Supplemental Information for:

Neighborhood-scale air quality, public health, and equity implications of multi-modal vehicle electrification

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Electricity Dispatch and EGU Emission Remapping Algorithm

To determine added electricity generation unit (EGU) emissions in the 30% electric all transport (*eAT*) scenario, we employ an electricity dispatch algorithm that provides a first-order approximation of altered EGU demand. We begin by determining the vehicle miles traveled (*VMTs*) for each vehicle type (*k*) in each U.S. county from the EPA's National Emissions Inventory[1]. For our 30% EV adoption scenario, *eAT*, we convert 30% of *VMTs* in each category *k* to electric *VMTs* (*eVMTs*) using Eq.1:

$$eVMT_{c,k} = VMT_{c,k} \cdot f_{EV} \quad (1)$$

where $eVMT_{c,k}$ is a proportion of a county's *VMTs* that will demand electricity for battery charging for vehicle type (*k*), $VMT_{c,k}$ is a county's total *VMTs* for vehicle type (*k*), and f_{EV} is the fractional EV adoption rate (0.3 in the *eAT* scenario). Given the variability in driving habits among vehicle owners, we note that simulating the electrification of 30% of *VMTs* is likely to be different from 30% of vehicles.

Newly converted *eVMTs* are then translated into increased electricity demand from each CONUS county via Eq. 2:

$$tE_c = \sum_1^k eVMT_{c,k} \cdot CE_k \cdot (1 - GGL)^{-1} \quad (2)$$

where $eVMT_{c,k}$ is the total $eVMTs$ within county c for all on-road MOVES vehicle types k (Table S2), CE_k is the mean charging efficiency for a representative vehicle type k (Table S2), GGL is the grid gross loss or average transmission and distribution loss of electricity across the U.S. energy grid, (5.1%)[2], and tE_c is the resulting total added electricity a county will demand from EGUs.

In the U.S., electricity is distributed in geographic zones referred to as North American Electric Reliability Corporation (NERC) entities (Figure 1). In our dispatch algorithm, we assume that electricity generated at an EGU is not distributed across NERC entity borders (note that this assumption is most accurate for WECC and TRE, which align with separate grids that are not synchronized with the rest of the country: flows across synchronized NERC entities in the Eastern interconnect are more common but ignored for this analysis). As such, our algorithm dispatches a county's electricity demand to EGUs residing within their host NERC entity. To account for emission-free renewable generation sources, i.e., solar, wind, and hydroelectric, we determine the 2016 percentage of electricity generated by renewable sources within a county's host NERC entity[2]. To determine the fraction of electricity within NERC entity n produced by renewable sources (fR_n) we divide the total amount of renewable electricity generated in a NERC entity n, by the total amount of electricity generated in NERC entity n using Eq 3:

$$fR_n = \sum_{m=1}^{M} tG_{R,n} \cdot \left(\sum_{m=1}^{M} tG_{nR,n} + \sum_{m=1}^{M} tG_{R,n}\right)^{-1} \tag{3}$$

where $tG_{R,n}$ is the total electricity generated by a renewable EGU j in NERC entity n, and $tG_{nR,n}$ is the total electricity generated by a non-renewable EGU j in NERC region n for all M EGUs in NERC entity n.

Using a NERC entity's renewability fraction, fR_n, we determine the amount of electricity that all non-renewable EGUs will need to generate, $E_{c,n}$, for county c in NERC entity n, based on that county's added electricity demand $tE_{c,n}$ using Eq. 4:

$$E_{c,n} = tE_{c,n} \cdot (1 - fR_n) \tag{4}$$

To determine which EGUs supply the added electricity demands of each county, we apply four weights using data from the EPA's eGRID-2016 database: (1) the NERC entity, (2) an EGU's generation capacity, (3) an EGU's average generator age, and (4) the distance between a county and EGU, as summarized in Eq. 5:

$$aE_{j,n} = \sum_{c=1}^{C} E_{c,n} \cdot \big((1 - fC_j) \cdot tG_j \big) \cdot (A_j \cdot D_{c,j})^{-1} \tag{5}$$

where $aE_{j,n}$ is the added electricity demand for EGU j in NERC entity n, fC_j is the capacity factor of EGU j, tG_j is the nameplate capacity of EGU j, A_j is the average age of EGU j's component generators, and $D_{c,j}$ is the distance between county c and EGU j. This calculation is performed for all C counties and j EGUs throughout CONUS. The age of an EGU is determined by averaging the ages of its component generators as of December 31, 2021. EGUs lacking 'year on-line' dates are assigned the national EGU age average[3]. An EGU's distance from a county is determined using an EGU's latitude and longitude and a county's centroid[4]. Assumptions behind our weighting scheme are as follows, we assume that: (a) electricity generated at EGUs is not distributed across NERC entity borders; (b) EGUs cannot produce electricity beyond their generation capacity and EGUs with higher nameplate capacities are preferentially chosen to supply needed demand; (c) age functions as a reasonable proxy for which plants increase capacity factor in response to higher system loads, i.e., an EGU's ability to change its net production during operation, thus newer EGUs will respond to a greater fraction of demand; and (d) EGUs more distal from a county will be responsible for fulfilling a smaller fraction of their energy demand relative to more proximal EGUs.

Emission factors, EF_j for each EGU j are calculated by dividing an EGU's baseline generation, tG_j, plus added demand, aE_j, by the baseline generation, such that an *EF* of 1 corresponds to no increase in electricity demand, while an *EF* of 2 would correspond to an added electricity demand double that of its baseline generation, as described by Eq. 6:

$$EF_j = (aE_j + tG_j) \cdot (tG_j)^{-1} \tag{6}$$

To account for the increase in emissions attendant with increased electricity production at EGUs, we multiply each EGU's baseline emissions by the fractional increase in generation demand that results from the *eAT* scenario as in Eq. 7:

$$mQ_{s,j} = Q_{s,j} \cdot EF_j \quad (7)$$

where an EGU j's emission rate Q for species s based on 2016 data is linearly scaled by its emission factor EF_j to produce species' s modified emission rate $mQ_{s,j}$.

To account for the reduction in on-road vehicle emissions, given that EVs do not emit tailpipe emissions, we reduce 30% of on-road emissions by multiplying each modal type's emission factor by 0.3 in the MOVES emission factor tables in SMOKE. Emission factor tables include emissions from refueling processes, thus these emissions are reduced as well. In addition to above mentioned assumptions, our first-order approximation of altered EGU demand and attendant emissions makes additional assumptions. We assume that EGU generation fuel types remain temporally consistent, meaning we do not account for daily, monthly, or seasonal variations in generation mix. We do not consider time-of-day charging, nor the ramifications associated with daytime versus nighttime charging and its upstream electricity generation. We assume that EGU emissions scale positively and linearly with increased electricity generation. For EVs, we assume that vehicles are charged in the county where they are driven, that is we constrain a county's VMTs (and thus electricity demand) to that county and do not consider VMTs driven in a county by a vehicle not residing (and thus charging) in that county; we expect this assumption to largely hold for LDVs but potentially not for long haul trucks, which could lead to underestimated air quality benefits from increased EGU demand in drive-through counties and overestimated air quality benefits from increased EGU demand at HDV charging hubs. We do not perform a life cycle analysis in this study, but rather focus on emissions associated with on-road operations and charging. Emissions from EV and EV components (e.g., battery) production, resource gathering, transportation, disposal, and other life-cycle-related processes are not considered here, but have been by others[5].

Table S1 | Baseline WRF-CMAQ performance metrics for simulated NO_2, MDA8O_3 and $PM_{2.5}$ concentrations in grid cells with EPA AQS stations. Variables *μd* and *μp* represent the observed and predicted values, respectively. *NMB%* is the normalized mean bias, *r* is the correlation coefficient, and *n* represents the annual average number of EPA AQS measurement stations. The number of EPA AQS measurement stations vary for each month with 115, 115, 73 and 119 sites for August and October 2018 and January and April 2019, respectively. For context, within our 1.3 km WRF-CMAQ simulation domain there are 90,720 grid cells. Table and values adapted from[6].

Pollutant	**Month**	μ_d	μ_p	***NMB%***	***r***
NO_2 (*n*=15)	Aug 2018	10.4	10.7	3.0	0.6
	Oct 2018	10.8	11.0	2.6	0.5
	Jan 2019	13.1	9.6	-27.0	0.6
	Apr 2019	11.2	10.6	-5.6	0.6
	Annualized	11.4	10.5	-6.7	0.6
MDA8O_3 (*n*=67)	Aug 2018	42.8	53.6	25.1	0.5
	Oct 2018	28.0	39.0	39.3	0.4
	Jan 2019	29.7	37.3	25.4	0.6
	Apr 2019	44.2	55.2	24.8	0.4
	Annualized	36.2	46.3	28.7	0.5
$PM_{2.5}$ (*n*=25)	Aug 2018	12.1	7.5	-38.2	0.3
	Oct 2018	6.8	7.9	16.4	0.4
	Jan 2019	9.4	9.8	4.4	0.5

	Apr 2019	7.6	6.3	-17.6	0.5
	Annualized	9.0	7.9	-8.8	0.4

Table S2 | On-road Transport Fleet Information Vehicle miles traveled (VMT), representative battery efficiency rates (BER), and cumulative total electricity demand (TED) resulting from 30% vehicle electrification for each vehicle type as classified in SMOKE's MOVES for all counties in the contiguous United States along with gross vehicle weight rating (GVWR) and vehicle class for all on-road vehicle types considered in our EV scenarios.

Vehicle Type		VMT (Billion)	BER (kWh/mile)	TED (GWh)
Motorcycle	Motorcycles (Gasoline)	19.51	0.1[7]	653.62
Passenger Car	Class 1 LD Gas Vehicles (0 – 6,000 lbs. GVWR)	1369.61	0.24[8]	102612.88
Passenger Truck	Class 2a LD Gas Vehicles (6,000 – 8,500 lbs.) Class 2b Trucks with 2 Axles and LD 2-Axle and 4-Tire Gas Trucks (8,501 – 10,000 lbs.)	1321.06	0.45[9]	187926.73

Light Commercial Truck	Class 2a LD Gas Vehicles (6,000 – 8,500 lbs.) Class 2b Trucks with 2 Axles and LD 2-Axle and 4-Tire Gas Trucks (8,501 – 10,000 lbs.)	148.31	0.71[10]	33287.28
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) Class 8a and 8b Heavy HD Gas Vehicles (GVWR >33,000 lbs.)	5.04	1.61[11]	2569.94
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[12]	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) Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR) Class 8a and 8b Heavy HD Gas Vehicles (GVWR >33,000 lbs.)	6.98	1.36[13]	2989.06
Refuse Truck	Class 2b Trucks with 2 Axles and at least 6 Tiers or Class 3 Light HD Gas Vehicles (8,501 -14,000 lbs. GVWR)	2.24	1.98[14]	1396.20

	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 Short-Haul Truck	Class 4 and 5 Light HD Gas Vehicles (14,001 -19,500 lbs. GVWR)	62.27	2.00[15]	39372.95
	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)			
Single Unit Long-Haul Truck	Class 2b Trucks with 2 Axles and at least 6 Tiers or Class 3 Light HD Gas Vehicles (8,501 -14,000 lbs. GVWR)	39.42	2.00[15]	24919.99

	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)			
Motor Home	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) Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR) Class 8a and 8b Heavy HD Gas Vehicles (GVWR >33,000 lbs.)	2.73	0.43[16]	373.68

Combination Short-Haul Truck	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR) Class 8a and 8b Heavy HD Gas Vehicles (GVWR >33,000 lbs.)	56.84	2.00[15]	35937.80
Combination Long-Haul Truck	Class 6 and 7 Medium HD Gas Vehicles (19,501 -33,000 lbs. GVWR)	106.26	2.00[15]	67182.95

Table S3 | EGU Information Identifying information for all electricity generating units (EGUs) in the modeling domain including generative increase per the *eAT* scenario, net 2016 baseline generation, power plant name, and operative status per eGRID's 2020 report.

ORIS	eAT Increase	2016 Generation (MWh)	Power Plant Name	Operating as of 2020?
957	9.64%	1731	Princeton (IL), City of Princeton - (IL)	Yes
54556	52.26%	248942	Ingredion Incorporated Argo Plant, Commonwealth Edison Co	Yes
886	32.06%	2548	Fisk, Commonwealth Edison Co	Yes
972	23.39%	4854	Winnetka, Village of Winnetka - (IL)	Yes
55438	66.19%	231282	Elgin Energy Center, LLC, Commonwealth Edison Co	Yes
55281	70.80%	39778	Southeast Chicago Energy Project, Commonwealth Edison Co	No
55296	71.03%	20164	Calumet Energy Team, LLC, Commonwealth Edison Co	Yes

55279	68.05%	382098	Aurora, Commonwealth Edison Co	Yes
55216	32.78%	583178	Morris Cogeneration, LLC, Commonwealth Edison Co	Yes
55109	56.94%	75128	Rocky Road Power, LLC, Commonwealth Edison Co	Yes
56462	82.17%	6441	Geneva Generation Facility, City of Geneva- (IL)	Yes
55131	20.62%	7195291	Kendall Energy Facility, Commonwealth Edison Co	Yes
55392	59.34%	435494	Zion Energy Center, Commonwealth Edison Co	Yes
883	15.97%	1772897	Waukegan, Commonwealth Edison Co	Yes
955	32.27%	40418	Peru (IL), City of Peru - (IL)	Yes
55236	37.56%	54965	Lee County Generating Station, LLC, Commonwealth Edison Co	Yes
55183	93.05%	1053862	Nelson Energy Center, Commonwealth Edison Co	Yes
960	15.17%	1976	North Ninth Street, Rochelle Municipal Utilities	Yes
856	6.57%	2811862	E D Edwards, Ameren Illinois Company	Yes
892	3.55%	1436468	Hennepin Power Station, Ameren Illinois Company	No
55253	63.88%	93734	Crete Energy Park, Commonwealth Edison Co	Yes
55199	54.26%	1196164	Elwood Energy Facility, Commonwealth Edison Co	Yes
55222	68.35%	63299	Lincoln Generating Facility, Commonwealth Edison Co	Yes
55250	59.72%	207434	University Park Energy, Commonwealth Edison Co	Yes
384	19.62%	1601067	Joliet 29, Commonwealth Edison Co	Yes
874	22.88%	206765	Joliet 9, Commonwealth Edison Co	Yes
884	18.18%	2112720	Will County, Commonwealth Edison Co	Yes
55640	58.42%	848299	LSP University Park, LLC, Commonwealth Edison Co	Yes
55238	41.93%	164918	Rockford Energy Center, Commonwealth Edison Co	Yes
55936	45.31%	118207	Rockford II Energy Center, Commonwealth Edison Co	Yes
6085	20.77%	4426067	R M Schahfer Generating Station, Northern Indiana Pub Serv Co	Yes
55259	30.58%	2769149	Whiting Clean Energy, Inc., Northern Indiana Pub Serv Co	Yes
997	12.29%	1701530	Michigan City Generating Station, Northern Indiana Pub Serv Co	Yes
55096	21.91%	291384	Portside Energy, Northern Indiana Pub Serv Co	Yes

995	14.15%	1778747	Bailly Generating Station, Northern Indiana Pub Serv Co	No
50240	22.26%	166005	Purdue University-Wade Utility, Duke Energy Indiana Inc	Yes
55229	52.78%	188440	Montpelier Electric Gen Station, Indiana Michigan Power Co	Yes
1880	21.11%	13889	Claude Vandyke, Wolverine Power Supply Coop	Yes
7258	35.55%	14034	48th Street Peaking Station, City of Holland	Yes
1844	15.83%	186	Marshall (MI), City of Marshall - (MI)	Yes
55101	53.29%	7080	Kalamazoo River Generating Station, ITC Transmission	Yes
50860	11.60%	100776	Kent County Waste to Energy Facility, Consumers Energy Co	Yes
10819	16.49%	162129	Ada Cogeneration LP, Consumers Energy Co	Yes
1881	12.43%	6806	Vestaburg, Wolverine Power Supply Coop	Yes
55402	41.18%	1041855	Renaissance Power, Michigan Electric Transmission Company	Yes
1695	11.26%	555994	B C Cobb, ITC Transmission	No
1825	13.81%	285805	J B Sims, City of Grand Haven - (MI)	Yes
1867	18.11%	50	Zeeland, City of Zeeland - (MI)	Yes
55087	26.45%	4000792	Zeeland Generating Station, ITC Transmission	Yes
1826	13.23%	25	Grand Haven Diesel Plant, City of Grand Haven - (MI)	No
1710	9.37%	6469844	J H Campbell, ITC Transmission	Yes
1830	15.16%	13915	James De Young, City of Holland	No
1855	15.92%	102	Sturgis City Diesel Plant, City of Sturgis	Yes
55297	23.80%	5982979	New Covert Generating Project, ITC Transmission	Yes
8023	12.14%	4976899	Columbia, American Transmission Co	Yes
55391	38.70%	395145	Rockgen Energy Center, American Transmission Co	Yes
3992	11.54%	96827	Blount Street, American Transmission Co	Yes
3991	18.80%	749	Fitchburg Generating Station, Madison Gas & Electric Co	No

7991	36.98%	521641	West Campus Cogeneration Facility, American Transmission Co	Yes
7203	80.42%	17399	South Fond Du Lac, American Transmission Co	Yes
7159	30.92%	101441	Concord, American Transmission Co	Yes
55011	25.08%	873036	Whitewater Cogeneration Facility, American Transmission Co	Yes
7270	41.70%	160537	Paris, American Transmission Co	Yes
6170	13.15%	6084250	Pleasant Prairie, American Transmission Co	No
7549	43.18%	9343	Milwaukee County, Wisconsin Electric Power Co	No
4041	11.67%	3853795	South Oak Creek, American Transmission Co	Yes
56068	35.35%	7835248	Elm Road Generating Station, American Transmission Co	Yes
4042	20.52%	444315	Valley (WEPCO), American Transmission Co	Yes
4040	12.31%	5818155	Port Washington Generating Station, American Transmission Co	Yes
4057	13.57%	16952	Rock River, American Transmission Co	No
4059	16.38%	1247	Sheepskin, American Transmission Co	No
55641	79.74%	2290661	Riverside Energy Center, American Transmission Co	Yes
56427	26.58%	11214	Ameresco Janesville, Wisconsin Power & Light Co	Yes
4050	8.17%	3455141	Edgewater (4050), American Transmission Co	Yes
56166	53.65%	77223	Sheboygan Falls Energy Facility, American Transmission Co	Yes
6253	25.11%	13272	Germantown Power Plant, American Transmission Co	Yes

Table S4 | Emission Rates Average on-road and point-source emission rates for primary pollutants emitted over the entire modeling domain for the baseline simulation, and the difference in emission rates resulting from the *eAT* scenario.

Emissions	Baseline		Difference (eAT – Baseline)		
	On-road (g/s)	EGUs (g/s)	On-road (g/s)	EGUs (g/s)	Total % Difference
CO	58236.44	445.25	-10151.80	74.68	-17.17%
NH_3	2976.38	48.93	-43.91	-3.31	-1.56%
NO_2	1121.86	95.76	-200.39	16.03	-15.14%
SO_2	262.22	958.40	-9.45	83.37	+6.06%
CH_4	4365.04	39.81	-42.68	8.50	-0.78%
VOC	11266.01	43.13	-942.47	1.34	-8.32%
PEC	259.50	4.77	-23.46	0.67	-8.62%
PSO_4	40.93	9.45	-2.56	1.22	-2.66%
PNH_4	12.89	1.51	-0.66	0.28	-2.64%
PNO_3	8.46	0.72	-0.20	0.14	-0.65%

Table S5 | Population Weighted Means Domain-average annualized population-weighted pollutant concentrations for NO_2, $PM_{2.5}$, and $MDA8O_3$. Population-weighted means are computed from the simulated baseline scenarios and compared to the *eAT* and *eAT_EF* simulations.

Pop. Weighted Means	Baseline	*eAT*	*eAT-Baseline*	*eAT_EF*	*eAT_EF-Baseline*
NO_2 (ppb)	8.11	7.15	-0.96	7.13	-0.98
$PM_{2.5}$ ($\mu g \cdot m^{-3}$)	7.75	7.55	-0.20	7.53	-0.22
$MDA8O_3$ (ppb)	45.39	45.69	0.30	45.70	0.31

Table S6 | Health Impacts Estimated deaths per year associated with baseline pollutant concentrations and changes in annual deaths due to changes in NO_2, $PM_{2.5}$, and $MDA8O_3$ concentrations in the *eAT* and *eAT_EF* scenarios. Negative values indicate premature deaths avoided per year due to pollutant reductions while positive values indicate additional premature deaths due to increases in pollutant concentrations. Lower and upper bounds of the 95% confidence interval corresponding to the respective β coefficient used are included parenthetically below each central estimate. Baseline deaths are calculated using Equation *(1)*, where Δx is the ambient pollutant concentration in the baseline simulation.

Health Impacts	Baseline Deaths	*eAT*	*eAT_EF*
NO_2	9,000	-1,120	-1,150
	(2,320 –13,210)	(-1,690 – -280)	(-1,730 – -290)
$PM_{2.5}$	6,840	-170	-190
	(2,320 – 11,210)	(-290 – -60)	(-320 – -60)
MDA8O_3	13,300	80	90
	(6,800 – 25,450)	(40 – 170)	(40 – 180)

Table S7 | Air Quality and Public Health Disparities (a) All cause mortality rates (deaths per 100,000 people) are computed by dividing the USALEEP tract mortality[17] by the population (30 years and over) of that tract[18] and multiplying by 100,000. (b) Mean pollutant concentration changes over least-white and most-white census tracts for the *eAT* and *eAT_EF* scenarios. Percent change as compared to simulated baseline pollutant concentrations in parentheses. (c) Changes in estimated attributable mortality rates due to changes in NO_2, $PM_{2.5}$, and O_3 concentrations in the *eAT* and *eAT_EF* scenarios for least-white (≤10% white) and most-white (≥90% white) census tracts in our CTM domain. Percent change in mortality rates for the *eAT* and *eAT_EF* scenarios are computed by dividing the pollutant-attributable change in mortality rate by the USLEEP tract level-derived mortality rate.

a) All-Cause Mortality Rates (per 100,000)	Least-white	Most-white

Mortality Rate	1,661.08	1,427.63		
b) Pollutant Change Disparities	*eAT*		*eAT_EF*	
	Least-white	Most-white	Least-white	Most-white
NO_2 (ppb)	-1.47 (-52.31%)	-0.33 (-11.74%)	-1.52 (-54.09%)	-0.34 (-12.09%)
$PM_{2.5}$ ($\mu g \cdot m^{-3}$)	-0.28 (-5.07%)	-0.10 (-1.81%)	-0.32 (-5.79%)	-0.11 (-1.99%)
$MDA8O_3$ (ppb)	0.59 (1.23%)	-0.02 (-0.04%)	0.66 (1.38%)	-0.02 (-0.04%)
c) Mortality Rate Change Disparities	*eAT*		*eAT_EF*	
	Least-white	Most-white	Least-white	Most-white
NO_2	-19.66 (-1.18%)	-3.81 (-0.27%)	-20.31 (-1.22%)	-3.92 (-0.27%)
$PM_{2.5}$	-2.75 (-0.17%)	-0.87 (-0.06%)	-3.15 (-0.19%)	-0.92 (-0.06%)
$MDA8O_3$	1.98 (0.12%)	-0.04 (0.00%)	2.21 (0.13%)	-0.04 (-0.00%)

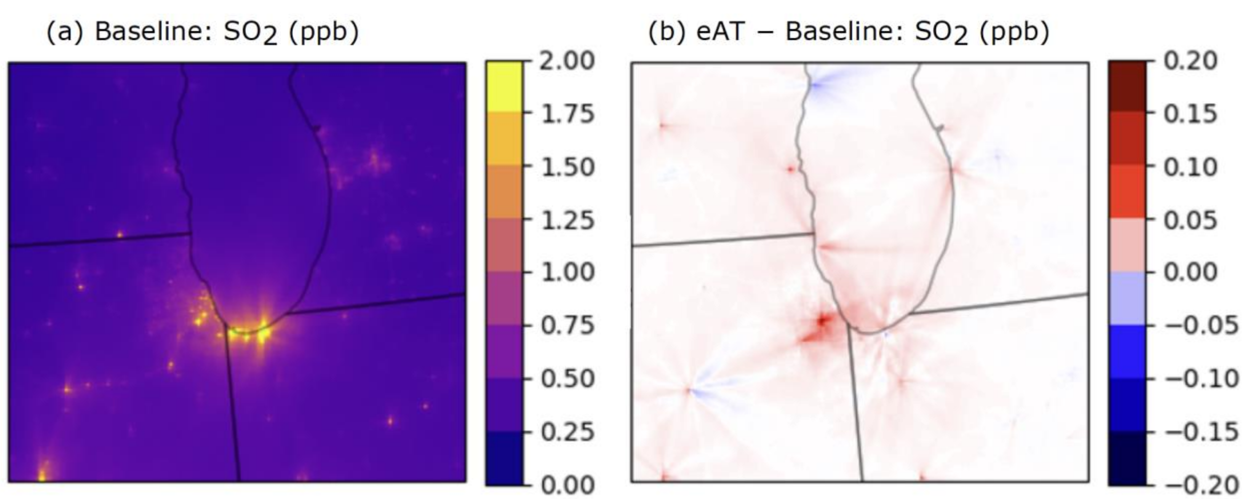

Figure S1 | Simulated SO_2 Concentrations Baseline (left) and *eAT* difference (right) in simulated SO_2 concentrations.

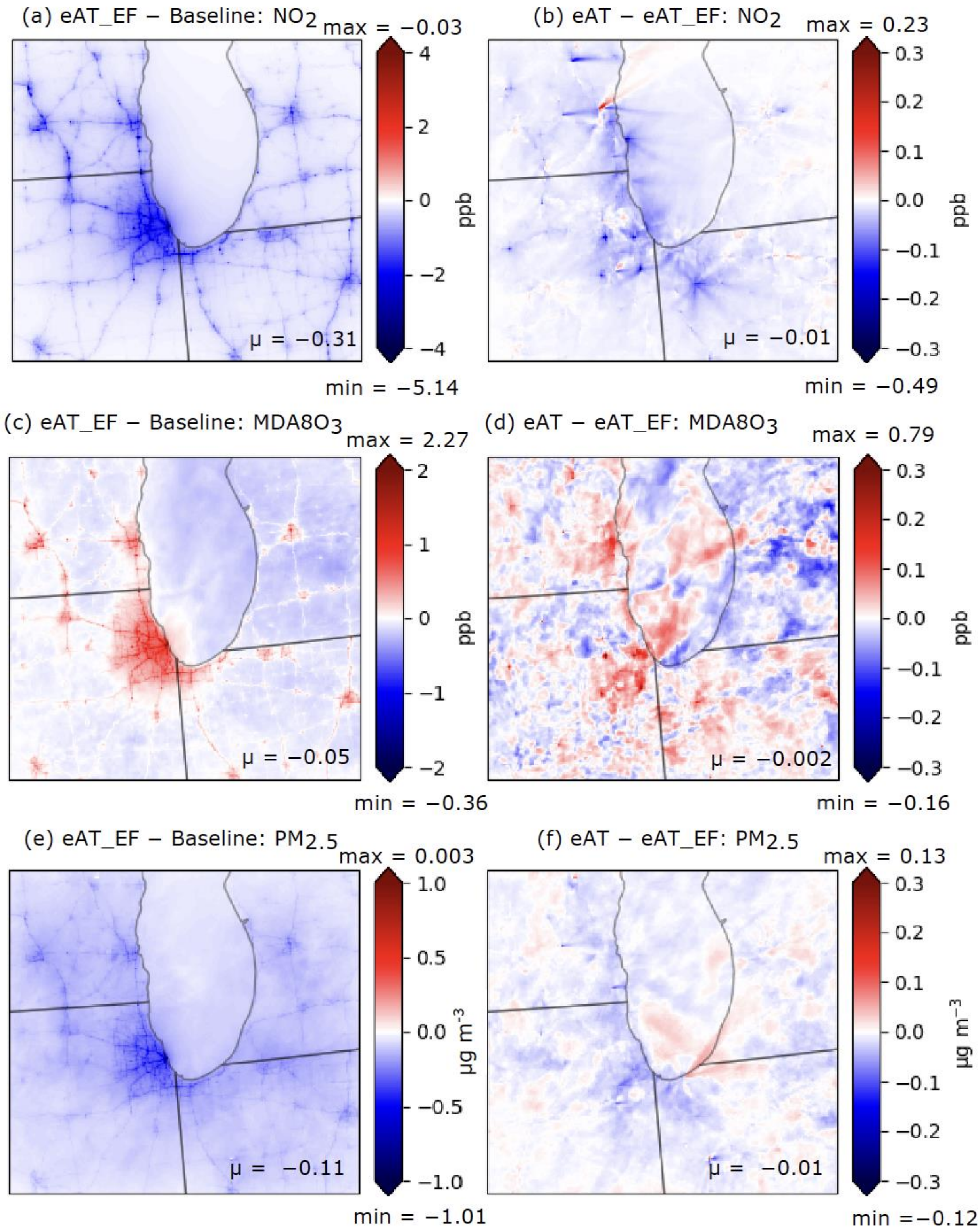
(a) eAT_EF − Baseline: NO_2
max = −0.03
μ = −0.31
min = −5.14
ppb
4
2
0
−2
−4
(b) eAT − eAT_EF: NO_2
max = 0.23
μ = −0.01
min = −0.49
ppb
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
(c) eAT_EF − Baseline: $MDA8O_3$
max = 2.27
μ = −0.05
min = −0.36
ppb
2
1
0
−1
−2
(d) eAT − eAT_EF: $MDA8O_3$
max = 0.79
μ = −0.002
min = −0.16
ppb
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
(e) eAT_EF − Baseline: $PM_{2.5}$
max = 0.003
μ = −0.11
min = −1.01
$\mu g\ m^{-3}$
1.0
0.5
0.0
−0.5
−1.0
(f) eAT − eAT_EF: $PM_{2.5}$
max = 0.13
μ = −0.01
min =−0.12
$\mu g\ m^{-3}$
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3

Figure S2 | *eAT_EF* Scenario Difference plots of pollutants between the annualized emission-free EGU scenario (*eAT_EF*) and the baseline (a, c, e) and between the *eAT* scenario using 2016 grid infrastructure and the annualized emission-free EGU scenario (*eAT_EF*) .

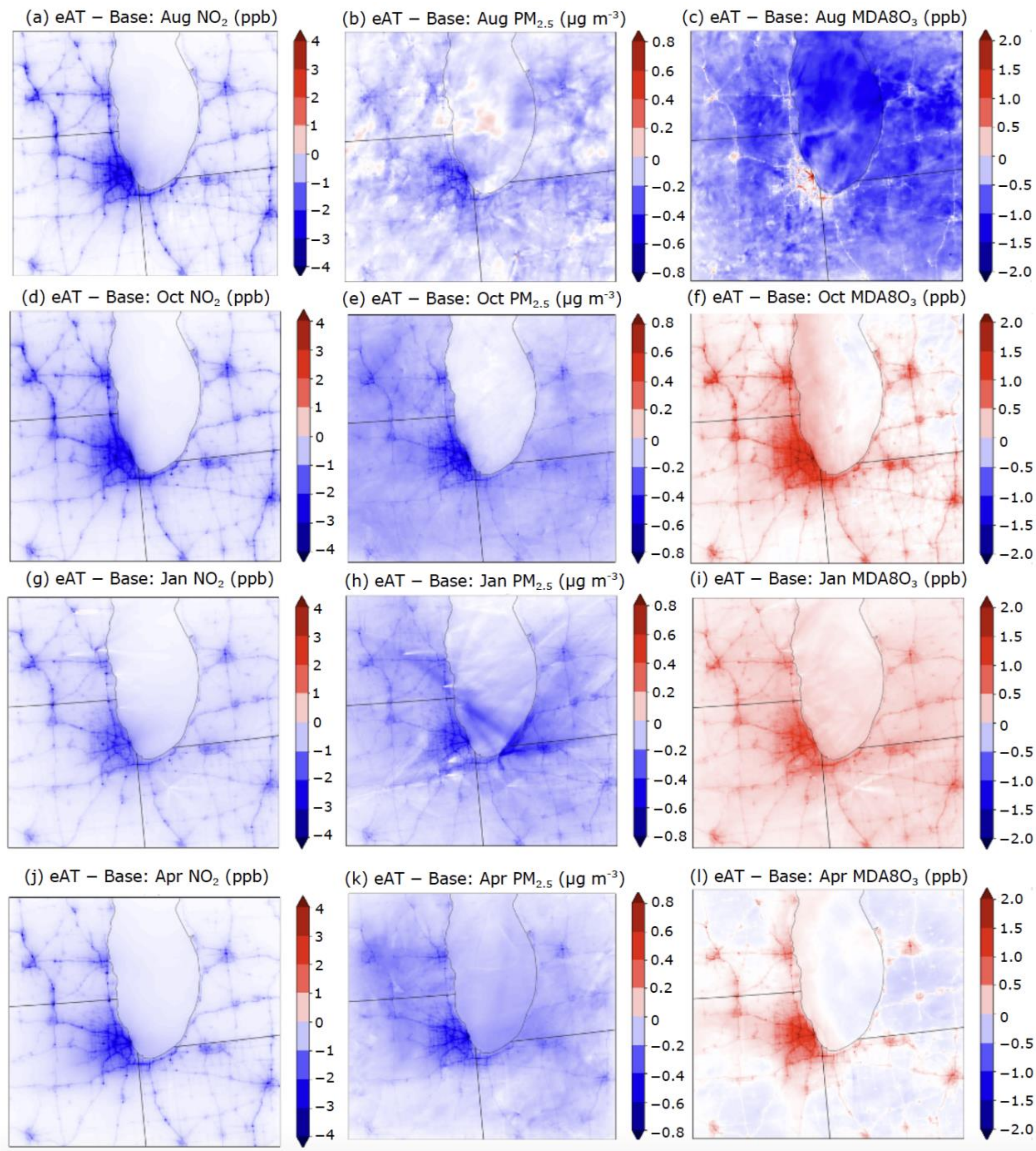

Figure S3 | Pollutant Seasonality Difference plots of NO_2, $PM_{2.5}$, and MDA8O_3 for the four modeled months for the *eAT* scenario compared to the baseline simulation.

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