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Mortality-based damages per ton due to the on-road mobile sector in the Northeastern and Mid-Atlantic U.S. by region, vehicle class and precursor

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Abstract
On-road vehicular emissions contribute to the formation of fine particulate matter and ozone which can lead to increased adverse health outcomes near the emission source and downwind. In this study, we present a transportation-specific modeling platform utilizing the community multiscale air quality model (CMAQ) with the decoupled direct method (DDM) to estimate the air quality and health impacts of on-road vehicular emissions from five vehicles classes; light-duty autos, light-duty trucks (LDT), medium-duty trucks, heavy-duty trucks (HDT), and buses (BUS), on PM$_{2.5}$ and O$_3$ concentrations at a 12 × 12 kilometer scale for 12 states and Washington D.C. as well as four large metropolitan statistical areas in the Northeast and Mid-Atlantic U.S. in 2016. CMAQ-DDM allows for the quantification of sensitivities from individual precursor emissions (NO$_X$, SO$_2$, NH$_3$, volatile organic compounds, and PM$_{2.5}$) in each state to pollution levels and health effects in downwind states. In the region we considered, LDT are responsible for the most PM$_{2.5}$-attributable premature mortalities at 1234 with 46% and 26% of those mortalities from directly emitted primary particulate matter and NH$_3$, respectively; and O$_3$-attributable premature mortalities at 1129 with 80% of those mortalities from NO$_X$ emissions. Based on a detailed source-receptor matrix of sensitivities with subsequent monetization of damages that we computed, we find that the largest damages-per-ton estimate is approximately $4 million per ton of directly emitted primary particulate matter from BUS in the New York-Newark-Jersey City metropolitan statistical area. We find that on-road vehicular NH$_3$ emissions are the second largest contributor to PM$_{2.5}$ concentrations and health impacts in the study region, and that reducing 1 ton of NH$_3$ emissions from LDT is ~75 times and from HDT is ~90 times greater in terms of damages reductions than a 1 ton reduction of NO$_X$. By quantifying the impacts by each combination of source region, vehicle class, and emissions precursor this study allows for a comprehensive understanding of the largest vehicular sources of air quality-related premature mortalities in a heavily populated part of the U.S. and can inform future policies aimed at reducing those impacts.

1. Introduction

Emissions from fossil fuel combustion by mobile sources contribute to poor air quality through the formation of air pollutants such as fine particulate matter (PM$_{2.5}$) and ozone (O$_3$). Exposure to these air pollutants has been associated with increased premature mortalities. The mobile source sector remains one of the largest contributors to PM$_{2.5}$ and O$_3$ globally and in the U.S. (Anenberg et al. 2017, Zawacki et al. 2018, Yang et al. 2019) with one study estimating ~385 000 PM$_{2.5}$ and O$_3$-attributable premature mortalities globally in 2015 from tailpipe emissions (Anenberg et al. 2019). In the U.S., road
transportation mobile sources have been estimated to be the largest source of air pollution related premature mortalities (Caiazzo et al. 2013), responsible for approximately 53,000 PM$_{2.5}$ and 5000 O$_3$-attributable premature mortalities.

Prior studies have quantified the health impacts from the on-road vehicle sector in the U.S. (Caiazzo et al. 2013, Dedoussi and Barrett 2014, Davidson et al. 2020 and Dedoussi et al. 2020) quantified premature mortalities in the U.S. from road transportation in 2005 and 2011. Caiazzo et al. (2013) broke down PM$_{2.5}$ and O$_3$ mortalities occurring in each state due to on-road emissions through zero-out approaches within a chemical transport model (CTM), but did not break down the contribution due to PM$_{2.5}$ and O$_3$ precursor emission species, source regions, or vehicle types. Dedoussi and Barrett (2014) broke down the PM$_{2.5}$ mortalities from on-road emissions by source states and emission precursors through an adjoint sensitivity analysis within a CTM but did not include O$_3$-attributable mortalities, and secondary organic aerosols were not included due to the limitations of the model. Both Caiazzo et al. (2013) and Dedoussi and Barrett (2014) performed their studies for inventory years of 2005 that did not account for recent mobile source emission regulations such as the Tier 3 Motor Vehicle Emission and Fuel standards. Wolfe et al. (2019) monetized PM$_{2.5}$ damages per ton of directly emitted PM$_{2.5}$, sulfur oxides (SO$_x$)/directly emitted sulfate (pSO$_x$), and nitrogen oxides (NO$_x$) from a subset of vehicle classes as defined in Davidson et al. (2020), but did not calculate O$_3$ damages per ton and did not calculate PM$_{2.5}$ damages per ton of on-road emissions of ammonia (NH$_3$) and volatile organic compounds (VOCs). Goodkind et al. (2019) utilized a reduced-complexity model (RCM) to calculate the PM$_{2.5}$ damages per ton of directly emitted PM$_{2.5}$, SO$_2$, VOC, NO$_x$, and NH$_3$ broken down by the on-road emission sector in 2011, but did not calculate O$_3$ damages per ton or account for differing effects of PM$_{2.5}$ season by season due to the nature of the RCM. Dedoussi et al. (2020) quantified PM$_{2.5}$ and O$_3$ mortalities in 2011 by source region, sector, and precursor through an adjoint sensitivity analysis but did not break down the on-road sector into vehicle types, secondary organic aerosols were excluded, and the coarse model resolution may not capture localized impacts in densely populated urban areas. Davidson et al. (2020) broke down the PM$_{2.5}$ and O$_3$ mortalities by vehicles’ fuel types in 2011 using source apportionment methodologies within a CTM, but did not break down impacts by source region or precursor emission species.

This study aims to address the gaps listed above and add to this growing list of literature by quantifying health impacts in a heavily populated region of the U.S., i.e. the Northeast and Mid-Atlantic U.S., broken down by five precursor emission species from five vehicle classes from 12 states and Washington D.C. and four metropolitan statistical areas (MSAs) in 2016. By quantifying impacts from these individual combinations of vehicle class/region/emissions precursor species, this study will be the first to quantify the PM$_{2.5}$ and O$_3$ premature mortalities in each of our 12 states, Washington D.C. and four MSAs attributable to precursor emissions from five distinct vehicle classes from each of the 12 states, Washington D.C. and four MSAs. We aim to quantify the largest total damages per ton estimates in each of these 12 states, Washington D.C. and four MSAs by vehicle class, precursor emission species, and emission source state/MSA. This study will utilize the decoupled direct method (DDM) forward sensitivity modeling technique in the community multiscale air quality model (CMAQ) that calculates sensitivities of PM$_{2.5}$ and O$_3$ concentrations to each of our variables of interest. This information is critical in developing effective emission control strategies, especially in a region as heavily populated as the Northeast and Mid-Atlantic U.S. which contains approximately 22% of the U.S. population.

The motivation for looking at this part of the U.S. and for utilizing this particular sensitivity methodology is research to support the Transportation, Equity, Climate, and Health Study (TRECH study). The TRECH study is an independent co-benefits study that looks to quantify potential health outcomes associated with a range of cap and invest scenarios under the proposed Transportation and Climate Initiative (TCI) (Transportation and Climate Initiative 2020), a set of policies aimed at mitigating climate impact by reducing emissions from on-road vehicles which is expected to have health benefits due to better air quality (Driscoll et al. 2015, Mittal et al. 2015, Buonocore et al. 2016, 2018). This research, that quantifies damages per ton due to vehicle classes by source regions, is a key component of the TRECH study that aims to quantify the air quality and health-related impacts of on-road vehicle classes’ emissions in each of the states that make up the TCI region as well as each state’s impact on other states within the region.

2. Methods

2.1. Air quality modeling

The CMAQ model is used to quantify PM$_{2.5}$ and O$_3$ concentrations across the model domain using a 2016 air quality modeling platform. The DDM sensitivity analysis (Dunker et al. 1984, Napelenok et al. 2006, 2008, Koo et al. 2007) as implemented in CMAQv5.2 (U.S. EPA Office of Research and Development 2017) with the Carbon Bond 6 revision 3 mechanism (CB6r3) (Luecken et al. 2019) is used to calculate sensitivities of PM$_{2.5}$ and O$_3$ concentrations in each model grid cell to precursor emissions from on-road vehicle classes in each source region (Towns et al. 2014). Sensitivities as calculated in the DDM framework describe the incremental change in pollutant concentrations with respect to model inputs.
across the domain to estimate how sensitive pollutant concentrations are to a specific model input. Our modeling domain covers the eastern half of the U.S. with 12 × 12 km horizontal grid cell resolution (figure S1 (available online at stacks.iop.org/ERL/16/065008/mediala)).

Precursor emissions to O3 from on-road vehicles are nitrogen oxides (NOX) and VOC; and precursor emissions to PM2.5 are NOX, VOC, sulfur dioxide (SO2), ammonia (NH3), and directly emitted primary PM2.5 (henceforth referred to as PPM). On-road vehicle emissions are taken from the U.S. Environmental Protection Agency’s (EPA) 2016v1 modeling platform based on the National Emissions Inventory (National Emissions Inventory Collaborative 2019, U.S. Environmental Protection Agency 2020). On-road emissions are generated using emission factors representative of all national fuel economy and GHG standards for vehicles as of October 2015 (U.S. Environmental Protection Agency 2015), county and source classification code (SCC)-specific activity data submitted by states for the year 2016 (U.S. Environmental Protection Agency 2020), and hourly meteorological data. Five distinct vehicle class emissions inventories were generated using the Sparse Matrix Operator Kernel Emission (Baek and Seppanen 2018) modeling system according to SCC values (table S6) grouped by the MOVES2014a vehicle types: light-duty autos (LDA), light-duty trucks (LDT), buses (BUS), medium-duty trucks (MDT), and heavy-duty trucks (HDT). Vehicle class emission inventories were generated for twelve states in the Northeast U.S. that make up the TCI region: Connecticut (CT), Delaware (DE), Maine (ME), Maryland (MD), Massachusetts (MA), New Hampshire (NH), New Jersey (NJ), New York (NY), Pennsylvania (PA), Rhode Island (RI), Vermont (VT), Virginia (VA); the District of Columbia (DC); and four large MSAs: the Boston-Cambridge-Newton, MA NH MSA (BOSMSA), New York-Newark-Jersey City, NY NJ PA (NYMSA), Philadelphia-Camden-Wilmington, PA NJ DE MD (PHILMSA), and the combined Baltimore-Columbia-Towson, MD and the Washington-Arlington-Alexandria, DC VA MD WV MSAs (BALMSA). Tables S1–S4 show the counties that comprise each of these source region MSAs. The resulting matrix of source-impact sensitivities are O3 and PM2.5 concentration sensitivities to the number of precursors × the number of vehicle classes × the number of source states/MSAs. Hence for O3, the number of sensitivities = 2 × 5 × 17 = 170; and for PM2.5, the number of sensitivities = 5 × 5 × 17 = 425. CMAQ-DDM simulations are run for January and July in 2016 to represent the winter and summer season, respectively. The results are then averaged to represent the annual contribution of precursor emissions from the selected vehicle classes and source regions to regional O3 and PM2.5 concentrations. Information regarding DDM calculations within CMAQ and model evaluation against observations can be found in the supporting information.

2.2. Health impact assessment
Exposure to elevated levels of ground-level O3 and PM2.5 concentrations have been associated with increased adverse health effects (Bell et al 2004, Laden et al 2006, Jerrett et al 2009, Krewski et al 2009) leading to the development of concentration response functions (CRFs) that quantify the increased risk of adverse health effects occurring per unit increase in pollutant concentration. To perform the health impact assessments for all of the simulations that were done, we built a health impact assessment tool BenMAPR. Similar to the U.S. EPA’s Benefits Mapping and Analysis Program (BenMAP) (Sacks et al 2018), BenMAPR is a geospatial air pollution health impact assessment modeling platform that links air pollution exposures to data on exposed populations and their background health. It then calculates the health impacts of these exposures using CRFs from the epidemiological literature.

For quantifying PM2.5-attributable premature mortalities, we make use of a CRF from a recently published meta-analysis (Vodonos et al 2018) that found a 1.29% (95% CI 1.09–1.5) increase in all-cause mortality per 10 µg m−3 increase in PM2.5. For O3-attributable premature mortalities, we use a CRF associating all-cause mortality to long-term O3 exposure with a hazards ratio of 1.02 (95%CI 1.01–1.04) per 10 ppb increase in O3 (Turner et al 2016). For both PM2.5 and O3-attributable premature mortalities, source region and vehicle-class specific contributions were calculated for adults 25 and over. We used linear approximations for each CRF as that has been found to be appropriate for U.S.—relevant changes in concentrations (Schwartz et al 2008, Vodonos et al 2018, Gilmore et al 2019).

We obtained population data at U.S. Census tract level split by age from the U.S. Census American Community Survey for the year 2018, the most recent year available. To obtain stable and generalizable mortality rate estimates, we used an average of county level baseline mortality rates from 1999 to 2016, the most recent years available from the U.S. Centers for Disease Control Wide-ranging Online Database for Epidemiologic Research. Baseline hospitalization and other adult morbidity data was obtained from BenMAP (Sacks et al 2018), which sources morbidity data from the Agency for Healthcare Research and Quality Healthcare Cost and Utilization Project (Agency for Healthcare Research and Quality, Rockville, MD 2020).

2.3. Emissions
Table 1 shows the emission totals in the TCI region by vehicle class for the months of January and July.
Tables S8–S12 show the same for each source region. LDT are the largest source of NO$_X$, VOC, and SO$_2$ emissions in the 13 states (DC henceforth referred to as the 13th state) that make up the TCI region (excluding the MSAs as they are contained within one or multiple states) with 14,140 and 17,185 tons of NO$_X$, 16,629 and 15,756 tons of VOC, and 218 and 284 tons of SO$_2$ emitted in January and July, respectively. LDA are the largest source of NH$_3$ emissions with 579 tons in January and 740 tons in July. For PPM emissions, LDA are the largest source in January with 417 tons while HDT are the largest source in July with 456 tons.

Summing emissions from vehicle classes, Pennsylvania is the largest source of NO$_X$ (8071 tons in January and 10,440 tons in July) and VOC (7463 tons in January and 7008 tons in July) emissions while New York is the largest source of SO$_2$ (99 tons in January and 134 tons in July), NH$_3$ (243 tons in January and 327 tons in July), and PPM (348 tons in January and 311 tons in July) emissions. In January, the individual largest emission sources for NO$_X$, SO$_2$, VOC, NH$_3$, and PPM are LDT from VA, LDT from PA, LDT from NY, LDA from NYMSA, and LDT from PA, respectively. In July, the individual largest emission sources for NO$_X$, SO$_2$, VOC, NH$_3$, and PPM are LDT from VA, LDT from PA, LDT from NY, LDA from NY, and HDT from PA, respectively.

Figures S2–S6 show the percentage of contribution to each of the total precursor emissions (from all sources) in each source region. Light-duty vehicles predominantly emit gas-phase precursors while heavy and medium duty trucks emit a larger portion of particle-phase emissions. Vehicular location and distribution will determine how precursor emissions from the vehicle classes in different source regions will impact PM$_{2.5}$ and O$_3$, both near the emission source and downwind.

### 3. Results

#### 3.1. Population-weighted exposure

Table 2 shows the population-weighted annual mean PM$_{2.5}$ and O$_3$ sensitivities to each vehicle class and precursor in the states that make up the TCI region. PM$_{2.5}$ sensitivities are annually averaged and O$_3$ sensitivities are the annual average of the daily 8-h maximum. We continue to exclude MSAs as source regions here so as to avoid double counting the vehicle emissions contained in both the MSA and states within that MSA. PM$_{2.5}$ sensitivities to PPM and NH$_3$ are the largest amongst the precursors to PM$_{2.5}$, while O$_3$ sensitivities to NO$_X$ are the largest amongst the precursors to O$_3$. LDA and LDT PM$_{2.5}$ sensitivities to VOC, NH$_3$, SO$_2$, and PPM are similar in magnitude, reflective of the magnitude and spatial distribution of the emissions of those vehicle classes. PM$_{2.5}$ sensitivities to VOC, NH$_3$, SO$_2$, and PPM are almost entirely positive across the domain for both months of simulation. PM$_{2.5}$ sensitivities to NO$_X$ emissions in January are negative in some areas. Aerosol NO$_3^-$ and NH$_4^+$ can have negative sensitivities to on-road NO$_X$ emissions primarily in urban areas of our domain during the winter months due to the chemical system and feedback of emitted precursors and the formation of SO$_2^{2-}$-NO$_3^-$-NH$_4^+$ components of PM$_{2.5}$. The main drivers of wintertime inorganic aerosol chemistry are oxidant availability, cloud water chemistry, and gas-particle partitioning which will influence how much SO$_2^{2-}$ is formed from SO$_2$ and the partitioning of NH$_3$ to NH$_4^+$ and NO$_X$ to NO$_3^-$. Recent studies in the Eastern U.S. (Shah et al. 2018, Vasilakos et al. 2018, Pye et al. 2020) have characterized the response of inorganic aerosols to these drivers and help to explain the negative sensitivities of NO$_3^-$ and NH$_4^+$ to on-road emissions of NO$_X$ in our domain during winter months.

### Table 1. Emissions of NO$_X$, VOC, SO$_2$, NH$_3$, and PPM in tons/month for January and July 2016 by each vehicle class.

| Source vehicle | NO$_X$ | VOC | SO$_2$ | NH$_3$ | PPM |
|----------------|--------|-----|--------|--------|-----|
| LDA            | 8638   | 15 258 | 186 | 579 | 417 |
| LDT            | 14 140 | 16 629 | 218 | 550 | 484 |
| MDT            | 4875   | 1466 | 17 | 35 | 259 |
| HDT            | 8840   | 900 | 24 | 42 | 363 |
| BUS            | 1594   | 342 | 3 | 7 | 68 |

| Source vehicle | NO$_X$ | VOC | SO$_2$ | NH$_3$ | PPM |
|----------------|--------|-----|--------|--------|-----|
| LDA            | 9862   | 14 130 | 242 | 740 | 203 |
| LDT            | 17 185 | 15 756 | 284 | 697 | 271 |
| MDT            | 6186   | 1758 | 22 | 44 | 304 |
| HDT            | 11 118 | 1073 | 32 | 53 | 456 |
| BUS            | 2017   | 394 | 5 | 8 | 86 |

### Table 2. Population-weighted sensitivities of PM$_{2.5}$ (μg m$^{-3}$) and O$_3$ (ppb) to precursors from each vehicle class averaged across the TCI region.

| Source vehicle | PM$_{2.5}$ NO$_X$ | VOC | SO$_2$ | PPM NO$_X$ | VOC |
|----------------|-------------------|-----|--------|-------------|-----|
| LDA            | 6.2 × 10$^{-4}$   | 1.7 × 10$^{-3}$ | 3.7 × 10$^{-3}$ | 1.7 × 10$^{-4}$ | 5.8 × 10$^{-3}$ |
| LDT            | 1.4 × 10$^{-3}$   | 1.9 × 10$^{-3}$ | 3.3 × 10$^{-3}$ | 1.9 × 10$^{-4}$ | 6.0 × 10$^{-3}$ |
| MDT            | 3.8 × 10$^{-4}$   | 2.4 × 10$^{-4}$ | 2.4 × 10$^{-4}$ | 1.5 × 10$^{-5}$ | 5.5 × 10$^{-3}$ |
| HDT            | 9.3 × 10$^{-4}$   | 1.3 × 10$^{-4}$ | 3.1 × 10$^{-4}$ | 1.9 × 10$^{-5}$ | 7.2 × 10$^{-3}$ |
| BUS            | 5.8 × 10$^{-5}$   | 6.0 × 10$^{-5}$ | 5.7 × 10$^{-5}$ | 3.2 × 10$^{-6}$ | 2.1 × 10$^{-3}$ |

| Source vehicle | O$_3$ NO$_X$ | VOC |
|----------------|-------------|-----|
| LDA            | 3.3 × 10$^{-2}$ | 1.5 × 10$^{-2}$ |
| LDT            | 6.3 × 10$^{-2}$ | 1.6 × 10$^{-2}$ |
| MDT            | 2.2 × 10$^{-2}$ | 2.6 × 10$^{-3}$ |
| HDT            | 4.0 × 10$^{-2}$ | 1.4 × 10$^{-3}$ |
| BUS            | 4.7 × 10$^{-3}$ | 7.2 × 10$^{-4}$ |
MDT and HDT PM$_{2.5}$ population-weighted sensitivities are largest with respect to PPM emissions consistent with what we see from the emission magnitudes as compared to LDT and LDA as well as emission percentages in each source region. BUS PM$_{2.5}$ population weighted sensitivities are the smallest of the vehicle classes with the only significant source of emissions from BUS coming from NY and VA.

O$_3$ population weighted sensitivities to NO$_X$ emissions are larger than sensitivities to VOC for each vehicle class. O$_3$ sensitivities to LDT NO$_X$ emissions are the largest at $6.3 \times 10^{-2}$ ppb across the TCI region followed by sensitivities to HDT NO$_X$ emissions at $4.0 \times 10^{-2}$ ppb. O$_3$ sensitivities to LDA and LDT VOC emissions are much larger than sensitivities to MDT, HDT, and BUS VOC emissions reflecting the magnitude of VOC emissions from each vehicle class.

### 3.2. Health impacts

Tables 3 and 4 show the total PM$_{2.5}$ and O$_3$-attributable premature mortalities across the TCI region by vehicle class and precursor. Percentage of premature mortalities from each precursor follows similar trends to the magnitudes of population weighted exposures. The largest source of both PM$_{2.5}$ and O$_3$-attributable premature mortalities are LDT at 1234 and 1229 mortalities, respectively. LDT PPM emissions are responsible for 46% of PM$_{2.5}$ mortalities, and LDT NO$_X$ emissions are responsible for 80% of O$_3$ mortalities. Tables S15–S26 show the breakdown of the total premature mortalities by source state. Looking at the largest PM$_{2.5}$ mortalities for each vehicle class, the largest percentage of mortalities occur in NY except for HDT where the largest percentage occurs in PA. When considering BUS emissions, 64.9% of premature mortalities occur in NY, with 62.1% of those mortalities from PPM emissions. This indicates that BUS PPM emissions in NY outweigh any other precursor and source region emissions from BUS. While not included in the total PM$_{2.5}$-attributable mortalities from states that make up the TCI region (table 3 and tables S15–S19), mortalities in the MSAs we considered were similar in amount to NY, and in some instances exceeded total mortalities in NY. PM$_{2.5}$ mortalities in NYMSA were 388.7, 354.1, 302.7, 251.8, and 137.1 for LDA, LDT, MDT, HDT, and BUS emissions, respectively, showing that more PM$_{2.5}$-attributable premature mortalities are occurring in the NYMSA due to each vehicle class rather than any individual state. This seems reasonable given the population density and vehicle activity in the counties that comprise the NYMSA. PM$_{2.5}$ mortalities for all four MSAs are in table S20.

Looking at the O$_3$ mortalities for each vehicle class, the largest percentage of mortalities occur in PA, except for BUS, where the largest percentage occurs in NJ (although the impacts are much smaller than the other vehicle classes due to the relatively small percentage of NO$_X$ and VOC emitted from BUS). Total PM$_{2.5}$-attributable mortalities exceed O$_3$-attributable mortalities in the TCI region, however the largest individual impact is O$_3$-attributable mortalities in PA by LDT emissions.

Figures 1 and 2 allocate the PM$_{2.5}$ and O$_3$-attributable premature mortalities in each receptor state/MSA in the TCI region to each source state’s/MSA’s vehicle emissions. Tables S27 and S28 show the exact values for each source and receptor where in each column, the number in bold represents the largest impact from a given source state/MSA. Here we have summed mortalities by precursor to give an estimate of the total premature mortalities due

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**Table 3.** Total premature mortalities in the TCI region due to long-term exposure to PM$_{2.5}$ attributable to each vehicle class and the percentage attributable to each precursor.

| Source vehicle | Mortalities | Percentage from emission precursor (%) | NO$_X$ | VOC | NH$_3$ | SO$_2$ | PPM |
|----------------|-------------|----------------------------------------|--------|-----|-------|-------|-----|
| LDA | 1153 (974–1341) | 14 | 15 | 26 | 1 | 47 |
| LDT | 1234 (1042–1434) | 12 | 15 | 26 | 1 | 46 |
| MDT | 601 (507–698) | 64 | 4 | 4 | 0 | 85 |
| HDT | 829 (701–964) | 6 | 1 | 4 | 0 | 83 |
| BUS | 206 (174–240) | 3 | 3 | 3 | 0 | 91 |

**Table 4.** Total premature mortalities in the TCI region due to long-term exposure to O$_3$ attributable to each vehicle class and the percentage attributable to each precursor.

| Source vehicle | Mortalities | Percentage from emission precursor (%) | NO$_X$ | VOC |
|----------------|-------------|----------------------------------------|--------|-----|
| LDA | 728 (364–1456) | 69 | 31 |
| LDT | 1129 (615–2459) | 80 | 20 |
| MDT | 395 (197–790) | 90 | 10 |
| HDT | 636 (318–1272) | 97 | 3 |
| BUS | 91 (45–181) | 88 | 12 |
Figure 1. Premature deaths in each receptor state/MSA due to long-term exposure to PM$_{2.5}$ attributable to each source state/MSA and vehicle class.

Figure 2. Premature deaths in each receptor state/MSA due to long-term exposure to O$_3$ attributable to each source state/MSA and vehicle class.
to the source state’s/MSA’s vehicle class. The largest amount of premature mortalities (335), from PM$_{2.5}$ or O$_3$, occurs in the NYMSA by emissions from LDA in NYMSA. As a source for PM$_{2.5}$-attributable mortalities, vehicles from MSAs make up 40% (34 of 85 possible instances) of the largest impacts seen in each receptor state/MSA. As a source for O$_3$-attributable mortalities, this number drops to 17.6% (15 of 85 possible instances). This is due to PM$_{2.5}$ impacts remaining localized to the emission source region, driven by large population-weighted sensitivities to NH$_3$ and PPM emissions, and O$_3$ impacts largely occurring downwind of the source. Large NO$_X$ emissions in MSAs and highly populated regions can cause O$_3$ depletion due to the photochemical regime, which can be seen with small negative impacts (approximately $-1$ premature mortalities) in DC from all vehicle class in DC, in BOSMSA from MDT and BUS in BOSMSA, and in RI from MDT and HDT in RI; and can be seen with large negative impacts (less than $-10$ premature mortalities) in NY from MDT in NYMSA, and in NY and NYMSA from BUS in NY and NYMSA. The most impacted region by PM$_{2.5}$-attributable mortalities is NYMSA for each vehicle class from NYMSA. The most impacted region by O$_3$-attributable mortalities from LDA, MDT, HDT, and BUS is also NYMSA with LDA and BUS emissions from NJ and MDT and HDT emissions from PA. For LDT, PA is the most impacted with emissions from PA.

To monetize the value of avoided mortalities we apply a value of statistical life approach as recommended by the EPA (U.S Environmental Protection Agency 2010) by multiplying the number of PM$_{2.5}$ and O$_3$ attributable premature mortalities by a 2016 USD ($) income-adjusted value of $10.3$ million. The monetized value of premature mortalities in each receptor state/MSA is divided by the emission amounts from each source region and vehicle class precursor to approximate the economic damages per ton of precursor emitted. Figure 3 shows the rank-ordered top 10 damages per ton for each receptor state/MSA, where total damages reflect the sum of PM$_{2.5}$ and O$_3$ attributable premature mortalities. By selecting only the top 10 damages per ton estimates in each receptor state/MSA, we are able to quantify the largest economic value of avoided deaths in each region with respect to any source region/vehicle class/precursor. Looking at precursors, we can see that the largest monetized value of health-related benefits can be achieved by reducing PPM and NH$_3$. As PPM and NH$_3$ are mainly responsible for localized impacts, each receptor state/MSA has itself as one of its largest contributing source regions in terms of damages per ton. The largest damages per ton is in NYMSA from BUS PPM in NYMSA at a little over $4$ million. Figures S19–S25 show the top 5 damages per ton for each of the five precursors for PM$_{2.5}$ and two for O$_3$. The top 5 damages per ton for NO$_X$ emissions to PM$_{2.5}$ range from $500$ to $4500$; VOC emissions to PM$_{2.5}$ range from $100$ to $16,000$; and SO$_2$ emissions to PM$_{2.5}$ range from $1300$ to $81,000$.  

4. Discussion

On-road emission sector’s impacts have been widely studied across the U.S. Caiazzo et al (2013) quantified premature mortalities in the U.S. from road transportation and attributed $52,800$ PM$_{2.5}$ and $5250$ O$_3$ mortalities in 2005 from 2005 emissions, while a follow up to that study (Dedoussi and Barrett 2014) found $47,780$ premature PM$_{2.5}$ mortalities. A recent study (Davidson et al 2020) attributed $9666$ PM$_{2.5}$ and $1939$ O$_3$ mortalities from 2011 emissions, compared to our findings of $4023$ PM$_{2.5}$ and $2979$ O$_3$ mortalities in 2016 from 2016 emissions in the TCI region. Davidson et al further evaluated outcomes based on vehicle class fuel types, where they attributed $2300$ PM$_{2.5}$ and $410$ O$_3$ mortalities to gas cars and motorcycles, and $2500$ and $700$ to light duty gas trucks. This compares to our findings that attribute $1153$ PM$_{2.5}$ and $728$ O$_3$ mortalities due to LDA, and $1234$ PM$_{2.5}$ and $1129$ O$_3$ mortalities due to LDT in the TCI region. Larger differences in O$_3$ mortalities in our study compared to Davidson et al can also be explained by different CRFs being used. Davidson et al utilized a seasonal O$_3$ mortality CRF while we use an annual O$_3$ mortality CRF. As a further comparison with Davidson et al, table S14 shows the total O$_3$ mortalities by vehicle class in the TCI region calculated with an annual O$_3$ mortality CRF (Turner et al 2016) and a pooled estimate from two studies (Zanobetti and Schwartz 2008, Levy et al, 2012), that has been used in health benefits assessments for climate policies (Driscoll et al 2015, Buonocore et al 2016). Since we have used an annual O$_3$ mortality CRF, we made sure to assess the model performance against hourly O$_3$ measurements for both January and July with monitoring networks that had an adequate number of measurements for both months in 2016 in the TCI region (See figures S9–S11 and table S13). Dedoussi and Barrett (2014) evaluated results based on source states and found that in 2005 2827, 3982, and 3702 PM$_{2.5}$ mortalities were attributable to PA, NY, and NJ, respectively, compared to our findings which show 854, 1085, and 731 PM$_{2.5}$ mortalities in 2016 from 2016 emissions, while a further estimate from two studies (Zanobetti and Schwartz 2008, Levy et al, 2012), that has been used in health benefits assessments for climate policies (Driscoll et al 2015, Buonocore et al 2016). Since we have used an annual O$_3$ mortality CRF, we made sure to assess the model performance against hourly O$_3$ measurements for both January and July with monitoring networks that had an adequate number of measurements for both months in 2016 in the TCI region (See figures S9–S11 and table S13). Dedoussi and Barrett (2014) evaluated results based on source states and found that in 2005 2827, 3982, and 3702 PM$_{2.5}$ mortalities were attributable to PA, NY, and NJ, respectively, compared to our findings which show 854, 1085, and 731 PM$_{2.5}$ mortalities from those same states in 2016. Estimates from Dedoussi and Barrett (2014) are larger than those estimated in this study likely due to 2005 mobile source emission inventories being larger than 2016. Dedoussi et al (2020) quantified total PM$_{2.5}$ and O$_3$ mortalities in each state due to on-road emissions from each other state. In 2011, they found on-road emissions from NY to be responsible for 1003 mortalities in NY and 115 in neighboring CT while we find the sum of our impacts from our five vehicle classes from NY to be responsible for 929 mortalities in NY and 112 in CT. Caiazzo et al evaluated outcomes in...
some major metropolitan areas and found that 3615 PM$_{2.5}$ mortalities and 3.76 O$_3$ mortalities in NYMSA were attributable to on-road emissions. If we sum across vehicle class emissions and consider NYMSA vehicles only, we attribute 1283 PM$_{2.5}$ mortalities and 120.7 O$_3$ mortalities in NYMSA to on-road emissions. Wolfe et al (2019) monetizes PM$_{2.5}$ damages per ton of directly emitted PM$_{2.5}$, SO$_2$/pSO$_4$, and NO$_X$ from the same vehicle classes as Davidson et al. They find the same trend as we do in the TCI region, with NO$_X$ emissions having the lowest damages per ton and PPM having the largest (table S34) with PPM estimates being two orders of magnitude larger than NO$_X$ estimates for all vehicle classes. Although difficult to
compare across studies due to differences in study designs, Wolfe et al found that the average damages per ton of PPM from light duty gas trucks in the Eastern U.S. in 2025 to be $450,000. We estimated average LDT damages per ton of PPM in the TCI region to be $97,000. Goodkind et al (2019) calculated the total PM$_{2.5}$ damages in the U.S. in 2011 from light gas vehicles to be $94.1 billion while we found total PM$_{2.5}$ damages in 2016 in the TCI region from LDA and LDT to be $25 billion.

While Wolfe et al and Caiazza et al look at impacts by precursors, they exclude on-road emissions of NH$_3$ in their analyses. We show that on-road emissions of NH$_3$ are the second largest contributor to regional on-road attributable—PM$_{2.5}$ concentrations, absolute health impacts (table 3), and damages per ton (figure 3) in the TCI region. NH$_3$ is emitted from vehicles as a by-product of catalytic technologies used in gasoline light duty vehicles (Suarez-Bertoa et al 2014, Li et al 2020) and diesel particle filters in heavy-duty diesel trucks (Preble et al 2019). Recent studies have assessed the importance of vehicular NH$_3$ as a contributor to PM$_{2.5}$ concentrations in urban regions (Chang et al 2016, 2019, Sun et al 2017, Osada et al 2019, He et al 2020). Dedoussi and Barrett (2014) found that reducing 1 Tg of NH$_3$ emissions from road transportation is ∼20 times greater in terms of damages reductions than a 1 Tg reduction of NO$_x$ across the U.S.. We find that in the TCI region reducing 1 ton of NH$_3$ emissions from LDT is ∼75 times and from HDT is ∼90 times greater in terms of damages reductions than a 1 ton reduction of NO$_x$. Hence, any strategy aimed at reducing the on-road vehicle sector’s impact on air pollution in urban areas must consider reducing vehicular NH$_3$ emissions.

In this study we have accounted for uncertainties in the premature mortality calculations by including 95% confidence intervals for each CRF. The confidence intervals reflect the variability in the results from the epidemiological studies used to construct the CRFs. We also accounted for uncertainty in the valuation of the health impacts by including lower and upper bounds for the 2016 USD ($) income-adjusted value of $10.3 million as given in S5. Tables S29–S33 show the valuation results with these lower and upper bounds for each vehicle class and source state’s impact on the TCI region. We have chosen not to include uncertainty estimates, either from the confidence intervals of the CRFs or from the bounds on the valuation amount, in the main results of this study which are the individual source/receptor impacts in figures 1–3 (tables S27 and S28); as the focus of these results is the intercomparison between precursor emissions by vehicle class and source region. The correlated uncertainties associated with each of these source/receptor estimates do not vary between the variables we are studying. We did not account for uncertainty in the CMAQ model output or emission inventory estimates as this would have been too computationally demanding given the study framework. However, this can be an extension for a future study.

We make use of DDM in this study to represent the impacts from entire emission sources. This is not the same as source apportionment and brute force methods. For an emissions-to-pollutant system that is highly nonlinear, DDM and brute force methods will give varying results. However, the on-road vehicle sector has been shown to be approximately linear up to a 100% perturbation for primary PM, secondary inorganic PM, and secondary organic aerosols (Koo et al 2009). Another point to consider with DDM is that by summing results from individual emission sectors we may be missing any inherent nonlinearity of the interactions between emission sectors. However, when summing health impact results we are confident the nonlinearities from summing emission sources are within the confidence intervals of the CRFs. The benefit of DDM is that sensitivities allow for additional perturbations in individual emission sectors to model the expected concentration change without re-running the model. We have chosen to run each simulation for two months of the year to represent seasonal variations similar to work done by Penn et al using CMAQ-DDM to quantify impacts from residential combustion and electricity generating unit emissions (Penn et al 2017) and aviation emissions (Penn et al 2017b); as the computational requirements to run CMAQ-DDM to compute O$_3$ and PM$_{2.5}$ sensitivities for each source region/vehicle class/precursor emission species at this grid resolution are immense. Future work will utilize these sensitivities to model impacts of emission reduction strategies as dictated by illustrative policies in the TCI region, as well as to develop new policies for consideration. This study developed a comprehensive source-receptor impact analysis for each state in the TCI region to determine the full impact from multiple vehicle classes and precursor emissions. The results in this study can help inform the design of effective emission perturbation strategies aimed at reducing air pollution and adverse health effects in individual states and MSAs, and further provide guidance for similar analyses to be performed for other source sectors.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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