states/regions to consider a given pollution reduction target jointly. However, technically this problem is very difficult to solve because a joint probability distribution for the entire system is needed. Because each state has different baseline pollutant concentrations as well as the upwind state issue we mentioned above, the feasible range for emissions reductions are different for individual states. In general, downwind states have a bigger range. So it is very possible that we won't be able to find a feasible solution for the entire system with the same reduction target. One option is to consider only downwind states jointly, because they are more likely to have big reduction ranges.

Another interpretation of Figure 3 is that, given the same reliability requirement, as the air quality target gets more stringent, the costs and benefits increase; but as costs increase faster than benefits, net benefits fall. The trade-off curves shift unfavorably from right to left.

A third interpretation of this analysis could be useful for setting air quality standards. If one were to draw a horizontal line parallel to the x-axis and across the three trade-off curves—an "iso net benefit" line—net benefits on this line are constant. Thus, the same value of net benefits can be achieved using different combinations of the air quality goal and the reliability requirement.

Figure 3. Trade-Off Between Expected Net Benefit and Reliability Level required to Reduce DEMD Peak Ozone Concentration from 96.3 ppb to 93.5, 94, and 94.5 ppb (left to right)



10. Conclusion and Future Work

In this paper, we developed an integrated cost-benefit analysis framework for ozone and fine particulate control, accounting for meteorological variability. This framework includes air quality simulation, sensitivity analysis, stochastic multi-objective air quality management, and stochastic cost-benefit analysis. We demonstrated a method to develop stochastic S-R relationships, and used those findings for an initial assessment of developing optimized control strategies.

This research shows the potential of the approach, and provides some very important results. In the first case, we examined the allocation of emissions reductions that optimizes net benefits for the entire study domain. We found that some states (IN, TN, and WV) had negative net benefits, implying aggregated reductions do not benefit the emitting state plus the other receptor states enough to offset the emitting state's control costs. Because emissions reductions in these three states are found to contribute to maximizing net benefits, one implication of these results is that states benefiting from these reductions should share the costs of emissions reductions in the upwind states as part of their own air quality plans.

The second case builds on the first case to take equity and distributional issues into account by adding the constraint that every state's net benefit be non-negative. It turns out that although this equity constraint results in benefits to the three negative benefit states of \$0.5 million per day, the entire domain encounters a net loss of \$0.1 million per day. Those losses to other states are therefore \$0.6 million, 1.2 times the gains to the three states, suggesting that policies to improve conditions for one group will hurt others significantly. Indeed, any policy to improve equity that departs from the optimal solution *necessarily* involves the losers losing more than the gainers gain.

In the third case, we investigate the trade-off between net benefits for the entire study domain and the reliability level to meet the air quality goal, using DEMD as an example. Because of meteorological variability, one could end up with either more frequent violations of the air quality standard or higher than expected control costs to meet the standard. Without taking into account this uncertainty and variability, one could end up with an inefficient or infeasible control strategy. For example, we find that costs to drop emissions increase dramatically beyond a 60% reliability level in order to meet the 93.5 ppb air quality goal. Interestingly, only a slightly higher goal (94.5 ppb) results in flat abatement costs up to an 85% reliability level. These findings and our general results suggest that, first, reliability considerations should be an important part of any air quality attainment strategy and that more research is needed on what levels of reliability are appropriate.

This is important in terms of regulatory accountability and resource allocation. If environmental improvement expectations are not realized given unretrievable commitment of emissions reduction resources, the credibility and the economic efficiency aspects of environmental quality enhancement are brought into question. If the likelihood of this result is high enough, it may be more prudent for decisionmakers to recognize and account for meteorological variability up front in the design of a NAAQS form and level and concomitant implementation plans. In particular, the same value of net benefits can be achieved using different combinations of the air quality goal and the reliability requirement. This finding could be useful for setting air quality standards because it provides the decisionmaker with some flexibility to meet social goals using different strategies, namely, a more stringent air quality goal with a lower level of reliability requirement or a less stringent air quality goal with a higher level of reliability requirement. Incorporating this type of thinking in planning for the attainment of air quality standards would require changes in the Clean Air Act to redefine what is meant by "attainment."

This project has several limitations. Due to project constraints, only two meteorological episodes were studied. While those episodes were chosen to represent very different meteorology, they still do not span the whole range of conditions that lead to elevated ozone levels, and certainly do not include periods leading to high particulate matter (i.e., during the winter). The number of episodes should be increased.

Second, the NO_x control costs were only available for electric utilities. As shown, much of the benefits from emissions controls are derived from lower PM, much of which is sulfurous or carbonaceous in nature. The type of analysis done here should be extended to include other PM species.

Third, this research only considers human health benefit. The coverage of effects categories (nonhuman health for PM and O_3 as well as the health endpoints for O_3) could also affect the results. In addition, we only consider elevated point NO_x emissions. Other sources (mobile) and pollutants (VOC) may affect the results.

Finally, we will use the modeling framework to study trading across states/regions and/or various pollutants, correlations issues within the air quality management model, and other equity criteria.

References

Alcamo, J., and J. Bartnicki. 1990. The Uncertainty of Atmospheric Source-Receptor Relationships in Europe, *Atmospheric Environment* 24A(8): 2169-2189.

Ang, A. H-S, and W. Tang. 1975. *Probability Concepts in Engineering Planning and Design*, New York: Wiley.

Bloyd, C., J. Camp, G. Conzelmann, J. Formento, J. Molburg, J. Shannon, M. Henrion, R. Sonnenblick, K. Soo Hoo, J. Kalagnanam, S. Siegel, R. Sinha, and M. Small, T. Sullivan, R. Marnicio, P. Ryan and R. Turner, D. Austin, D. Burtraw, D. Farrell, T. Green, A. Krupnick, and E. Mansur. 1996. Tracking and Analysis Framework (TAF) Model Documentation and Users Guide. Argonne National Laboratory, ANL/DIS/TM-36, December.

Boylan, J. W., Odman, M. T., Wilkinson, J. G., Russell, A. G., Doty, K., Norris, W. and McNider, R. 2002. Development of a Comprehensive, Multiscale 'One Atmosphere' Modeling System: Application to the Southern Appalachian Mountains. *Atmospheric Environment* 36(23): 3721-3734.

Cooper, W. W., H. Hemphill, Z. Huang, S. Li, V. Lelas, and D. W. Sullivan. 1996. Survey of Mathematical Programming Models in Air Pollution Management, *European Journal of Operational Research* 96: 1-35.

Ellis, J. H., E. A. McBean, and G. J. Farquhar. 1985. Chance Constrained/Stochastic Linear Programming Model for Acid Rain Abatement – I. Complete Colinearity and Noncolinearity, *Atmospheric Environment* 19(6): 925-937.

Greenberg, H. J. 1995. Mathematical Programming Models for Environmental Quality Control, *Operations Research* 43(4): 578-622.

Hanna, S.R., Z. Lu, H.C. Frey, N. Wheeler, J. Vukovich, S. Arunachalam, M. Fernau, and D.A. Hansen. 2001. Uncertainties in Predicted Ozone Concentrations Due to Input Uncertainties for the UAM-V Photochemical Grid Model Applied to the July 1995 OTAG Domain, *Atmospheric Environment* 35: 891-903.

Kumar, N., M.T. Odman, and A.G. Russell. 1994. Multiscale Air Quality Modeling: Application to Southern California. *Journal of Geophysical Research* 99: 5385-5397.

Krupnick, A. J., V. D. McConnell, M. Cannon, T. Stoessell, and M. B. Batz. 2000. Cost-Effective NO_x Control in the Eastern United States, RFF Discussion Paper 00-18, April, Washington, DC: Resources for the Future.

Morrison, M. B., and E. S. Rubin. 1985. A Linear Programming Model for Acid Rain Policy Analysis, *Journal of Air Pollution Control Association* 35(11): 1137-1148.

NPS. 2000. National Park Service Air Quality Research Division Fort Collins. Anonymous ftp at ftp://alta_vista.cira.colostate.edu in /data/improve.

Pechan, E.H., and Associates, Inc. 1997. *The Emission Reduction and Cost Analysis Model for NO_x (ERCAM-NO_x)*. September. Report EPA-68-D3-0035, Work Assignment No. II-63. Ozone Policy and Strategies Group. Research Triangle Park, NC: U.S. EPA.

Pechan, E.H., and Associates, Inc. 2002. Southern Appalachian Mountains Initiative (SAMI) Emissions Projections to 2010 and 2040: Growth and Control Data and Emission Estimation Methodologies, Report prepared for the Southern Appalachian Mountains Initiative, Asheville, NC.

Pielke, R. A., Cotton, W. R., Walko, R. L., Tremback, C. J., Lyons, W. A., Grasso, L. D., Nicholls, M. E., Moran, M. D., Wesley, D. A., Lee, T. J., and Copeland, J. H. 1992. A Comprehensive Meteorological Modeling System - RAMS. *Meteorology and Atmospheric Physics* 49: 69-91.

Rao, S.T., T.D. Mount, and G. Dorris. 1999. Least Cost Control Strategies to Reduce Ozone in the Northeastern Urban Corridor. The NY State Department of Environmental Conservation, Division of Air Resources, Albany, NY.

Sullivan, D.W. 1997. A Chance Constrained Programming Approach to Air Quality Management, Ph.D. Thesis, The University of Texas at Austin.

U.S. EPA. 2001. *EPA AIRS Data*. U.S. Environmental Protection Agency, Office of Air Quality Planning & Standards, Information Transfer & Program Integration Division, Information Transfer Group. www.epa.gov/airsdata.

Watanabe, T., and H. Ellis. 1993. Stochastic Programming Models for Air Quality Management, *Computers and Operations Research* 20(6): 651-663.

Wilkinson, J.G., C.F. Loomis, D.E. McNally, R.A. Emigh, and T.W. Tesche. 1994. *Technical Formulation Document: SARMAP/LMOS Emissions Modeling System (EMS-95)*. AG-90/TS26 & AG-90/TS27. Pittsburgh, PA: Alpine Geophysics.

Winston, W.L. 1995. *Introduction to Mathematical Programming: Applications and Algorithms*, 2nd ed., Belmont, CA: Duxbury Press.

Yang, Y.J., J.W. Wilkinson, and A.G. Russell. 1997. Fast, Direct Sensitivity Analysis of Multidimensional Photochemical Models. *Environmental Science and Technology* 31: 2859-2868.

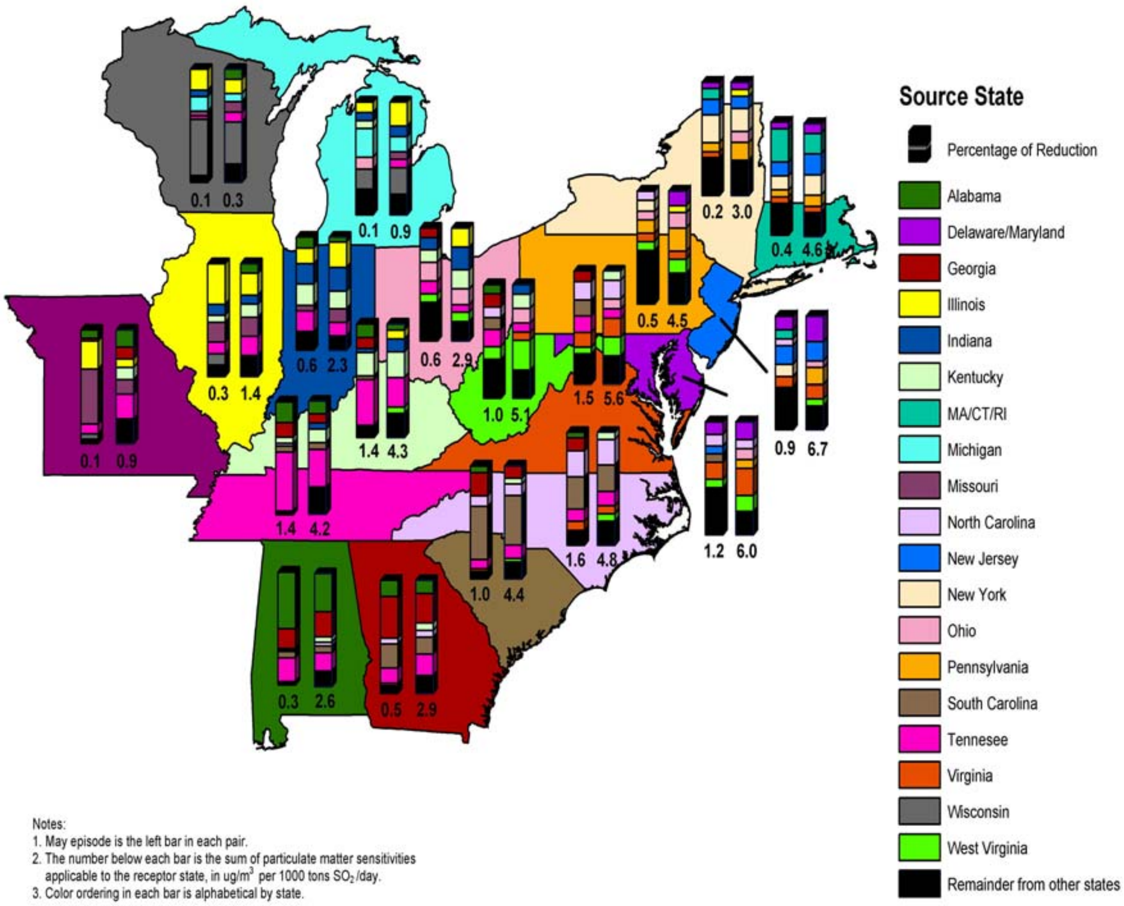


Figure 1. May and July 24-hour average $PM_{2.5}$ sensitivity with respect to total SO_2 reduction ($\mu g/m^3$ per 1,000 tons/day). Relative sensitivities for each state of the top six contributing states/regions and "all other states" for the effect of a unit reduction in SO_2 emissions on 24-hour average area weighted $PM_{2.5}$ concentrations for both the July and May episodes.