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Modeling variability in air pollution-related health damages from individual airport emissions

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ABSTRACT

In this study, we modeled concentrations of fine particulate matter ($PM_{2.5}$) and ozone (O_3) attributable to precursor emissions from individual airports in the United States, developing airport-specific health damage functions (deaths per 1000 t of precursor emissions) and physically-interpretable regression models to explain variability in these functions. We applied the Community Multiscale Air Quality model using the Decoupled Direct Method to isolate $PM_{2.5}$- or O_3-related contributions from precursor pollutants emitted by 66 individual airports. We linked airport- and pollutant-specific concentrations with population data and literature-based concentration-response functions to create health damage functions. Deaths per 1000 t of primary $PM_{2.5}$ emissions ranged from 3 to 160 across airports, with variability explained by population patterns within 500 km of the airport. Deaths per 1000 t of precursors for secondary $PM_{2.5}$ varied across airports from 0.1 to 2.7 for NOx, 0.06 to 2.9 for SO_2, and 0.06 to 11 for VOCs, with variability explained by population patterns and ambient concentrations influencing particle formation. Deaths per 1000 t of O_3 precursors ranged from −0.004 to 1.0 for NOx and 0.03 to 1.5 for VOCs, with strong seasonality and influence of ambient concentrations. Our findings reinforce the importance of location- and source-specific health damage functions in design of health-maximizing emissions control policies.

1. Background and introduction

Exposure to ground-level ozone (O_3) and fine particulate matter ($PM_{2.5}$) is associated with adverse health impacts, including cardiovascular and respiratory premature mortality (Jerrett et al., 2009; Krewski et al., 2009). $PM_{2.5}$ and O_3 are believed to dominate health impacts caused by air pollutants (Brook, 2002). To minimize public health impacts, air pollution management requires information regarding the contribution of different individual sources to ambient pollutant concentrations and associated health effects. These health effects can be summarized through health damage function models, which quantify health impacts per unit emissions through the combination of predicted changes in air quality, population patterns, baseline health effect incidence rates, and concentration-response functions derived from the epidemiological literature (Levy et al., 2009; Tagaris et al., 2009; Hubbell et al., 2009; Fann and Risley, 2011).

Due to the long-range transport and secondary atmospheric formation of both $PM_{2.5}$ and O_3, associated health risks will manifest on a regional scale, necessitating the use of a chemistry-transport model like the Community Multiscale Air Quality (CMAQ) model to predict air quality changes. CMAQ simulates the formation and fate of pollutants given meteorological and ambient conditions in a one-atmosphere setting (modeling tropospheric ozone, aerosols and air toxics and their interactions) (Byun and Ching, 1999; Byun and Schere, 2006; Fann et al., 2012), allowing meteorology and emissions to interact at once. CMAQ has been evaluated comprehensively (Foley et al., 2010; Simon et al., 2012; Arnold et al., 2003) and applied to simulate O_3 (Hogrefe et al., 2004) and $PM_{2.5}$ concentrations in multiple regions of the United States (US) and elsewhere (Wesson et al., 2010; Zhang, 2004). CMAQ has been used extensively for health impact analyses, largely looking at entire source sectors of multi-source combinations (Fann et al., 2013), with fewer applications focused on individual source impacts (Bergin et al., 2008).

To understand the impacts of individual sources within CMAQ,

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there are multiple options within CMAQ ranging from simple "brute-force methods" or somewhat sophisticated source apportionment methods such as the Integrated Source Apportionment Method (ISAM) to advanced forward or inverse sensitivity approaches such as the Decoupled Direct Method (DDM) and adjoint approaches respectively. First-order sensitivities have previously been calculated by varying input parameters in separate model simulations and analyzing the change in predicted concentrations, an easy to interpret approach referred to as the "brute-force method" (Dunker, 1984; Dunker et al., 2002), though computationally demanding and susceptible to noise (or unwanted signals) due to small changes in inputs (Koo et al., 2007). The Decoupled Direct Method (DDM) improves upon the brute-force method, decoupling sensitivity equations from model equations, allowing for computational efficiency, stability and accuracy of values (Dunker, 1984; Dunker et al., 2002; Koo et al., 2007). DDM-3D is an advanced sensitivity analysis technique that computes the first order and more recently second order semi-normalized sensitivity in three dimensions to perturbations in any input field such as emissions, initial or boundary condition, etc. DDM-3D can be used to analyze the sensitivity of ambient concentrations to individual source emissions. Adjoint approaches are useful to find individual sources or source regions that contribute to a pre-defined cost function (an air quality or health metric), but cannot be used to determine the impact of a specific source. We specifically chose DDM-3D to perform our source attributions given that aircraft emissions are a small percent of all anthropogenic emissions, and since DDM-3D is superior to "brute force" to assess small changes in inputs (Napelenok et al., 2006). To date, DDM has been implemented in air quality models (including CMAQ and others) to identify how sources impact O_3 and $PM_{2.5}$ concentrations for policy analysis or health risk modeling at a regional or national scale (Bergin et al., 2008; Dunker, 1984; Dunker et al., 2002; Odman et al., 2002; Digar et al., 2011), but has not been incorporated into individual source health damage function modeling.

Although air quality management would benefit greatly from insights about health damages from individual sources, prior studies examining variability in health damage functions have typically focused on between-sector rather than within-sector variability, where sectors are defined as grouped sources of emissions, like the on-road mobile sector or industrial point source sector. These prior studies have not had a sufficient sample size of individual sources using an advanced atmospheric model. For example, Fann et al. (2013) estimated damage functions for $PM_{2.5}$ and O_3 for individual source sectors between 2005 and 2016, but they did not explore within-sector variability. Levy et al. (2009) estimated $PM_{2.5}$-related damage functions from individual coal-fired power plants, but relied on a simpler atmospheric model that may not adequately capture secondary pollutant formation. Buonocore et al. (2014) utilized a CMAQ brute-force method to examine variability in health damage functions of individual power plants across the mid-Atlantic, but had a limited sample size given challenges in separating plumes from individual power plants within CMAQ runs.

One important source sector for which health damage function modeling would be informative is aviation. Airport emissions are garnering more concern due to rapid growth of air transport and expected expansion to meet population needs going forward (Amato et al., 2010; Kurniawan and Khardi, 2011; Kinsey et al., 2011; Woody et al., 2011; United States Department of Transportation, 2015) while emissions from other prominent sources are expected to decrease (Levy et al., 2012). However, few studies have characterized the health impacts of individual airports or airport-related emissions specifically (Wolfe et al., 2014; Ashok et al., 2014). CMAQ has been used to estimate mortality risks from three airports in the eastern US (Arunachalam et al., 2011) and to quantify health benefits of nationwide aviation emissions reductions (Ashok et al., 2013). However, due to their lack of focus on individual emitted pollutants from a significant number of individual airports, these analyses do not provide a comprehensive foundation for national-scale air quality management.

In this study, we analyze the contribution of 66 individual airports to ambient air pollution and quantify related health damage functions. We designed CMAQ-DDM airport group runs to capture the majority of fuel burned in the aviation sector, used image segmentation techniques to extract individual airport contributions from multi-airport DDM surfaces, and created physically interpretable regional predictors of health damage functions within regression models (e.g., exposed population and background atmospheric conditions). This would allow for health damage functions to be estimated for any airport in the continental US, and our modeling approach would generalize to other source sectors contributing to ambient air pollution and related health effects.

2. Methods

2.1. Study design

We used CMAQ-DDM (Dunker, 1984; Napelenok et al., 2006) to isolate O_3-and $PM_{2.5}$-related contributions from individual airport-related precursor pollutants. These airport-specific and precursor-specific pollutant concentrations were then spatially linked with population and mortality rate data (Centers for Disease Control and Prevention, 2015) and literature-based concentration-response functions for mortality. We estimated health damage functions as mortality risk per 1000 t of emissions for all ambient concentration – pollutant precursor relationships. We included primary elemental carbon (PEC), primary organic carbon (POC), and primary sulfate (PSO_4) as primary $PM_{2.5}$ precursors; nitrogen oxides (NOx), sulfur dioxide (SO_2), and volatile organic compounds (VOCs) as secondary $PM_{2.5}$ precursors; and NOx and VOCs as O_3 precursors (Table S1). Regression models were created to explain variability in airport-specific health damage functions as a function of population, meteorological, and chemistry-related predictors.

2.2. CMAQ-DDM design and modeling

Because of the computationally intensive nature of CMAQ-DDM and the number of airports across the US, and given our objective to directly model the majority of nation-wide aircraft emissions, we needed to incorporate multiple airports into a single DDM run. However, the outputs would only be interpretable if the concentration surfaces from each individual airport within a run could be readily separated from one another. We therefore conducted extensive preliminary analyses to determine optimal run design.

In a pilot analysis, we used CMAQ-DDM to model concentration surfaces for 99 top fuel-burning airports individually for 1-week periods in January and July, and the resultant sensitivity fields were viewed in ArcMap v.10.1. Based on visualized spread of secondarily formed $PM_{2.5}$ concentrations (which has a greater spatial extent than primarily emitted $PM_{2.5}$), individual airports were grouped together that were expected to have non-overlapping air quality impacts. We chose 66 airports (Fig. 1), including many of the largest airports as characterized by fuel burned annually and airports that allow for geographic representation across the continental US. These 66 airports accounted for 77% of total annual fuel burned for the nation's commercial passenger flights in 2005. We used a 2005 modeling platform to build upon 2005–2025 aviation sector growth analyses in Woody et al. (2011) and Levy et al. (2012) to isolate impacts from individual airports (Levy et al., 2012; Woody et al., 2011). To minimize computational resource requirements, airports with non-overlapping sensitivity footprints were combined into groups (Table S2). In total, 31 model runs were conducted: one each for the 30 groups containing the 66 airports, plus a single additional run simulating the total contributions of all airports in the modeling domain.

CMAQ v.4.7.1 instrumented with DDM in three dimensions (DDM-3D) was used to generate sensitivities of $PM_{2.5}$ and O_3 concentrations to