

Air quality and health implications of electrifying heavy-duty vehicles assessed at equity-relevant neighborhood-scales.

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Supporting Information Text

WRF-CMAQ Model Set-Up. The two-way coupled WRF-CMAQ model was used to simulate air pollution concentrations over Southern Lake Michigan at a 1.3 km horizontal resolution following the methodology of (1). This is done by a) Running a nested WRF-only simulation at (i) 12 km, (ii) 4 km, and (iii) 1.3 km, b) Using the WRF output to create meteorologically informed emissions with SMOKE at 4 km and 1.3 km, c) Running a coupled WRF-CMAQ simulation at 4 km, with boundary conditions from the 12 km WRF simulation and chemical and initial conditions from CAM-Chem (2, 3) and d) Running the 1.3 km WRF-CMAQ simulation using meteorology and chemistry boundary conditions from the 4 km run. Both the 4 km and 1.3 km simulations integrate the Carbon Bond Mechanism version 6 and aerosol module version 6 with aqueous chemistry (cb6r3_ae6_aq).

WRF simulations are set with 35 vertical layers with a bottom layer of ~20 m and the following physics schemes: (i) Morrison 2-moment microphysics scheme (4), (ii) Kain-Fritsch (KF2) cumulus cloud parameterization version 2 (5), (iii) Asymmetric Convective Model version 2 (ACM2) (6), and (iv) Pleim-Xiu land surface model (7). The Rapid Radiative Transfer Model for GCMs (RRTMG) (8) was used for both the shortwave and longwave radiation schemes. Further description of the model set-up used to derive baseline pollutant concentrations can be found in Montgomery et al. (9).

Model Evaluation. In this section we compare the simulated pollutant concentrations for each month and averaged across all four months to observations from the EPA AQS stations within the 1.3km domain (Table S1). The number of available EPA stations within the 1.3km domain varied for each month and pollutant. In this comparison, we only use a small fraction of the 1.3 km domain grid cells which correspond to the station locations. Our simulations perform well and generally meet suggested benchmarks (9).

Emission Remapping Algorithm. In this section we describe in detail the method with which we calculate the marginal increase in energy demand needed to charge EVs at the county level and allocate this altered energy demand to energy generating units (EGUs) based on weighted factors. To estimate the marginal increase in energy demand, we start by selecting 30% of all HDV VMTs and shifting them to EVMT – electric VMTs. We then calculate the resulting marginal increase in energy demand per county (tE^c) as a function of the $EVMT$ and the charging efficiency (CE) per vehicle type (k) (Eq. S1). Additionally, we account for the distribution and transmission loss of electricity across the U.S. grid by using a grid gross loss (GGL) of 5.1% (10).

$$tE^c = \sum_1^k EVMT^{c,k} \cdot CE^k \cdot (1 - GGL)^{-1} \quad (S1)$$

The marginal energy demand to charge 30% of HDVs (tE^c) is then distributed to EGUs by first identifying the portion that would be dispatched to renewables (eGRID-2016 dataset; EPA, 2022). Using the NERC region's renewability fraction in which the county lies, we omit that portion of energy from being dispatched to non-renewable EGUs. We also account for the portion of electricity dispatched to nuclear EGUs. Secondly, we distribute the remaining energy demand ($E^{c,n}$) to each non-renewable EGU (j) by using an augmented version of an emission remapping algorithm first presented in Schnell et al. (12) (Eq. S2). The augmented algorithm incorporates four main weights:

1. **Location** (n) - The county needing the additional electricity and the EGU supplying it must lie within the same NERC (North American Electricity Reliability Corporation) region.
 - Sources: U.S. Census Cartographic boundary shapefiles (13) and NERC shapefiles (14).
2. **Distance** ($D^{c,j}$) - Within the same NERC region, the closest EGU to the county in need of the electricity is preferred to EGUs further away.
 - Sources: Centroid of each county (13) and distance between the each county and surrounding EGUs (11)
3. **Age** (A) The younger the EGU, the larger the fraction of the demand it will supply as opposed to older units. Here we assume age is representative of ramp rate.

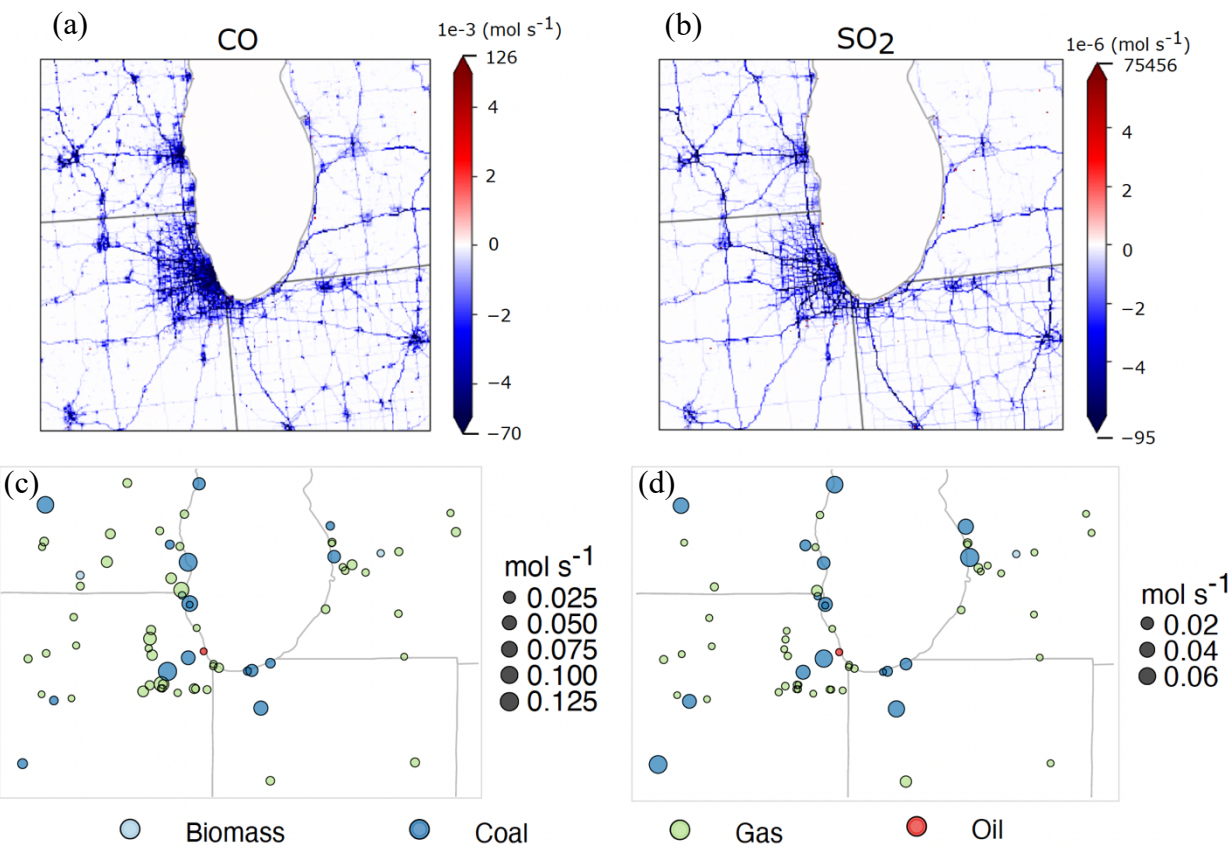
- Sources: Age of each EGU is represented by the average age of all the generators within the EGU or assigned the national EGU age average of 40 years depending on available data (11)
4. **Capacity** (fC) – EGUs with a higher current net generation capacity are preferred to supply the additional demand.
- Sources: The eGRID-2016 database (11) is used for Net Generation data and Capacity factors.

$$aE^{j,n} = \sum_{c=1}^C E^{c,n} \cdot ((1 - fC^j) \cdot tG^j) \cdot (A^j \cdot D^{c,j})^{-1} \quad 99 \quad (S2)$$

Finally, we calculate each EGU's emission factor (EF^j) which we use to estimate modified emissions by adding the marginal increase in energy demand ($aE^{j,n}$) to the baseline net annual energy generation and divide by the facility's net annual generation for 2016. The modified emission rates for each EGU and pollutant ($mQ^{s,j}$) are then calculated by linearly scaling the EGU's baseline pollutant specific emission rate ($Q^{s,j}$) by its emission factor (EF^j) (Eq. S3).

$$mQ^{s,j} = Q^{s,j} \cdot EF^j \quad (S3)$$

Seasonality in MDA8O₃ differences. In August, differences in MDA8O₃ concentrations between the eHDV scenario and baseline have a similar spatial distribution to annual differences although the spatial extent exhibiting MDA8O₃ increases is smaller. This pattern also holds for April, however, MDA8O₃ decreases in rural and downwind areas are lesser. Conversely, in October and January we note increases in MDA8O₃ concentrations across most of the domain with large increases in metropolitan areas and lesser increases in non-urban regions (Fig. S3). The seasonality of simulated MDA8O₃ may be partially explained by the seasonality of VOC-to-NO_x ratios (Table S5). For all months, we simulated baseline VOC/NO_x ratios greater than 7 ppbC/ppb in rural regions and less than 5 ppbC/ppb in urban areas except for August. The low VOC/NO_x ratios for October, January and April explain the overall increases in MDA8O₃ concentration across most of the domain following NO_x emission reductions. In August, simulated baseline rural and urban VOC/NO_x ratios are on average 15 ppbC/ppb and 7 ppbC/ppb, respectively. This indicates that the urban environment in August is likely in a transitional regime which explains the small spatial extent of increases in MDA8O₃ concentrations in August following eHDV adoption (Fig. S3).



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Fig. S1. (a) CO and (b) SO₂ on-road and EGU emission changes for the 30% adoption of eHDVs as compared to the baseline scenario in mol s^{-1} . Numbers at the tails of each scale indicate the minimum and maximum differences in emissions. Point source emission changes for (c) CO and (d) SO₂ at EGUs by fuel type.

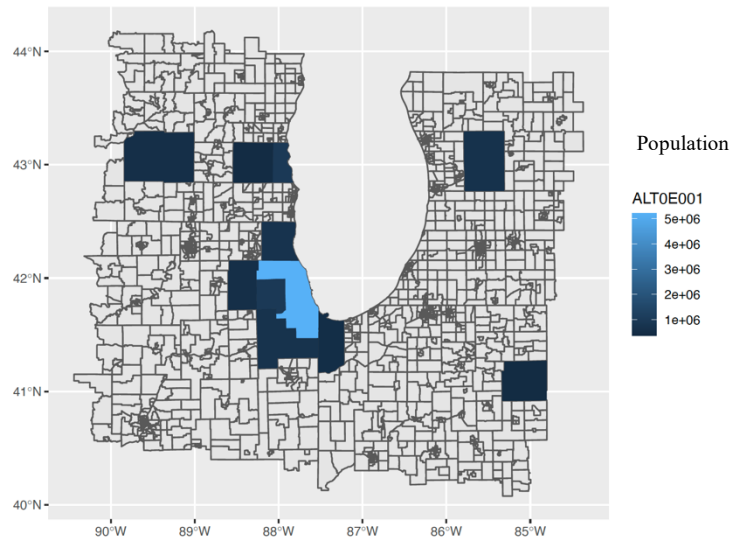


Fig. S2. Definition of urban areas derived by selecting the census tracts with the highest (>95th percentile) number of residents within our 1.3 km domain. Areas outside those depicted above represent rural areas.

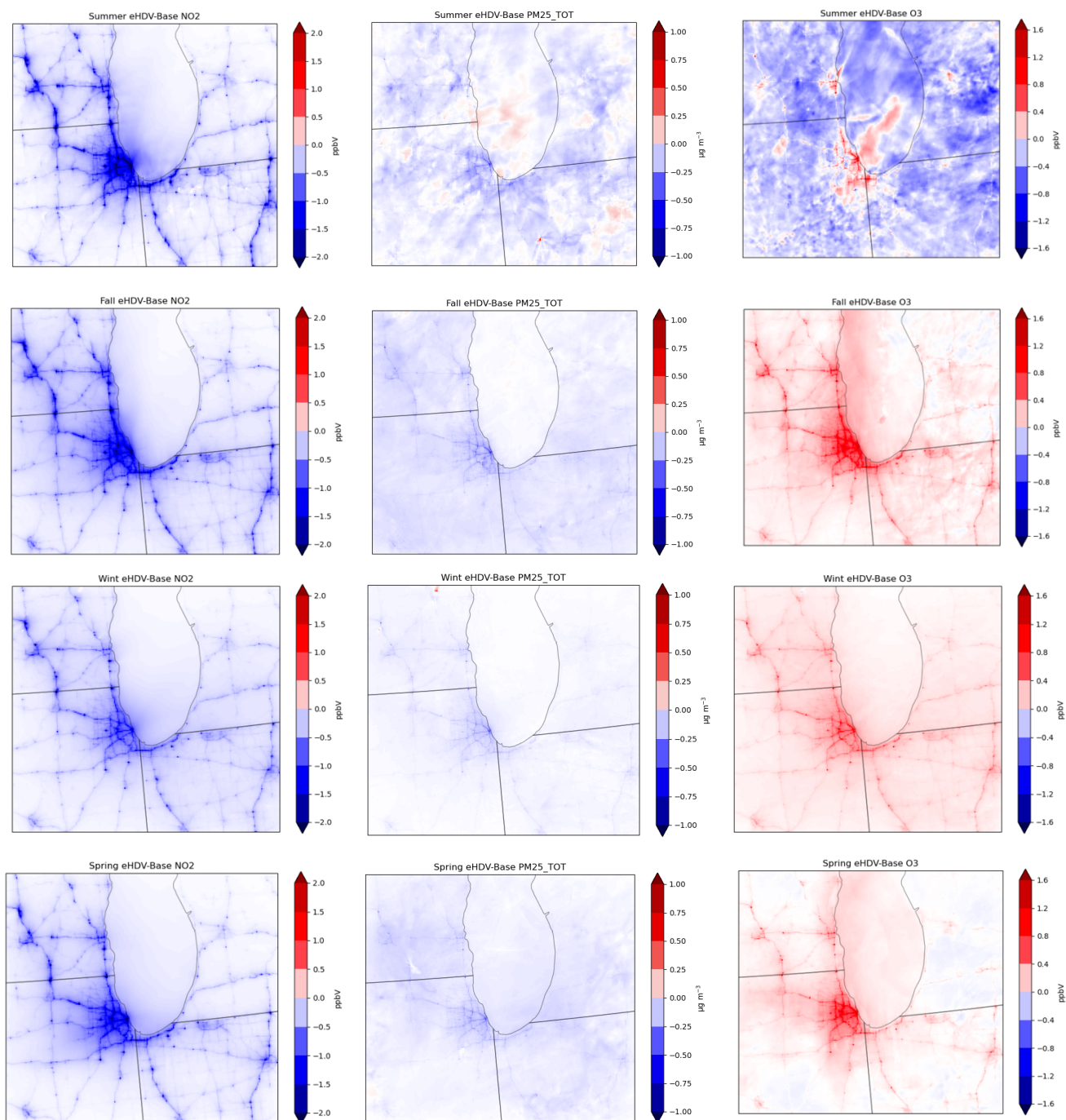


Fig. S3. Simulated Baseline NO₂ (first column), PM_{2.5} (middle column) and MDA8O₃ (third column) concentrations for Aug (top row), Oct (second row), Jan (third row) and Apr (final row).

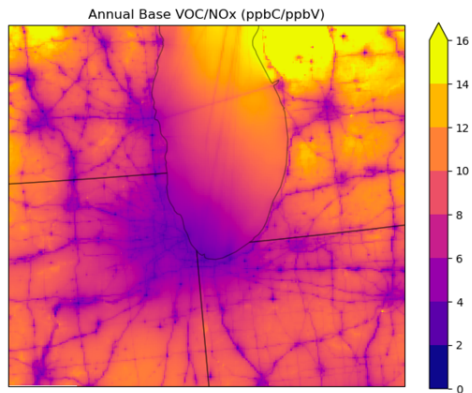


Fig. S4. Simulated annual mean baseline VOC to NO_x ratio (ppbC/ppb)

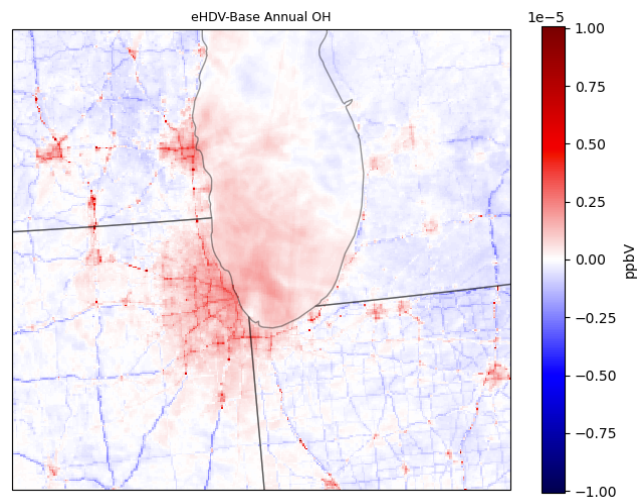


Fig. S5. Simulated annual mean differences in OH concentrations (ppb) between the eHDV and baseline simulations.

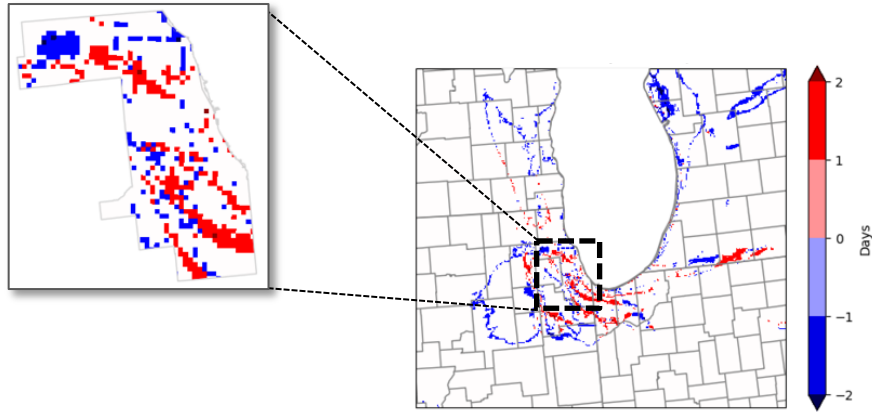


Fig. S6. Number of days with simulated differences in MDA8O₃ concentrations higher than 70 ppb for the eHDV compared to the baseline scenario across the study domain and Cook County.

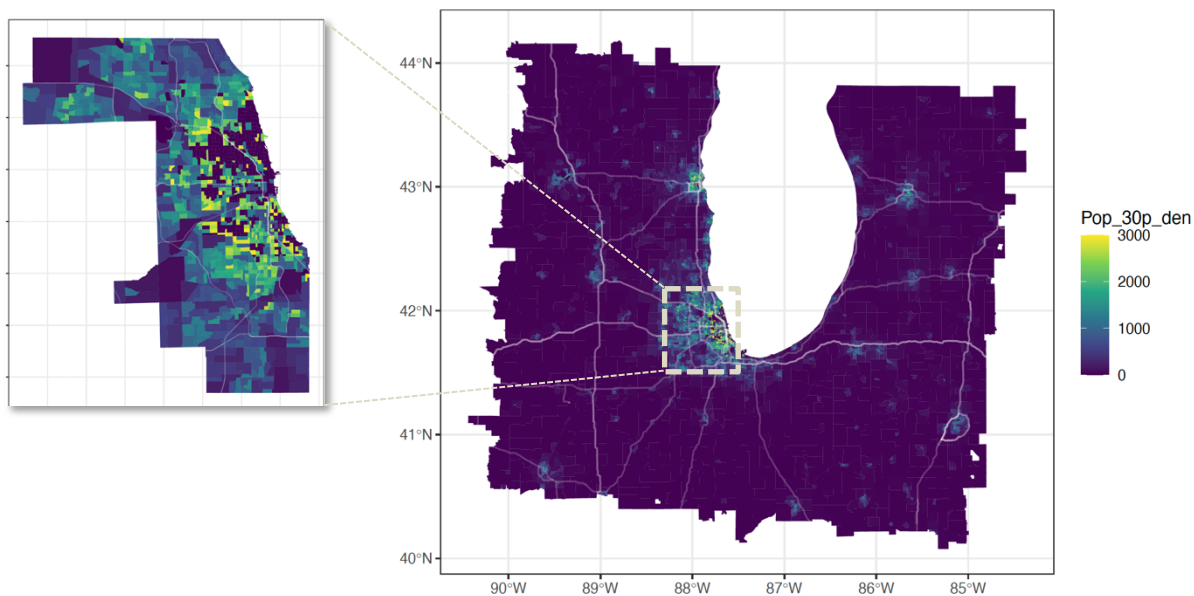
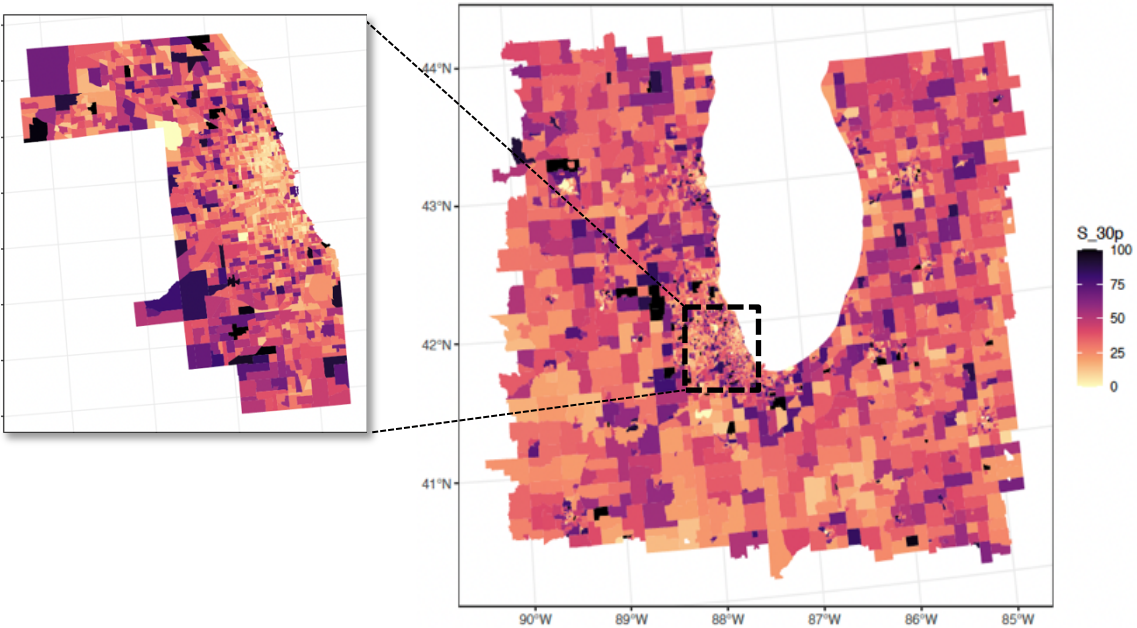


Fig. S7. Census Tract-level population density for ages 30 years and over. Population data is from the National Historical Geographic Information System (NHGIS 2015-2019). White lines indicate primary roads.



207 **Fig. S8.** Census Tract-level all-cause baseline mortality data for ages 30 years and over based on
208 baseline mortality rates from Industrial Economic and population data from National Historical
209 Geographic Information System (NHGIS 2015-2019).
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Table S1. WRF-CMAQ performance metrics for simulated NO₂, MDA8O₃ and PM_{2.5} concentrations at 1.3 km as compared to EPA AQS station observations. μ_d and μ_p represent the observed and predicted values, respectively and n represents the number of EPA AQS measurement stations. The number of EPA AQS measurement stations vary for each month with 120, 120, 78 and 125 sites for August and October 2018 and January and April 2019, respectively. Table and values adapted from (9).

Var	Month	μ_d	μ_p	MB	r
NO₂ (ppb) (n=15)	Aug 2018	10.4	10.7	0.2	0.6
	Oct 2018	10.8	11.0	0.5	0.5
	Jan 2019	13.1	9.6	-3.5	0.6
	Apr 2019	11.2	10.6	-0.9	0.6
	Annual	11.4	10.5	-0.9	0.6
MDA8O₃ (ppb) (n=67)	Aug 2018	42.8	53.6	10.7	0.5
	Oct 2018	28.0	39.0	11.0	0.4
	Jan 2019	29.7	37.3	7.5	0.6
	Apr 2019	44.2	55.2	11.0	0.4
	Annual	36.2	46.3	10.1	0.5
PM_{2.5} ($\mu\text{g m}^{-3}$) (n=25)	Aug 2018	12.1	7.5	-4.7	0.3
	Oct 2018	6.8	7.9	1.0	0.4
	Jan 2019	9.4	9.8	0.3	0.5
	Apr 2019	7.6	6.3	-1.4	0.5
	Annual	9.0	7.9	-1.2	0.4

Table S2. Baseline Vehicle Miles Traveled (VMT) and Battery Efficiency Rate (BER) for each heavy-duty vehicle type over the entire U.S. The Total Electricity Demand (TED) represents the electricity demand for charging 30% of the U.S. heavy-duty VMT per vehicle type. Each vehicle type listed below is not mapped one-to-one to a regulatory class but instead vehicle types are distributed between regulatory classes based on gross vehicle weight rating (GVWR) classification defined by the Federal Highway Administration (FHWA) (15).

Vehicle Type		Heavy Duty Vehicles		
		VMT (Billion)	BER (kWh/mile)	TED (GWh)
Intercity Bus	Class 4 and 5 Light HD Gas Vehicles (14,001 -19,500 lbs. GVWR)			
	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)	5.04	1.61 ^a	2569.94
	Class 8a and 8b Heavy HD Gas Vehicles (GVWR >33,000 lbs)			
Transit Bus	Class 4 and 5 Light HD Gas Vehicles (14,001 -19,500 lbs. GVWR)			
	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)	2.92	2.01 ^b	1851.99
	Class 8a and 8b Heavy HD Gas Vehicles (GVWR >33,000 lbs)			
School Bus	Class 2b Trucks with 2 Axles and at least 6 Tiers or Class 3 Light HD Gas Vehicles (8,501 -14,000 lbs. GVWR)			
	Class 4 and 5 Light HD Gas Vehicles (14,001 -19,500 lbs. GVWR)	6.98	1.36 ^c	2989.06
	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)			
Refuse Truck	Class 8a and 8b Heavy HD Gas Vehicles (GVWR >33,000 lbs)			
	Class 2b Trucks with 2 Axles and at least 6 Tiers or Class 3 Light HD Gas Vehicles (8,501 -14,000 lbs. GVWR)			
	Class 4 and 5 Light HD Gas Vehicles (14,001 -19,500 lbs. GVWR)	2.24	1.98 ^d	1396.20
Single Unit Short-Haul Truck	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)			
	Class 2b Trucks with 2 Axles and at least 6 Tiers or Class 3 Light HD Gas Vehicles (8,501 -14,000 lbs. GVWR)	62.27	2.00 ^e	39372.95
	Class 4 and 5 Light HD Gas Vehicles (14,001 -19,500 lbs. GVWR)			

	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)			
	Class 2b Trucks with 2 Axles and at least 6 Tiers or Class 3 Light HD Gas Vehicles (8,501 -14,000 lbs. GVWR)			
Single Unit Long-Haul Truck	Class 4 and 5 Light HD Gas Vehicles (14,001 -19,500 lbs. GVWR)	39.42	2.00 ^e	24919.99
	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)			
	Class 2b Trucks with 2 Axles and at least 6 Tiers or Class 3 Light HD Gas Vehicles (8,501 -14,000 lbs. GVWR)			
	Class 4 and 5 Light HD Gas Vehicles (14,001 -19,500 lbs. GVWR)			
Motor Home	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)	2.73	0.43 ^f	373.68
	Class 8a and 8b Heavy HD Gas Vehicles (GVWR >33,000 lbs)			
Combination Short-Haul Truck	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)	56.84	2.00 ^e	35937.80
	Class 8a and 8b Heavy HD Gas Vehicles (GVWR >33,000 lbs)			
Combination Long-Haul Truck	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)	106.26	2.00 ^e	67182.95
	Class 8a and 8b Heavy HD Gas Vehicles (GVWR >33,000 lbs)			
Total				176594.56

^a(16) ^b(17) ^c(18) ^d(19) ^e(20) ^f(21)

Table S3. Time averaged percentage differences in on-road and EGU emissions. PEC, PSO₄, PNH₄ and PNO₃ represent the emissions of EC, SO₄, NH₄ and NO₃ aerosols, respectively. VOC emissions only represent anthropogenic emissions and do not include any biogenic VOCs.

Emissions	Baseline		Difference (eHDV – Baseline)		
	On-road (g/s)	EGUs (g/s)	On-road (g/s)	EGUs (g/s)	Total % Diff
CO	65650.88	512.58	-730.58	33.57	-1.05
NH ₃	4200.58	33.89	-4.26	3.24	-0.02
NO _x	7165.51	746.64	-586.43	51.65	-6.76
SO ₂	207.52	1129.44	-2.05	43.50	+3.10
VOC	11478.73	43.53	-97.63	2.91	-0.82
PEC	280.14	5.37	-17.80	0.44	-6.08
PSO ₄	44.76	10.11	-2.02	0.77	-2.29
PNH ₄	13.97	1.93	-0.25	0.19	-0.40
PNO ₃	13.65	0.95	-0.13	0.09	-0.26

Table S4. Urban/Rural ratios calculated from annual mean simulated pollutant concentrations at the census tract level using urban and rural definitions as illustrated in Fig.S2.

Urban/Rural Ratio	Baseline	eHDV - Baseline
NO ₂	2.8	3.5
MDA8O ₃	0.9	16.5
PM _{2.5}	1.3	2.0

Table S5. Rural and Urban VOC/NO_x ratios for each simulation month and averaged across all months. Urban and rural definitions are the same as those presented in Fig. S2.

VOC/NO_x Ratio	Rural	Urban
Aug 2018	14.57	6.89
Oct 2018	7.41	4.22
Jan 2019	7.35	4.39
Apr 2019	7.93	4.34
Annual	9.04	4.88

Table S6. Differences in annual mean simulated pollutant concentrations and estimated attributable deaths across least and most White populations. Census tracts having “least White” and “most White” populations are determined using the first decile (0 to 10th percentile) and tenth decile (90th to 100th percentile), respectively. For example, census tracts identified as ‘least Whites’ have a White population fraction which falls in the first decile. These decile thresholds are defined using demographic values across all census tracts within our domain.

Pollutant Differences	Least Whites	Most Whites
NO ₂ (ppb)	-0.83	-0.17
MDA8O ₃ (ppb)	+0.38	+0.01
PM _{2.5} (µg m ⁻³)	-0.11	-0.04
Att. Mort. Differences (deaths)		
NO ₂	-13.3% (-77)	-3.4% (-23)
MDA8O ₃	+16.9% (+9)	+0.9% (+0.5)
PM _{2.5}	-12.0% (-8)	-6.0% (-4)

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