Resource allocation for mitigating regional air pollution–related mortality: A summertime case study for five cities in the United States

Kuo-Jen Liao⁎, Xiangting Hou⁎, and Matthew J. Strickland

⁎Department of Environmental Engineering, Texas A&M University–Kingsville, Kingsville, TX, USA; ⁎School of Community Health Sciences, University of Nevada, Reno, Reno, NV, USA

ABSTRACT

An important issue of regional air quality management is to allocate air quality management funds to maximize environmental and human health benefits. In this study, we use an innovative approach to tackle this air quality management issue. We develop an innovative resource allocation model that allows identification of air pollutant emission control strategies that maximize mortality avoidances subject to a resource constraint. We first present the development of the resource allocation model and then a case study to show how the model can be used to identify resource allocation strategies that maximize mortality avoidances for top five Metropolitan Statistical Areas (MSAs) (i.e., New York, Los Angeles, Chicago, Dallas–Fort Worth, and Philadelphia) in the continental United States collectively. Given budget constraints in the U.S. Environmental Protection Agency’s (EPA) Clean Air Act assessment, the results of the case study suggest that controls of sulfur dioxide (SO₂) and primary carbon (PC) emissions from EPA Regions 2, 3, 5, 6, and 9 would have significant health benefits for the five selected cities collectively. Around 30,800 air pollution–related mortalities could be avoided during the selected 2-week summertime episode for the five cities collectively if the budget could be allocated based on the results of the resource allocation model. Although only five U.S. cities during a 2-week episode are considered in the case study, the resource allocation model can be used by decision-makers to plan air pollution mitigation strategies to achieve the most significant health benefits for other seasons and more cities over a region or the continental U.S.

Implications: Effective allocations of air quality management resources are challenging and complicated, and it is desired to have a tool that can help decision-makers better allocate the funds to maximize health benefits of air pollution mitigation. An innovative resource allocation model developed in this study can help decision-makers identify the best resource allocation strategies for multiple cities collectively. The results of a case study suggest that controls of primary carbon and sulfur dioxides emissions would achieve the most significant health benefits for five selected cities collectively.

Introduction

This paper accompanies our previous publication that presents the development of an optimization model (i.e., OPtimal Emission Reduction Alternatives [OPERA]) for regional air quality management (Liao and Hou, 2015). OPERA allows identification of optimal (i.e., least-cost) emission control strategies for achieving specific multipollutant air quality targets (e.g., National Ambient Air Quality Standards [NAAQS]) at multiple locations simultaneously. In our previous study, we conducted a case study for achieving the 2008 ozone and 2006 PM2.5 (i.e., particulate matter with an aerodynamic diameter less than 2.5 μm) NAAQS (U.S. Environmental Protection Agency [EPA], 2015) in the summer of 2007 for five nonattainment cities (i.e., Atlanta, Chicago, Washington, D.C., New York, and Philadelphia) in the eastern United States (U.S.).

Another important issue of regional air quality management is to allocate air pollution mitigation resources to maximize environmental and human health benefits. In this study, we use an innovative approach to tackle this air quality management issue. Specifically, we develop a resource allocation model to identify the “optimal” resource allocation strategies that maximize human health benefits of air quality protection subject to a resource constraint (i.e., budgets). In this study, the human health benefits are quantified by mortalities avoided attributed to ambient air pollution (i.e., ozone
and PM$_{2.5}$ mitigation. Ambient ozone and PM$_{2.5}$ have adverse effects on human health (EPA, 2009, 2013; World Health Organization [WHO], 2008) and are two of the criteria pollutants regulated by NAAQS. Ambient ozone formation is driven by complex non-linear photochemistry of nitrogen oxides (NO$_x$), volatile organic compounds (VOCs), and other species (Sillman, 1999, 2003). On the other hand, PM$_{2.5}$ can be directly emitted (i.e., primary PM$_{2.5}$) (Kim et al., 2000a, 2000b) or formed in the atmosphere (i.e., secondary PM$_{2.5}$) (Poschl, 2005). Ambient ozone and secondary PM$_{2.5}$ share common precursors (i.e., NO$_x$ and VOCs) (Meng et al., 1997), and their formation may affect each other (Liao et al., 2008). In recent years, several studies have tried to address the multipollutant air quality management issue. In a review by Hidy and Pennell (2010), factors involved in the implementation of risk- and results-based multipollutant air quality management strategies are summarized and discussed. Chow and Watson (2011) study multiple complex relationships between several pollutants and their effects on human health and the environment. Cohan et al. (2007) present how to develop multipollutant air quality management strategies for multipollutant locations in the U.S. state of Georgia.

As required by the Clean Air Act (CAA), the EPA and states collaborate on developing State Implementation Plans (SIPs) to protect the environment and human health from air pollution (42 U.S.C. §7401 et seq., 1970). Although the cross-boundary transport of air pollutants is significant (Hains et al., 2008; Liao et al., 2014), SIPs are usually designed to comply with air quality standards in nonattainment areas of single states (Cohan et al., 2007). Because regional air quality and human health are affected by air pollutants emitted from multiple sources in multiple states (Liao et al., 2014; Hou et al., 2015), air quality management is a regional issue, and policy decisions should be made on a regional basis (e.g., EPA’s Clean Air Interstate Rule [CAIR] and Cross-State Air Pollution Rule (CSAPR) for East U.S.). This paper presents the development of an innovative resource allocation model that can identify ambient ozone and PM$_{2.5}$ mitigation strategies that maximize human health benefits of air quality protection for multiple cities collectively.

The resource allocation model takes into account (1) air quality sensitivities to emission controls, (2) human health responses to air quality, (3) costs of air pollutant emission controls, and (4) limitations of resources (i.e., budgets) for air quality protection. We also present a case study to show how the model can be used to identify resource allocation strategies that maximize mortality avoidances for top five Metropolitan Statistical Areas (MSAs) (i.e., New York, Los Angeles, Chicago, Dallas-Fort Worth, and Philadelphia) in the continental U.S. collectively.

To construct the resource allocation model for air quality management and human health protection, responses of air quality to emissions need to be quantified. In this study, we investigate responses of air quality in the top five MSAs to emissions of precursors from the 10 EPA regions (Figure S1 in Supplemental Material). The MSAs are chosen based on the 2010 Census data (Table 1), and the locations of the MSAs cover important economic centers in the U.S. The total population of the five MSAs accounted for about 17.5% of the national population in the U.S. All of the five MSAs were ozone nonattainment areas in 2010 based on the 2008 standard (i.e., 75 ppb). The Philadelphia and Los Angeles MSAs were also PM$_{2.5}$ nonattainment areas in 2010 based on the 2006 standard (i.e., 35 μg/m$^3$ for daily PM$_{2.5}$ concentrations or 15 μg/m$^3$ for yearly PM$_{2.5}$ concentrations).

**Methods**

*Regional air quality modeling and sensitivity analysis*

In this study, Community Multiscale Air Quality Model (CMAQ) version 5.0.2 (Byun and Schere, 2006), with the decoupled direct method (DDM) (Dunker et al., 2002; Yang et al., 1997), is used to simulate baseline air quality and its responses to changes in emissions (i.e., sensitivities) for 10 EPA regions (Figure S1). CMAQ is a state-of-the-art regional air quality model, and CMAQ-DDM is a well-established modeling system for calculating sensitivities of air pollutant concentrations to emission changes (Napelenok et al., 2006). In the modeling setup, a 12 km-by-12 km horizontal resolution and 22 vertical layers are applied to the CMAQ-DDM simulations. The air quality modeling domain covers the continental U.S. and parts of Canada and Mexico (Figure S2). Emissions of air pollutant precursors, required for the CMAQ-DDM simulations, are obtained from the Air Quality Model Evaluation International Initiative Phase 2 (AQMEII-2) (Campbell et al., 2015).

**Table 1.** Five U.S. largest MSAs and their population in 2010.

| Rank | MSA                                   | 2010 Population | $y_0$  |
|------|--------------------------------------|-----------------|-------|
| 1    | New York-Newark-Jersey City, NY-NJ-PA| 19,567,410      | 0.01333 |
| 2    | Los Angeles-Long Beach-Anaheim, CA   | 12,828,837      | 0.01146 |
| 3    | Chicago-Naperville-Elgin, IL-IN-WI   | 9,461,105       | 0.01383 |
| 4    | Dallas-Fort Worth-Arlington, TX      | 6,426,214       | 0.01161 |
| 5    | Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | 5,965,343 | 0.01457 |

Notes: $y_0$ represents the baseline mortality rate per 100 people during the 2-week modeling episode (i.e., August 8 to August 21, 2010).
The AQMEII-2 project coordinates efforts from scientists in Europe and North America to advance regional air quality models and model evaluation methodologies (Rao et al., 2010). Emission inventories for the year 2010 are used in the AQMEII-2 simulations for both Europe and North America. Wildfire and power plant emissions for 2010 for North America were projected from the 2008 National Emission Inventory (NEI) with year-specific adjustments. The Weather Research and Forecasting Model (WRF) version 3.6.1 (Skamarock et al., 2008), with input from the National Centers for Environmental Prediction (NCEP) Final Analysis data set (http://rda.ucar.edu/datasets/ds083.2/), is utilized to process meteorological data for the CMAQ-DDM simulations.

Ozone is a seasonal pollutant, and its concentrations in summer months are typically higher than in winter months. Therefore, the modeling episode is chosen based on measured ozone concentrations in the summer of 2010. The modeling episode is from August 8 to August 21, 2010, since several of the MSAs had high ozone levels during the period (Figure S3). Results of the first five modeling days are excluded to eliminate influences of uncertainties in initial conditions on the modeling results. The matrices of ozone and PM_{2.5} air quality employed in this study are daily maximum 8-hr average O_3 and 24-hr average PM_{2.5} concentrations, respectively, since they are used in NAAQS and many other air quality studies. We specifically examine sensitivities of daily maximum 8-hr average ozone concentrations to anthropogenic NO_x and VOC emissions as well as sensitivities of 24-hr average PM_{2.5} concentrations to anthropogenic NO_x, VOC, sulfur dioxide (SO_2), and primary carbon (PC) emissions based on the results of the CMAQ-DDM simulation. Finally, changes in air pollutant levels due to emission reductions are presented in the following form:

$$\Delta X_i \approx \sum S_{i,j,k} \cdot \epsilon_{j,k}$$  \hspace{1cm} (1)

where $\Delta X_i$(ppb) is the change in concentration of pollutant $i$, $S_{i,j,k}$(ppb) is the sensitivity of pollutant $i$ to emission $j$ from region $k$, and $\epsilon_{j,k}$(ton/ton) is the reduction ratio of emission $j$ from region $k$. Equation 1 represents changes in concentrations of pollutant $i$ due to controls of precursors $1 - j$ from regions $1 - k$. For ozone concentration reductions, the numbers of $i$, $j$, and $k$ are 1, 2, and 10, respectively, since one air pollutant (i.e., ozone), two air pollutant precursors (i.e., NO_x and VOCs), and 10 regions (i.e., 10 EPA regions) are considered. On the other hand, for PM_{2.5}, the numbers of $i$, $j$, and $k$ are 1, 4, and 10, respectively, since four PM_{2.5} precursors (i.e., NO_x, VOCs, SO_2, and PC) instead of two are considered.

### Estimates of air pollution–associated health effects

In epidemiologic studies, the relationship between pollutant concentrations and population responses is characterized by concentration-response (C-R) functions, and different forms of C-R functions are used in various studies. In this study, the C-R functions for ozone and PM_{2.5} air quality are obtained from literature in which C-R functions are presented in a log-linear form (eq 2). The log-linear form for the C-R function is commonly used to estimate the percent change in an adverse health effect associated with a given change in air pollutant levels (Schwartz, 1995; Schwartz et al., 2002; Zeger et al., 2000). The human health responses to changes in ozone and PM_{2.5} levels can be derived from the C-R functions and presented in the following form:

$$\Delta y = y_0(1 - e^{-\beta \Delta X})$$  \hspace{1cm} (2)

where $\Delta y$ is the estimated change in the rate of the health outcome (e.g., mortality) due to changes in air pollutant levels, $y_0$ is the baseline incidence rate of the health outcome, $\Delta X$ is the change in pollutant concentration, and $\beta$ is the coefficient of association between air pollutant concentrations and health outcomes. In this study, $\Delta X$ is calculated using eq 1, and $y_0$ is obtained from the U.S. Centers for Disease Control and Prevention (CDC) Wide-ranging Online Data for Epidemiologic Research (WONDER) database (http://wonder.cdc.gov/). We use an age-weighted baseline mortality rate $y_0$ in eq 2. For example, the mortality rate $y_0$ for the New York MSA is calculated as 0.01333 deaths per 100 people during the 2-week modeling episode (Table 1). $\beta$ for annual PM is 0.014842 per 1 $\mu g/m^3$, which is obtained from a study of six cities in the northeastern U.S. (Laden et al., 2006). $\beta$ for daily maximum 8-hr average ozone is 0.000795 per 1 ppb, which is obtained from a meta-analysis of 144 effect estimates from 39 time-series studies (Bell et al., 2005). The number of deaths avoided (i.e., $\Delta$Mortality) is obtained by multiplying $\Delta y$ by the relevant population (i.e., the number of individuals exposed to air pollution) presented in Table 1.

$$\Delta$Mortality = $\Delta y \cdot population = y_0(1 - e^{-\beta \Delta X}) \cdot population$$  \hspace{1cm} (3)

Bell et al. (2004) find that the association between ozone concentrations and mortality is not confounded by PM_{2.5} levels; therefore, we assume that human
health responses to ozone and PM$_{2.5}$ are independent, and the total mortality avoidances are the summation of those induced by the ozone and PM$_{2.5}$ air quality improvement.

**Estimates of emission control costs**

Cost functions are another component of the resource allocation model we need to develop in this study. A detailed discussion of the methodology of developing cost functions for controls of air pollutants from various emission sources is presented by Liao and Hou (2015), and the approach is briefly described here. Here, the costs of emission reductions are calculated using results of a EPA emission control analysis tool, AirControlNET (Pechan, 2006). AirControlNET uses EPA’s 1999 National Emission Inventory (NEI) as a source of emission data (http://www.epa.gov/ttn/chief/net/1999inventory.html), and its results provide ratios of emissions reduced and associated annualized per-ton costs, i.e., the per-ton costs of emission reductions are expressed as Cost$_{j,k}$($\Delta$ε$_{j,k}$), and $\Delta$ε$_{j,k}$ is the ratio of emission reductions in the percentage of species $j$ emitted from region $k$. Overall, 40 cost functions are developed to present the costs of controls of anthropogenic NO$_x$, VOCs, SO$_2$, and PC emissions from the 10 EPA regions.

**Development of resource allocation model**

Office of Air and Radiation of the EPA (2010) estimates that annual cost values of complying with the Clean Air Act for 2010 were $43,900 (million 2006$), which included costs of reductions in six major criteria pollutants (VOCs, NO$_x$, SO$_2$, CO [carbon monoxide], PM$_{10}$, and PM$_{2.5}$), ammonia (NH$_3$), and hazardous air pollutants (HAPs) attributed to regional and local controls over the U.S. Since we only consider controls of VOCs, NO$_x$, SO$_2$, and primary PM$_{2.5}$ emissions in the case study, we assume 70% of the total cost could be used to reduce emissions of the four pollutants from regional sources. Furthermore, the total of population of the top five U.S. cities accounted for about 17.5% of the total U. S. pollution in 2010, and the total budget used in our case study is $5,400 ($= 43,900 \times 0.7 \times 0.175$) (millions 2006$).

The least-cost model (i.e., OPERA) presented in our previous publication is a mathematical programming model in which the objective is to identify the least-cost air quality management strategy for achieving multi-pollutant air quality targets (Liao and Hou, 2015). In this study, the mathematical programming technique is also used to formulate the resource allocation model (eqs 4–6). The equation that calculates the mortality avoidance (eq 3) is used as the objective function (eq 4) in the resource allocation model. To identify the optimal solutions to the resource allocation problem, some constraints need to be satisfied. First, the total costs of air pollutant emission controls, estimated using AirControlNET, should be less than or equal to available budgets ($R_k$) for protecting human health from air pollution (eq 5). Furthermore, emission reduction ratios for each emission source should be within the lower (= 0) and upper limits ($U_{j,k}$) of feasible emission reduction ranges (eq 6). In formulating the model for the case study, the upper limits of the emission reductions are obtained from AirControlNET. Finally, the optimal resource allocation strategies identified by the model represent emission control measures that maximize mortality avoidances given the resource constraint.

$$\text{Maximize } \sum_{c=1}^{n} \Delta\text{mortality}_c$$

Subject to:

$$\sum_{j=1}^{p} \text{Cost}_{j,k}(\Delta\text{ε}_{j,k}) \leq R_k \quad k = 1, 2, \ldots, m$$

$$0 \leq \Delta\text{ε}_{j,k} \leq U_{j,k}$$

where $c$, $j$, and $k$ present the MSAs, precursors, and regions, respectively. $n$, $p$, and $m$ are the number of MSAs, precursors, and regions, respectively. As discussed previously, in 2010, the total available budget $R$ for air quality management for the top five MSAs is about 5,400 million. Since the objective function and the cost constraints for emission controls are nonlinear, the resource allocation model is a nonlinear mathematical programming problem and solved by MATLAB (MathWorks, 2009).

**Results and discussion**

**Baseline air quality**

The results of the CMAQ modeling show higher ambient ozone concentrations in the northeastern and southwestern U.S. as well as the Gulf of Mexico compared with concentrations in other U.S. regions during the study episode (Figure S4a). On the other hand, peak PM$_{2.5}$ levels occurred on the East Coast, Pacific Coast, the Gulf of Mexico, and the Great Lakes regions where the selected MSAs are all located (Figure S4b). Many factors, such as emission inventories, chemical mechanisms, meteorological inputs, and boundary/initial
conditions, could influence regional air quality modeling results (Fox 1984; Hanna et al., 2001). To assess the robustness of the modeling results, we use the EPA’s Air Quality System (AQS) observation data to evaluate the modeled air quality. The EPA recommends statistical measures to assess abilities of models to reproduce observed air quality concentrations. The mean normalized bias (MNB; within ±15%) and mean normalized gross error (MNGE; ≤35%) are recommended by the EPA to evaluate the model performance of ambient ozone simulations. For PM_{2.5} modeling performance, the mean fractional bias (FBIAS; ±30% to ±50%) and mean fractional error (FERROR; ≤75%) thresholds recommended by the EPA are employed here (EPA, 1991, 2005). Two air quality matrices, daily average PM_{2.5} and daily maximum 8-hr average ozone concentrations, corresponding to the form of NAAQS, are applied to evaluate the model performance. Table S1 shows the results of the evaluation, which indicate that CMAQ underestimates ozone and PM_{2.5} concentrations in several cities during the modeling episode. Since the primary objective of this study is to demonstrate the development of the resource allocation model and its application, we do not further examine the details of the underestimations of ozone and PM_{2.5} concentrations here.

**Sensitivity of ambient ozone and PM_{2.5} to precursor emissions**

In the case study, we choose the day with the highest ambient ozone levels during the modeling episode to examine contributions of emissions from the 10 EPA regions to ambient ozone and PM_{2.5} levels in the five MSAs (Figure 1). For ambient ozone concentrations, the CMAQ-DDM results show ozone formation in the New York and Chicago MSAs had a “VOC-limited” regime, since sensitivities of ozone concentrations in the two cities to NO_x and VOC emissions are negative and positive, respectively (Figure 1). The results also show that VOC emissions from the regions where the MSAs are located (Region 2 for New York and Region 5 for Chicago) were the most significant contributors to ozone formation in the MSAs. For Los Angeles, controls of VOC or NO_x emissions from the region where Los Angeles is located (i.e., EPA Region 9) would decrease ozone formation. On the other hand, emissions from EPA Region 4 (i.e., southeastern U.S.) had a ~8 ppb contribution to ambient ozone levels in Dallas-Fort Worth, which is located in EPA Region 6. Moreover, ambient ozone air quality in the Philadelphia MSA could be affected by emissions from several regions, especially VOC emissions from EPA Regions 2 and 3, followed by NO_x emission from the local region. Overall, the results show the importance of cross-region transport of pollutants and imply that ozone air quality management should be considered on a regional basis, and multiple cities should be examined together rather than separately.

Unlike the ozone sensitivity, which includes only two precursors (i.e., NO_x and VOCs), for PM_{2.5} sensitivities, we consider emissions of four precursors (i.e., NO_x, VOCs, SO_2, and PC). Figure 1 shows sensitivities of 24-hr average PM_{2.5} concentrations in the five MSAs to NO_x, VOC, SO_2, and PC emissions from the 10 EPA regions. The New York and Philadelphia MSAs are both located in the northeastern U.S., and PM_{2.5} concentrations in the two MSAs shared similar characteristics of emission sources of precursors. For example, the precursors emitted from EPA Regions 1–5 influenced PM_{2.5} levels in the New York and Philadelphia MSAs significantly. Emissions of PC from the region where Los Angeles, Chicago, or Dallas-Fort Worth is located had the most significant contributions to PM_{2.5} concentrations in the cities. For example, the contributions of PC emissions from Regions 9, 5, and 6 to PM_{2.5} concentrations in Los Angeles, Chicago, and Dallas-Fort Worth were about 1.5, 10, and 9 μg/m^3, respectively. PM_{2.5} concentrations in the Chicago MSA were also slightly affected by emissions nationwide, particularly in its neighboring regions. Overall, the results of the sensitivity analysis imply that controls of NO_x, SO_2, and PC emissions were generally more effective than controls of VOC emissions for reducing PM_{2.5} concentrations in the five MSAs.

**Cost of air pollutant emission controls**

As reductions of the four precursors emitted from the 10 U.S. regions are examined in this study, 40 (= 4 precursors × 10 regions) cost functions are developed based on the results of AirControlNET (Figure 2). The figure shows that costs of emission reductions for each of the 10 EPA regions do not increase linearly; higher ratios of emission cuts are expected to be more expensive based on per-mass reductions. Regression analyses are used to estimate the relationship between emission reductions and associated per-ton costs. The results show that power and exponential functions closely approximate the relationships between emission reductions and their related costs. The per-ton costs of reducing a given pollutant (e.g., SO_2) differ slightly from region to region, since emission characteristics of air pollutants and control approaches for the regions are different. In general, the results show that per-ton costs of NO_x and VOC emission reductions are much higher than controls of SO_2 and PC emissions from the 10 EPA regions. The sum of the 40 cost functions is used as eq 5 (i.e., the budget constraint) of the resource allocation model.
Figure 1. Sensitivities of ozone (unit: ppb) and PM$_{2.5}$ (unit: $\mu$g/m$^3$) concentrations to precursor emissions from the 10 EPA regions. Sensitivities to SO$_2$ emissions from Regions 4 and 8, VOC emissions from Regions 8 and 10, and PC from Regions 1, 7, 8, and 10 are small and not shown in the figure.

Figure 2. Cost functions of reductions in emissions from the 10 EPA regions.
Optimal resource allocation strategies for mitigating air pollution–related mortalities

It’s important to distinguish “optimal” used in this and our previous studies (Liao and Hou, 2015). The optimal resource allocation strategies in this study are those maximizing health benefits subject to a resource constraint, whereas the optimal air quality management strategies in our previous studies are the least-cost air pollution mitigation strategies to achieve specific air quality targets. Specially, the optimal resource allocation strategies in the case study are those reducing the largest number of ozone- and PM<sub>2.5</sub>-related deaths in the five MSAs collectively. The results of the resource allocation model show that controls of SO<sub>2</sub> and PC emissions would be more effective in reducing air pollution–related mortality (Table 2). It is because PM<sub>2.5</sub> has significant health effects, and controlling of SO<sub>2</sub> and PC emissions would be cost-effective to mitigate PM<sub>2.5</sub> air pollution and its associated health outcomes. To maximize PM<sub>2.5</sub>-related health benefits, SO<sub>2</sub> emissions from several U.S. regions (i.e., Regions 1, 2, 3, and 9) require a more than 50% reduction. PC emissions from EPA Regions 1, 2, 3, 5, 6, and 9 would need to be reduced by ~55%, 62%, 51%, 42%, 49%, and 52%, respectively. Controls of NO<sub>x</sub> and VOC emissions would reduce ozone concentrations in the MSAs. However, controls of NO<sub>x</sub> and VOC emissions are expensive, and ozone-related mortalities are less significant than PM<sub>2.5</sub>-related mortalities (i.e., no. of mortality/1 ppb ozone < no. of mortality/1 μg/m<sup>3</sup> PM<sub>2.5</sub>). The largest reduction in NO<sub>x</sub> emissions is from EPA Region 2 (~23%), followed by EPA Regions 7 (~20%) and 1 (~18%). For VOC emission controls, the largest reduction is 18% for VOC emissions from EPA Region 2. Region 10 requires small emission reductions (i.e., no more than 6.5%), since reductions in emissions from Region 10 had small effects on air quality and air pollution–related mortalities in the five selected cities. If major cities (e.g., Portland and Seattle) were included in the calculation, required reductions in emissions from Region 10 would be larger, since the emission reductions would benefit human health in cities in Region 10.

Table 2. Emission reductions (in percentage) for achieving the maximal human health benefits for the five MSAs collectively.

| Region | NO<sub>x</sub> | VOCs | SO<sub>2</sub> | PC |
|--------|--------------|------|--------------|----|
| Region 1 | 18.0 | 8.7 | 96.0 | 54.8 |
| Region 2 | 22.9 | 18.0 | 74.0 | 61.7 |
| Region 3 | 11.6 | ~0 | 50.4 | 50.9 |
| Region 4 | 5.8 | 8.2 | 16.0 | 1.2 |
| Region 5 | 15.1 | 8.9 | 37.2 | 42.4 |
| Region 6 | 19.3 | 11.0 | 8.8 | 48.7 |
| Region 7 | 20.4 | 5.8 | 29.7 | 7.5 |
| Region 8 | 17.2 | 3.7 | 17.8 | 2.4 |
| Region 9 | 8.5 | 12.0 | 89.3 | 51.9 |
| Region 10 | 6.5 | 4.2 | ~0 | ~0 |

The resource allocation model also provides costs of controlling emissions from the 10 EPA regions (Table 3). To achieve the most significant health benefits, the majority of the resource would be used to reduce the SO<sub>2</sub> ($2,337 million) and PC ($1,869 million) emissions. When allocations of resources to the 10 regions are considered, the majority of the resource would be used to reduce emissions from Regions 2, 3, 5, 6, and 9. The most significant resource would be used to reduce emissions from Region 5 ($1,200 million), followed by Regions 9 ($899 million), Region 2 ($857 million), Region 6 ($812 million), and Region 3 ($780 million). Region 10 would need only a small amount of resources (i.e., $13 million), since controls of required reductions in emissions from Region 10 are small.

If budgets could be applied to control regional emissions to protect public health accordingly, around 30,800 air pollutant–related mortalities could be avoided in the selected MSAs during the 2-week studying period (Table 4). Previous studies show that PM<sub>2.5</sub> has more significant mortality effects than ambient ozone (Fann and Risley, 2013; Garrett and Casimiro, 2011), and the results of this study also imply that improving ambient PM<sub>2.5</sub> levels could achieve more health benefits than ozone pollution mitigation (given the limited resource). Based on the results of the resource allocation modeling, most

| Table 3. Funds needed to reduce the emission from the 10 EPA regions (in million $). |
|---------------------------------|--------|--------|---------|--------|--------|
| Region                          | NO<sub>x</sub> | VOCs | SO<sub>2</sub> | PC | Regional Total |
|---------------------------------|--------|------|--------------|----|---------------|
| Region 1                        | 97     | 15   | 150          | 97 | 359           |
| Region 2                        | 243    | 115  | 369          | 131| 857           |
| Region 3                        | 52     | 89   | 470          | 170| 780           |
| Region 4                        | 24     | 11   | 124          | 3  | 162           |
| Region 5                        | 144    | 57   | 596          | 403| 1,200         |
| Region 6                        | 60     | 40   | 66           | 646| 812           |
| Region 7                        | 43     | 15   | 11           | 11 | 213           |
| Region 8                        | 49     | 1    | 53           | 1  | 104           |
| Region 9                        | 62     | 75   | 353          | 407| 899           |
| Region 10                       | 11     | 1    | 0            | 0  | 13            |
| Pollution Total                 | 787    | 407  | 2,337        | 1,869| 5,400        |

| Table 4. Largest mortality avoidances for the selected 2 weeks due to air pollutant emission reductions. |
|---------------------------------|--------|--------|---------|--------|
| Mortality                       | New York | Los Angeles | Chicago | Dallas-Fort Worth | Philadelphia | All Cities |
| Ozone-related mortality         | 700 | 100 | 200 | 200 | 100 | 1,300 |
| PM<sub>2.5</sub>-related mortality | 11,100 | 6,700 | 6,200 | 2,300 | 3,200 | 29,500 |
| Total                           | 11,800 | 6,800 | 6,400 | 2,500 | 3,300 | ~30,800 |
of the funds should be used to reduce PC and SO2 emissions to improve PM$_{2.5}$ air quality. The results show that reductions in PM$_{2.5}$-related mortalities (29,500) are much higher than ozone-related mortalities (1,300) if the funds could be allocated in a way suggested by the results of the resource allocation model (Table 4). As a key pillar of the economy and the city with the largest population, the mortality in the New York MSA could be reduced by around 11,800 during the study period. Mortality avoidances for Los Angeles, Chicago, Dallas-Fort Worth, and Philadelphia were 6,800, 6,400, 2,500, and 3,300, respectively. Among all the MSAs, the Dallas-Fort Worth MSA obtained the least health benefits from the emission reductions determined by the resource allocation model. An estimated 200 ozone-related mortalities and 2,300 PM$_{2.5}$-related mortalities could be avoided in Dallas-Fort Worth during the studying period. It’s noted that the mortality avoiding could be underestimated due to the underestimation of ozone and PM$_{2.5}$ concentrations (Table S1), and air quality model assimilations could be used to reduce the uncertainties in the results in the future.

Effects of resources on mortality avoidance

A further analysis is conducted to investigate how air quality protection resources (i.e., budget) could affect mortality avoidances due to air quality improvement. Specifically, we perturb the budget by ±5%, 10%, 15%, and 20% and use the new budgets to update the constraint in the resource allocation model (i.e., eq 5). Perturbations in the budgets within the range of ±20% are realistic for current regional air quality planning. The results show that responses of mortality avoidances the budget perturbations were small (Table 5). A 5%, 10%, 15%, and 20% increase in the budget would decrease the mortality by ~1.0%, 1.6%, 2.3%, and 2.9%, respectively. On the other hand, if the budgets decreased by 5%, 10%, 15%, and 20%, the avoided deaths would decrease by about 1.0%, 1.6%, 2.6%, and 3.6%, respectively. Overall, the results show that mortality avoidances were more sensitive to reductions in the budget than the budget increases.

Limitations and uncertainties

The results of the resources allocation modeling could be significantly affected by the cost functions used in the model. AirControlNET only includes control measures based on the EPA 1999 emission inventory, which may not fully represent current air pollutant emissions and their control costs. However, AirControlNET, to the best of our knowledge, is the best cost analysis tool that fits into the objective of this study. More recent emissions and their control costs should be considered in developing resource allocation strategies when more up-to-date cost analysis tools are available in the future. For the case study, CMAQ-DDM only simulates first-order (i.e., linear) sensitivities of air pollutants to emission reductions. It’s well known that ambient ozone and PM$_{2.5}$ formation is a nonlinear process (Cohan et al., 2005; Koo et al., 2007), and ignorance of high-order (i.e., second-order) sensitivities could induce uncertainties in the results of resource allocation modeling. Furthermore, the coefficients in the C-R function obtained from previous epidemiologic studies may not apply equally well to all the five MSAs. More detailed analysis of responses of mortalities to changes in air pollutant emissions for different cities will be needed to reduce uncertainties in the results of resource allocation modeling. Additionally, human responses to exposure to multiple air pollutants are complex and may have interactions, but in this study, we assumed that ozone and PM$_{2.5}$ concentrations are independent variables in the C-R function. Other detailed discussions on limitations of the model and uncertainties in the results of the case study are presented in Supplemental Material. The potential uncertainties and biases are not specifically examined here, as the primary objective of this study is to show the development of an innovative resource allocation model and its application.

Conclusions

The primary goal of air pollution mitigation is to protect the environment and human health. Since there is a resource limit (i.e., budgets) for air pollution controls, it is essential to identify effective air pollution mitigation strategies to maximize human health benefits over a region. In this study, we develop an innovative resource allocation model that allows identification of air pollutant emission control strategies that maximize mortality

| Perturbation | Avoided Ozone (in millions) | Avoided PM$_{2.5}$ (in millions) | Difference (in percentage) |
|---------------|-----------------------------|----------------------------------|---------------------------|
| Budget in 2010| 5,400                       | 30,796                           | —                         |
| 20% more      | 6,480                       | 31,727                           | +2.92                     |
| 15% more      | 6,210                       | 31,507                           | +2.27                     |
| 10% more      | 5,940                       | 31,280                           | +1.62                     |
| 5% more       | 5,760                       | 31,123                           | +0.97                     |
| 5% less       | 5,130                       | 30,536                           | −0.97                     |
| 10% less      | 4,860                       | 30,261                           | −1.62                     |
| 15% less      | 4,590                       | 29,968                           | −2.60                     |
| 20% less      | 4,320                       | 29,652                           | −3.57                     |
avoidances subject to a resource constraint. The resource allocation approach is formulated as a mathematical programming model, and four pieces of information—air quality sensitivities, health responses, budgets, and reduction limits—are needed for the resource allocation model.

Given the cost values in EPA’s CAA assessment, the results of the case study suggest that controls of SO$_2$ and PC emissions would achieve the most significant health benefits for the five selected MSAs collectively. The results also show that the majority of the resource would be used controls of SO$_2$ and PC emissions from Regions 2, 3, 5, 6, and 9. Around 30,800 air pollution-related mortalities could be avoided during the selected period for the five selected MSAs if the budgets could be allocated following the results of the resource allocation modeling. Although only air quality in five U.S. cities during a 2-week summertime episode are considered in this study, the resource allocation model can be used to develop air quality management strategies for other seasons and more cities if health responses and air quality sensitivities for different seasons and areas can be determined.

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About the authors

Kuo-Jen Liao is an assistant professor of Environmental Engineering at Texas A&M University–Kingsville in Kingsville, TX.

Xiangting Hou received her Ph.D. degree in environmental engineering from Texas A&M University–Kingsville in December 2015.

Matthew J. Strickland is an associate professor in the School of Community Health Sciences, University of Nevada, Reno.

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