



**Evaluation of the air quality impacts of clean
combustion technologies, emissions controls and
fleet electrification in the Houston Metropolitan
Area for the year 2040**

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EXECUTIVE SUMMARY

Transportation is a major source of air pollution in the Houston Metropolitan Area (which for this report, we are considering as the 8-county region of Harris, Chambers, Liberty, and Montgomery, Waller, Fort Bend, Brazoria, and Galveston counties). Transportation-related pollution is predicted to worsen with growing population and regional port expansion. The population in the region is expected to grow by 50% by 2040, and on-road vehicle traffic, which includes trucks and passenger vehicles, is predicted to increase anywhere from 30%-80% by 2040. With an increase in both population and on-road vehicles, transportation-related emissions would likewise increase.

Pollution can be mitigated through control strategies, which include improved clean combustion technologies, tailpipe emissions controls, and fleet electrification. Regulatory Impact Assessments, which systematically evaluate benefits and costs of regulations, often include only short-term projections for these kinds of strategies. This report provides a detailed assessment of the impact of these control strategies for the year 2040, in order to understand how significant implementation of emission control strategies could help improve air quality in the Houston region.

This study evaluates the effects of fleet electrification, replacement/retrofit with new combustion technologies/emissions controls on regional air quality and health. Four emissions control scenarios, which represent a variety of combinations of emissions controls, were modeled to determine the impact of emissions control technology on both total emissions and on human health. These models were scaled to account for future increases in motor vehicle activity and population. The models also accounted for changes to the electric grid to account for the predicted retirement of coal plants.

Scenario 1: A “Business-As-Usual (BAU)” scenario represents present day emissions and fleet composition with no turnover. It was modeled to demonstrate the impact of policies that incite no major move toward emissions controls from combustion technology or electrification. In this scenario, where the fuel mix is approximately the same as today’s mix but more cars and trucks are on the road, nitrogen oxides (NO_x) emissions would increase by 56.9% and fine particulate matter (PM_{2.5}) would increase by 61.1% relative to 2013 values.

Scenario 2: In a Moderate Electrification scenario, 33% of vehicles rely on clean combustion technology, 35% are electrified, and 32% reflect a similar mix to the 2013 region-wide fleet. Here, NO_x emissions would be reduced by 47.2% and PM_{2.5} would be reduced by 45.8%.

Scenario 3: In an Aggressive Electrification Scenario, where 15% of vehicles rely on clean combustion technology, 70% would be electrified, and 15% would reflect a similar mix to the 2013 region-wide fleet, NO_x emissions would be reduced by 75.3% and PM_{2.5} emissions would be reduced by 74.6%.

Scenario 4: A Complete Turnover Scenario represents a case where 65% of vehicles would rely on clean combustion technology, 35% would be electrified, and no vehicles would be on the road with a fuel mix similar to the 2013 region-wide fleet. In this scenario, emissions would be nearly eliminated: NO_x would be reduced by 94.9% and PM_{2.5} emissions would be reduced by 94.8%.

This study demonstrates that fleet electrification and new technologies can improve regional air quality and human health endpoints.



KEY FINDINGS

- Control technologies have the potential to significantly reduce emissions.
- If all on-road vehicles implemented clean combustion technology or were electrified, emissions across the board would be reduced by over 90% from 2013 levels.
- The business-as-usual case demonstrated mild ozone reductions near highways, but those reductions were very limited. Overall, ozone increased over large populated areas in this scenario.
- The other scenarios where emissions control technologies were used saw slightly increased ozone concentrations near highways, but had significant reductions in ozone, particularly in densely populated areas.
- Implementing these control technologies would also significantly decrease both emergency room visits and mortality associated with exposure to ozone and PM2.5.
- The business-as-usual case, where no additional emissions control strategies were implemented, would lead to an additional 122 deaths.
- Complete turnover scenario, where the entire fleet utilizes emissions control or electrification, would result in 246 fewer deaths from ozone and PM2.5 exposure.
- The modeled health benefits of the Complete Turnover scenario, where every vehicle on the road is either electrified or using other emissions control strategies, would provide about \$152 million in benefits from prevented mortality from reduced exposure to ozone and \$1.99 billion in benefits from prevented mortality from reduced exposure to PM2.5.
- The business-as-usual scenario would result in over 1200 asthma cases per year, whereas the complete turnover scenario would result in 24,652 fewer asthma cases per year.
- The complete turnover scenario would prevent over 18,000 school loss days, whereas the business-as-usual scenario would cause 833 days of school loss.

BACKGROUND



The 2010 US Census ranked Houston as the 4th largest city nationally. The United States Environmental Protection Agency classifies Houston as a nonattainment area for ozone and as borderline attainment for fine particulate matter (PM_{2.5}) as indicated by EPA's Green Book (<https://www.epa.gov/green-book>). The ozone nonattainment area includes city of Houston, in Harris County, as well as the bordering counties of Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, and Waller. Identifying the sources of particulate matter and ozone-forming pollutants is imperative in order to develop appropriate control policy to improve air quality and health endpoints within the region.

Given the region's urban nature, emissions from transportation serve as major sources of nitrogen oxides (NO_x) and volatile organic compounds (VOCs). These compounds react in the presence of sunlight to form ozone. In addition to ozone precursors, vehicular traffic also emits particulate matter pollution like organic and elemental carbon (Roy et al., 2016; May et al., 2013a, b; Gordon et al., 2013; George et al., 2014, 2015).

Gasoline motor vehicles and diesel trucks dominate urban transportation in the United States. The 2013 H-GAC Regional Goods Movement Plan indicates that the population of the region is projected to grow by 50% in 2040 to 9.6 million, which will almost certainly result in increased motor vehicle activity. A couple of studies have been conducted to project future vehicular activity. A study by the Texas Transportation Institute projects the number of trucks in the 8-county area to increase by 40%-80% (TCEQ, 2015), and number of gasoline vehicles to increase by 30-50% by 2040. This study provides a forward-looking analysis to evaluate the air quality impacts of increased transportation activity, the effects of control technologies and strategies, and the corresponding impact of the studied parameters on health endpoints.



Several strategies exist to offset air quality impacts of increased transportation activity. Among them, accelerated fleet turnover is most well-known and implies a significant fraction of the motor vehicle fleet being replaced with newer technology to result in maximum emission reduction. These technologies include Gasoline Direct Injection and tailpipe emission control systems such as Selective Catalytic Reduction (SCR) for NO_x emissions from both gasoline and diesel vehicles, and Diesel Particulate Filter (DPF) and Diesel Oxidation Catalysts (DOC) for PM_{2.5} and VOC emissions from diesel vehicles. Another alternative to reduce emissions is fleet electrification, the replacement of a certain fraction of the fleet with electric vehicles. Adding more electric vehicles into the fleet invariably results in an additional load on power generating infrastructure.

MOTIVATION

The effects of alternative strategies to reduce motor vehicle emissions needs to be investigated thoroughly using a Regulatory Impact Assessment framework. Such steps are usually taken by the United States Environmental Protection Agency (USEPA) whenever a new control rule is promulgated. The purpose of such studies is to consider the impacts of new control technologies and strategies on emissions in an air quality model to understand their effects and, using a health-effects model, to understand how the stricter standards or reduced emissions affect health endpoints. This is necessary since cleaner air will reduce mortality, morbidity, asthma cases and hospital visits (USEPA, 2017b). Examples of these sorts of investigations include the Cross-State Air Pollution Rule, CSAPR (USEPA, 2015) and the National Ambient Air Quality Standards for PM_{2.5} (USEPA, 2015). However, most of these analyses look only over a 10-year horizon. The Energy Information Administration (EIA)'s Annual Energy Outlook projects fuel consumption and other activity parameters far into the future, but do not account for emissions, their air quality impacts and changes in human health endpoints. Projections into a far-off year, such as 2040, can help in understanding the impacts of significant turnover in fleet composition and their effects on emission reduction, air quality and human health.

Most urban regions are typically VOC-limited, where ozone concentrations are primarily driven by VOC emissions. However, the Houston region has a unique distinction nationally by comprising both NO_x and VOC-limited areas (Choi et al., 2012). Reducing only gasoline or diesel emissions may not be adequate to solve the problem of ozone pollution in Houston because the partial reduction of NO_x emissions in many places can cause ozone concentrations to increase due to their NO_x-saturated character. Therefore, we would need to account for substantial reductions in NO_x emissions from both gasoline and diesel transportation sources to make the region NO_x-limited, so that controlling NO_x emissions can reduce ozone across the area.

Understanding ozone drivers over an urban region which has both NO_x- and VOC-limited areas entails the use of fine resolution (~ 1 km) modeling. In a previous study (Pan et al., 2017b), we developed and evaluated a fine-resolution model to understand ozone concentrations and its key drivers over Houston for September 2013.



In this study, we extend the framework to understand motor vehicle emissions, fleet electrification and control strategies, and their associated air quality and health impacts.

In this space, this study executed the following tasks:

- (1) Developed emissions scenarios for gasoline and diesel vehicles, corresponding to varying degrees of emission control, fleet electrification and fleet turnover.
- (2) Implemented these emissions scenarios in a chemical transport model to understand their impacts on regional ozone and PM_{2.5}, including its speciated components such as sulfate, nitrate, elemental and organic carbon. Calculated the change in concentrations of these species with respect to the base year of 2013 for each scenario.
- (3) Calculated the changes in health endpoints for each scenario with respect to the base year.

METHODOLOGY

THE CHEMICAL TRANSPORT MODEL

The USEPA's Community Multiscale Air Quality (CMAQ) model (Byun and Schere, 2006) was used for this study. This is a chemical transport model which solves the continuity mass-balance equation, simulating the atmospheric processes of emission, advection, reaction, dry and wet deposition and chemistry for a given geographical region by discretizing the region into several horizontal, lateral and vertical grid cells. Our group has had extensive experience using this model, as is evident from several publications (e.g., Choi et al., 2009; Choi et al., 2010; Choi et al., 2012; Choi, 2014; Choi and Souri, 2015a, b; Czader et al., 2015a, b; Diao et al., 2016a, 2016b; Li et al., 2016; Pan et al., 2015, 2017a,b; Souri et al., 2016a, 2016b). We will be using a 1-km grid over the Houston area and surrounding counties, which include Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, and Waller.



THE METEOROLOGICAL MODEL

The Weather Research and Forecasting (WRF) model (Skamarock et al., 2008) provided meteorological fields for this study. We have evaluated existing analysis datasets and decided to use the National Centers for Environmental Prediction's (NCEP) North American Regional Reanalysis (NARR) as input. The NARR data are based on an NCEP Eta 221 regional North American grid (Lambert Conformal) (additional information is available here: <http://www.nco.ncep.noaa.gov/pmb/docs/on388/tableb.html>) at 29 pressure levels. Its horizontal resolution is 32-km, and the frequency is 3-hourly.

THE EMISSIONS MODEL

The USEPA's National Emissions Inventory of 2011 (NEI2011) was processed using the USEPA's Sparse Matrix Operator Kernel Emissions (SMOKE) model (Houyoux et al., 2000), to produce model-ready emissions. SMOKE performs gridding, temporal allocation, and speciation lumping for a given chemical mechanism to prepare model-ready emissions. Additional details are online: <https://www.cmascenter.org/smoke/>. The procedures for this study involved merging the updated gasoline and diesel motor vehicle emissions from the Motor Vehicle Emissions Simulator (MOVES) model (USEPA, 2017a) into the base emissions inventory.

THE MOTOR VEHICLE EMISSIONS MODEL

This study used the USEPA's Motor Vehicle Emissions Simulator (MOVES) model (USEPA, 2017a), which calculates emissions from gasoline and diesel on-road vehicles as a function of speed, road type, and meteorological conditions. The model is instrumented to change motor vehicle population (VPOP) and vehicle miles traveled (VMT) for a future year, which we used to make projections for 2040. For this study, emissions from gasoline and diesel vehicles for the 8-county area were modeled. The emissions comprise of multiple modes. Rates per distance typically represent tailpipe (exhaust) emissions, while rates per vehicle represent evaporative and crankcase emissions. In addition, truck drivers often spend the night inside the vehicle's cabin, where the air conditioning is powered by the truck engine. This phenomenon is called hoteling and can give rise to significant nighttime emissions.

EMISSIONS CONTROLS AND FLEET TURNOVER

Fleet-average emissions are a function of (a) percentage reduction brought about by new controls and (b) fleet turnover which corresponds to the fraction of the fleet fitted with these new controls (typically newer vehicles/engines), represented as:

$$EF_i(2040) = EF_i(2013)[f_{replaced}(1 - f_{control}) + 1 - f_{replaced}] \quad (1)$$

Where $EF_i(2040)$ and $EF_i(2013)$ are the projected fleet-average emission factors for 2040 (future year) and 2013 (base year), respectively; $f_{control}$ represents the percentage reduction due to a control technology, while $f_{replaced}$ represents the fraction of the fleet that has been replaced or fitted with the new control technology, typically referred to as “fleet turnover”. Examples of tailpipe emissions control technologies for NO_x emissions include Selective Catalytic Reduction and NO_x absorbers. Diesel Oxidation Catalysts reduce VOC emissions from diesel exhaust while Diesel Particulate Filters (DPFs) reduce PM_{2.5} emissions. Evaporative emissions, typically reported per vehicle, result from fuel volatilization.



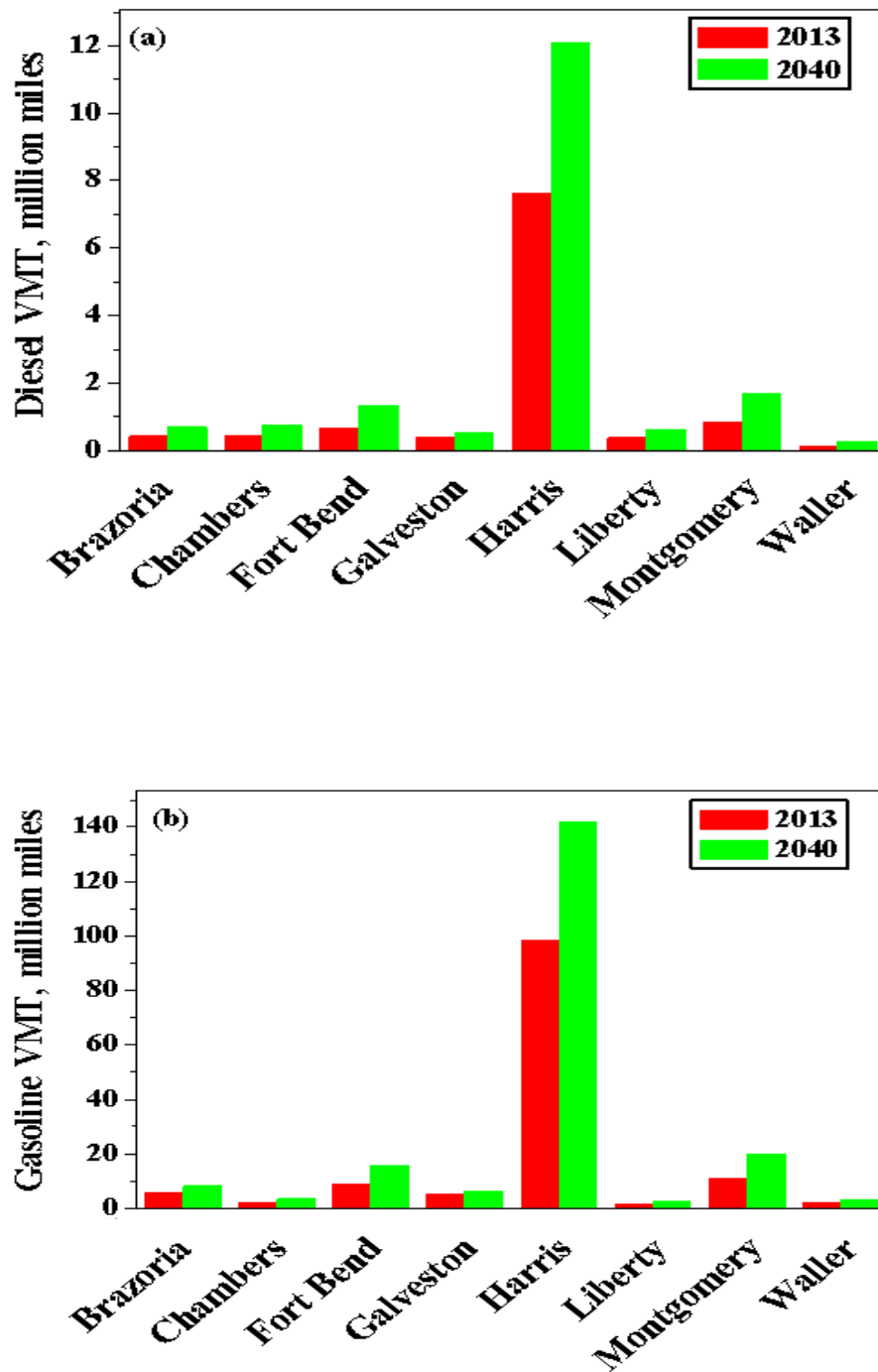


Figure 1: (a) Diesel and (b) gasoline vehicle miles traveled (VMT) projections. The scaling factors used in this study are the ratio of the 2040 and 2013 numbers.

FUTURE ACTIVITY PROJECTIONS

Projections for VPOP and VMT were taken from calculations performed by the Texas Transportation Institute (TTI) for the Texas Commission for Environmental Quality (TCEQ, 2015). The authors performed activity calculations from 1999, projected to 2050. The activity data for each vehicle type (e.g. gasoline passenger cars, pickup trucks, medium duty and heavy duty diesel trucks) were obtained through personal communication with Dennis Perkinson at TTI. Their findings project aggregate VMT to change by 30%-80% over the 8-county area. The aggregate activity was fractionated into 24 different gasoline and diesel vehicle types, from which two surrogate profiles for the 8-county area were developed, namely Houston and Beaumont. The gasoline-diesel split for VMT for the base year is 93%-7% for Houston and 82%-18% for Beaumont. The split changes marginally in favor of diesel in 2040, 92%-8% for Houston and 81%-19% for Beaumont. The higher diesel fraction over suburban Beaumont could be explained by the fact that diesel truck traffic is comparable across urban and suburban regions while gasoline activity is significantly higher in the urban, hence depressing the diesel fraction.

The Brazoria, Fort Bend, Galveston, Harris, Montgomery, and Waller counties were represented by Houston, while Chambers and Liberty were represented by Beaumont. These profiles were used to project gasoline and diesel VMTs in 2040, indicated in panels (a) and (b), with their specific scaling factors in (c). The projected gasoline VMTs are roughly one order of magnitude higher than diesel, due to the higher gasoline vehicles population. The gasoline and diesel projected scaling factors closely mirror the total VMT, indicating the change in VMT is more significant than that in the gasoline-diesel split. However, there is one subtle difference: the diesel scaling factor is slightly magnified, while the gasoline one is slightly depressed. For example in Harris County, the total VMT changes by a factor of 1.46, while the diesel VMT changes by 1.59 and gasoline by 1.45. This could be attributed to the marginal shift in favor of diesel (~9% increase). These VMT profiles were also used for county and fuel-specific vehicle population (VPOP) projections.

FUTURE MODELING SCENARIOS

Several emissions scenarios were considered to account for the uncertainty in fleet turnover and electrification. In Table 1, “Clean Combustion Technologies” indicates the percentage of the fleet in 2040 that uses or is retrofitted with state-of-the-art combustion and emission control technologies, “Electric” represents the percentage of the fleet comprising electric vehicles, while “Current” represents the fraction carrying over from the base year of 2013 that is not retrofitted or replaced. The scaling factor represents the bracketed term in Equation (1), which is a function of both control technology efficiency and fleet turnover, applied to aggregate (distance, vehicle and hoteling) gasoline and diesel emissions. Activities were scaled using county and fuel specific information from Figure 1. The same scaling factors were used for VMT and hoteling activity projections.

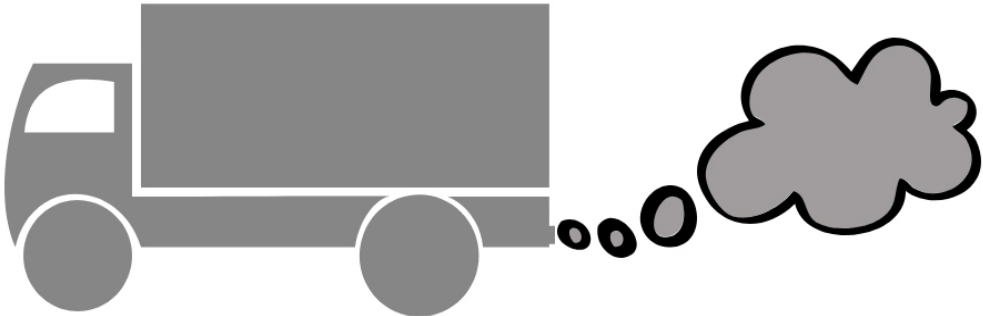
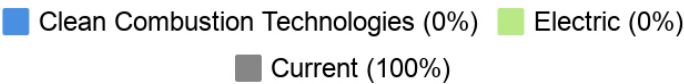
The Business As Usual (BAU) case represents a “worst case” scenario, with no new technology vehicles incorporated into the fleet or the existing fleet is not retrofitted. The Moderate Electrification case is based on the assumptions of a Bloomberg New Energy Finance report (BNEF, 2016), which predicted that 35% of global vehicles would be electric by 2040. The Aggressive Electrification (AE) case assumes a fraction twice that of the ME case. Complete Turnover (CT) represents a scenario where the total fleet comprises either of state of the art technology or electric vehicles.

Table 1: Future projects scenarios based on varying fleet electrification and turnover.

Percentage Fleet Turnover			
Scenario	Clean Combustion Technologies	Electric	Current
Base-year (2013 or BASE)	0	0	100
Business as usual (BAU)	0	0	100
Moderate Electrification (ME)	33	35	32
Aggressive Electrification (AE)	15	70	15
Complete Turnover (CT)	65	35	0

PROJECTED SCENARIOS BASED ON VARYING FLEET ELECTRIFICATION AND TURNOVER

Base-year (2013 or BASE)



Business as usual (BAU)

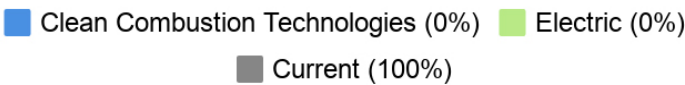
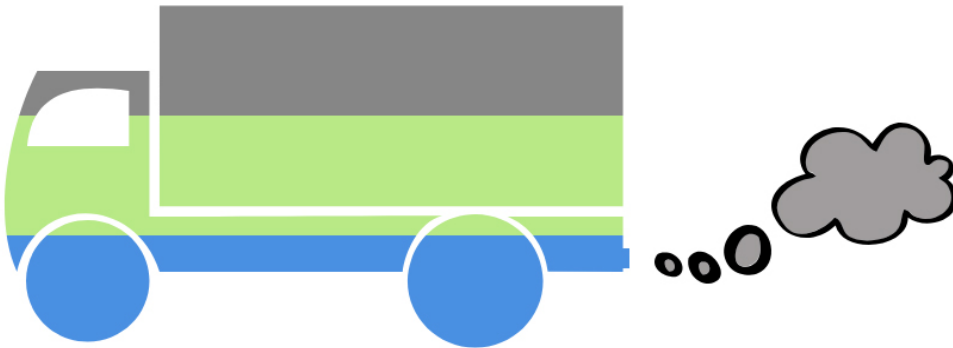


Figure 2: Emissions factor in each case.

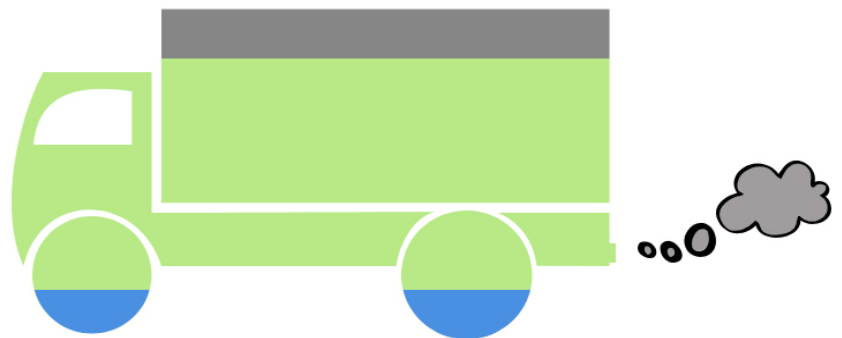
Moderate Electrification (ME)

■ Clean Combustion Technologies (33%) ■ Electric (35%)
■ Current (32%)



Aggressive Electrification (AE)

■ Clean Combustion Technologies (15%) ■ Electric (70%)
■ Current (15%)



Complete Turnover (CT)

■ Clean Combustion Technologies (65%) ■ Electric (35%)
■ Current (0%)

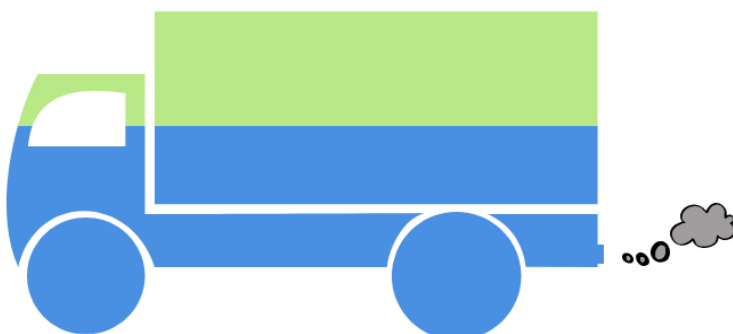


Figure 2: Emissions factor in each case.

ELECTRICITY LOAD DUE TO MOTOR VEHICLE ELECTRIFICATION

The added electricity required to power the motor vehicle fleet could potentially result in increased emissions from Electricity Generating Units (EGUs). However, several projections from the Electricity Reliability Council of Texas (ERCOT) (Borkar et al., 2016) have indicated that the projected electricity generation in 2040 will be in western Texas, resulting in no new emissions in the 8-county area. An example of the projected siting from the “Business As Usual” ERCOT scenario is shown in Figure 2; this scenario was used for the current study. The ERCOT projections indicate significant retirement of fossil-fired capacity in 2031 for southeastern Texas. We added no future capacity in our simulations but needed to account for capacity downsizing in order to represent a more realistic scenario in 2040.

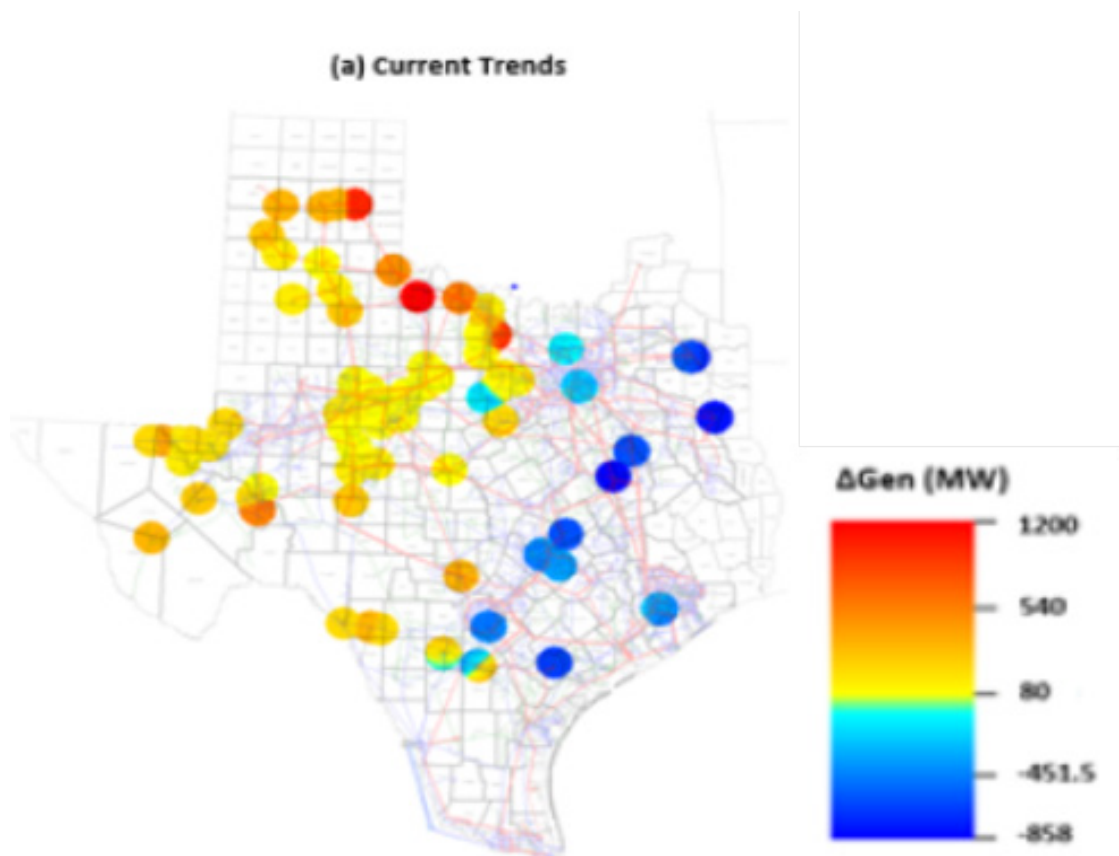
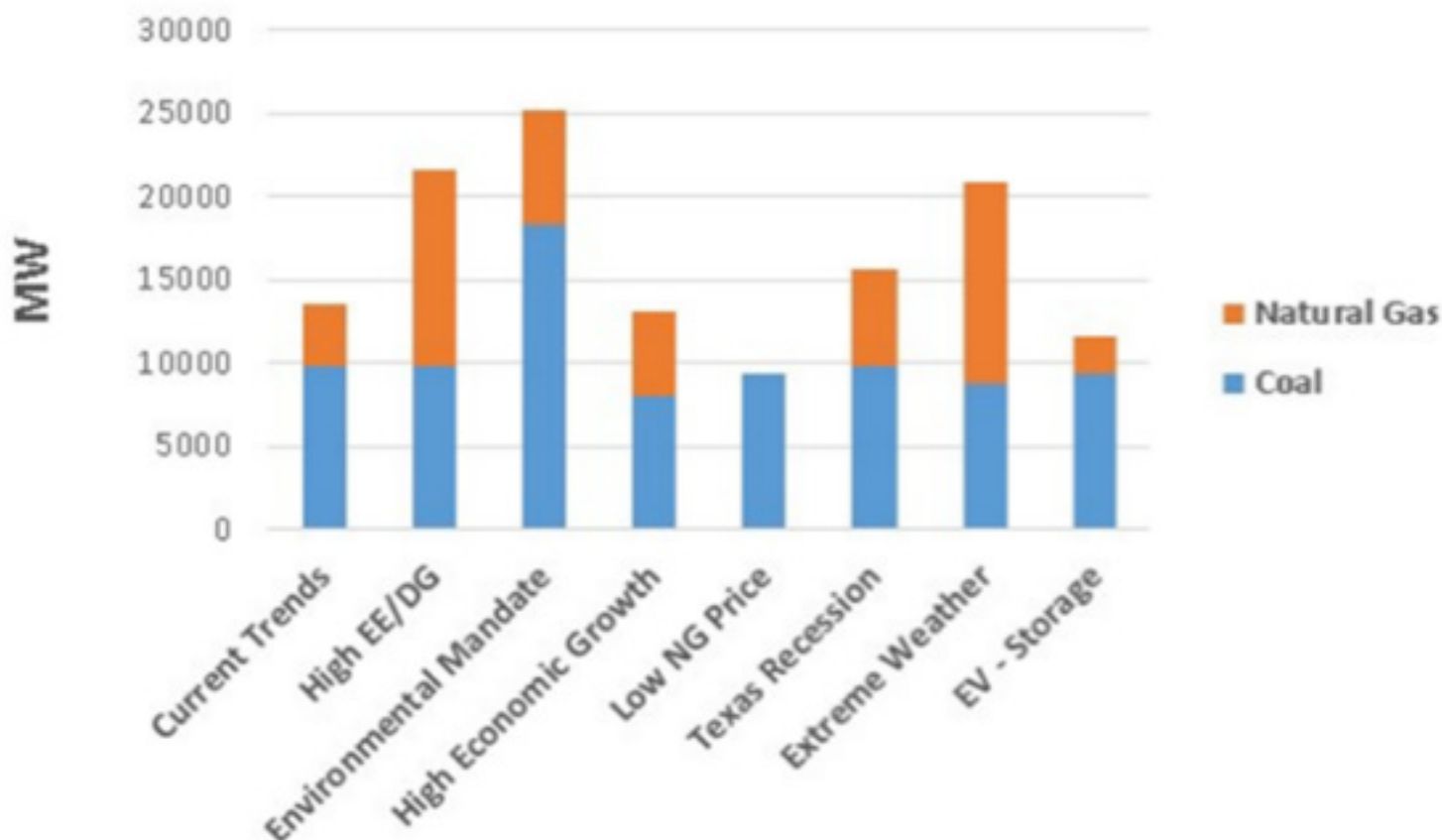


Figure 3: Map of generation capacity retirement across Texas in 2031 for ERCOT’s Current Trends scenario (above), and capacity retirements for coal and natural gas for all of ERCOT’s modeled scenarios (next page).



Future electricity capacity was estimated by assuming a linear decline in coal and gas generation over the 8-county area. For example, Figure 3 (previous page) indicates that around 500 MW will cumulatively retire in 2031. The panel on this page indicates the ratio of coal retirements to that of gas being 3:1. In other words, the coal-gas split is 75%-25%. Applying this to the Current Trends case, 375 MW of coal and 125 MW of natural gas capacity will cumulatively be retired by 2031.

Assuming a linear decline rate (recommended by Warren Lasher, personal communication, 2017) starting from 2013, the rate of decline for coal capacity is $375/18 = 21$ MW/yr. Similarly, the decline rate for natural gas is ~ 7 MW/yr. Multiplying these numbers by 27 years (2040-2013) provides the predicted number of cumulative retirements by 2040.

Hence, cumulative coal retirement in 2040 = $21 \times 27 = 567$, ~ 600 MW.

Cumulative natural gas retirement in 2040 = $7 \times 27 = 189$, ~ 200 MW.

Scaling factor for coal = $[\text{Coal (2013)} - 600] / \text{Coal (2013)} = 0.89$ ($\sim 11\%$ decrease)

Scaling factor for natural gas = $[\text{NG (2013)} - 200] / \text{NG (2013)} = 0.99$ (1% decrease).

THE HEALTH IMPACTS MODEL

The U.S. EPA Environmental Benefits Mapping and Analysis Program (BenMAP) Community Edition version 1.3 (U.S. EPA, 2017b) was used to estimate health impacts and corresponding economic costs for each future scenario. This is a Geographic Information Systems (GIS)-based model that estimates changes in the incidence of adverse health effects and associated monetary value due to changing ambient air pollution concentrations (Fann et al., 2012). The air quality inputs of the model include a baseline scenario (2013) and the four emission control scenarios (BAU, AE, ME, and CT in Table 1). The health impact calculations in BenMAP are based on Concentration-Response (C-R) functions, also known as health impact functions. These functions define a mathematical relationship relating a decrease in adverse health effects with a concentration of air pollutants. A commonly used type is the log-linear format:

$$\Delta y = (1 - e^{(-\beta \cdot \Delta x)}) \times y_0 \times \text{Pop} \quad (2)$$

Where Δy represents the change in the incidence of adverse health effects, β the concentration-response coefficient, Δx change in air quality (e.g. O_3 concentrations), y_0 the baseline incidence rates, and Pop the affected population.

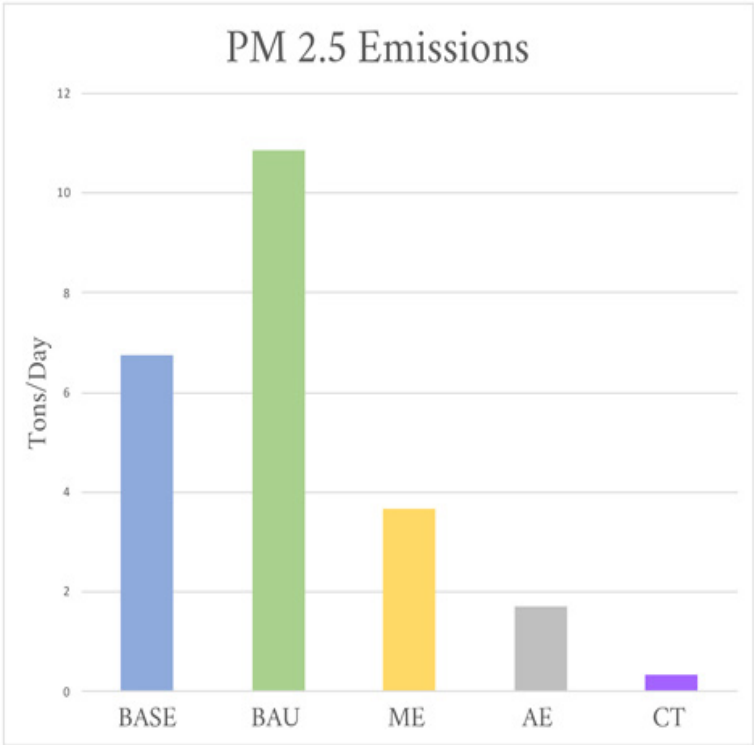
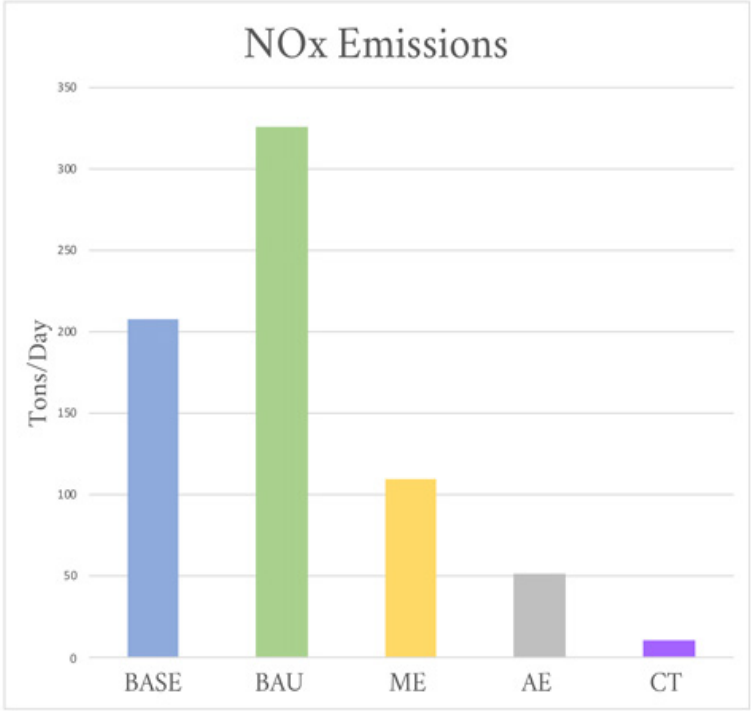
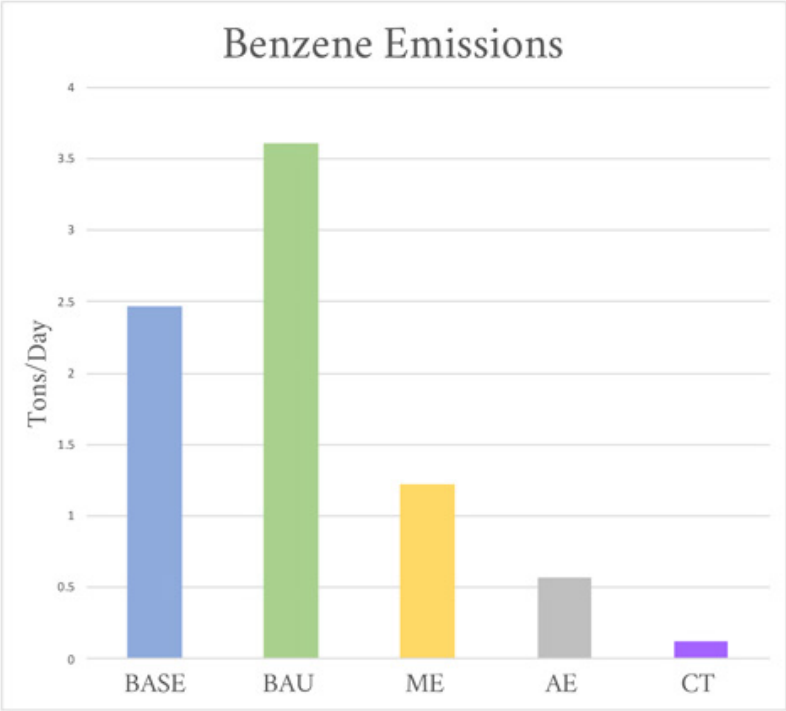
The relationship between changes in air pollutants concentrations and incidence of health outcome (i.e., β) have been assessed through several epidemiological studies. These studies have produced a number of C-R functions that have been incorporated into the BenMAP model. Additionally, the BenMAP model calculates the economic cost of avoided premature mortality using a “value of statistical life” (VSL) approach, which is the aggregate monetary value that a large group of people would be willing to pay to slightly reduce the risk of premature death in the population (U.S. EPA, 2017b). The economic costs for morbidities were estimated using the cost of illness, which includes direct medical costs and lost earnings associated with illness.

Table 2. Episode-average 8-county aggregate on-road mobile emissions in the BASE case and comparative changes for the future scenarios.

Species	BASE [tons/day]	Difference to BASE			
		Business as Usual (BAU) %	BAU [tons/day]	Moderate Electrification (ME) %	ME [tons/day]
CO	1220.64	48.6	1813.87	-50.0	610.32
NO _x	207.51	56.9	325.58	-47.2	109.57
NH ₃	5.51	50.8	8.31	-49.2	2.80
SO ₂	1.69	50.9	2.55	-49.2	0.86
PM ₁₀	16.88	55.3	26.21	-47.7	8.83
PM _{2.5}	6.75	61.1	10.87	-45.8	3.66
non-HAP TOGs	72.81	48.3	107.98	-50.1	36.33
Benzene	2.47	46.3	3.61	-50.8	1.22
Formaldehyde	1.66	60.5	2.66	-45.8	0.90
Acetaldehyde	1.15	54.3	1.77	-48.0	0.60
Acrolein	0.11	63.1	0.18	-45.1	0.06
1,3-butadiene	0.44	46.5	0.64	-50.7	0.22
Naphthalene	0.21	58.1	0.33	-46.8	0.11
N ₂ O	3.19	44.5	4.61	-51.4	1.55
CO ₂	92967.76	52.4	141682.87	-48.7	47692.46
CH ₄	3.33	54.0	5.13	-46.8	1.77

Species	BASE [tons/day]	Difference to BASE			
		Aggressive Electrification (AE) %	AE. [tons/day]	Complete Turnover (CT) %	CT [tons/day]
CO	1220.64	-76.6	285.63	-95.2	58.59
NO _x	207.51	-75.3	51.25	-94.9	10.58
NH ₃	5.51	-76.2	1.31	-95.1	0.27
SO ₂	1.69	-76.2	0.40	-95.1	0.08
PM ₁₀	16.88	-75.5	4.14	-94.9	0.86
PM _{2.5}	6.75	-74.6	1.71	-94.8	0.35
non-HAP TOGs	72.81	-76.6	17.04	-95.2	3.49
Benzene	2.47	-77.0	0.57	-95.2	0.12
Formaldehyde	1.66	-74.5	0.42	-94.6	0.09
Acetaldehyde	1.15	-75.7	0.28	-94.9	0.06
Acrolein	0.11	-74.3	0.03	-94.7	0.01
1,3-butadiene	0.44	-76.9	0.10	-95.2	0.02
Naphthalene	0.21	-75.1	0.05	-94.9	0.01
N ₂ O	3.19	-77.2	0.73	-95.3	0.15
CO ₂	92967.76	-76.0	22312.26	-95.0	4648.39
CH ₄	3.33	-73.9	0.87	-92.9	0.24

Figure 4: Visualizations of Table 2 emissions for selected pollutants: Benzene, PM 2.5, and NOx.



RESULTS:

EMISSION SCENARIOS AND CORRESPONDING CHANGES

Because the emissions inventories are “ground-zero” for a modeling study, comparison of pollutant emissions for each scenario provides insight into potential air quality changes. Table 2 (see page 21) compares projected emissions with the 2013 base case. The Business as Usual Case in 2040 exhibits significant increases in species emissions with respect to the 2013 base case due to the lack of control/retrofit imposition. The other cases show significant decreases in emissions, with 46%-51% for Moderate Electrification and above 93% for Complete Turnover, consistent with the assumptions used to develop these scenarios.

THE SIMULATION DOMAIN, EPISODE, AND MISCELLANEOUS DETAILS

The simulation domain comprises the 8-county area surrounding Houston at a 1-km resolution and is depicted in Figure 5. Simulations were run for September, using meteorology for 2013. Boundary conditions were obtained from a real-time air quality forecasting system over the United States using the above mentioned CMAQ model at a coarser 12 km resolution; additional details about this modeling system are online: <http://spock.geosc.uh.edu>.

Additionally, both VOC and PM_{2.5} emissions need to be speciated for use in the CMAQ model. This is because VOCs differ significantly in their formation to form ozone and secondary organic aerosol due to markedly different molecular structures (e.g. Carter, 1994; Presto et al., 2010; Tkacik et al., 2012, Roy et al., 2016). Additionally, PM_{2.5} comprises a large number of species with widely differing properties. For example, elemental carbon (EC) emissions from gasoline and diesel vehicles is a known global warming agent, while sulfate aerosol resulting from the chemistry of SO₂ emissions acts to cool the atmosphere. The speciation was performed as per the Carbon Bond version 5 (CB05) chemistry mechanism (Yarwood et al., 2005), with speciation profiles being taken from the SPECIATE database (USEPA, 2016).

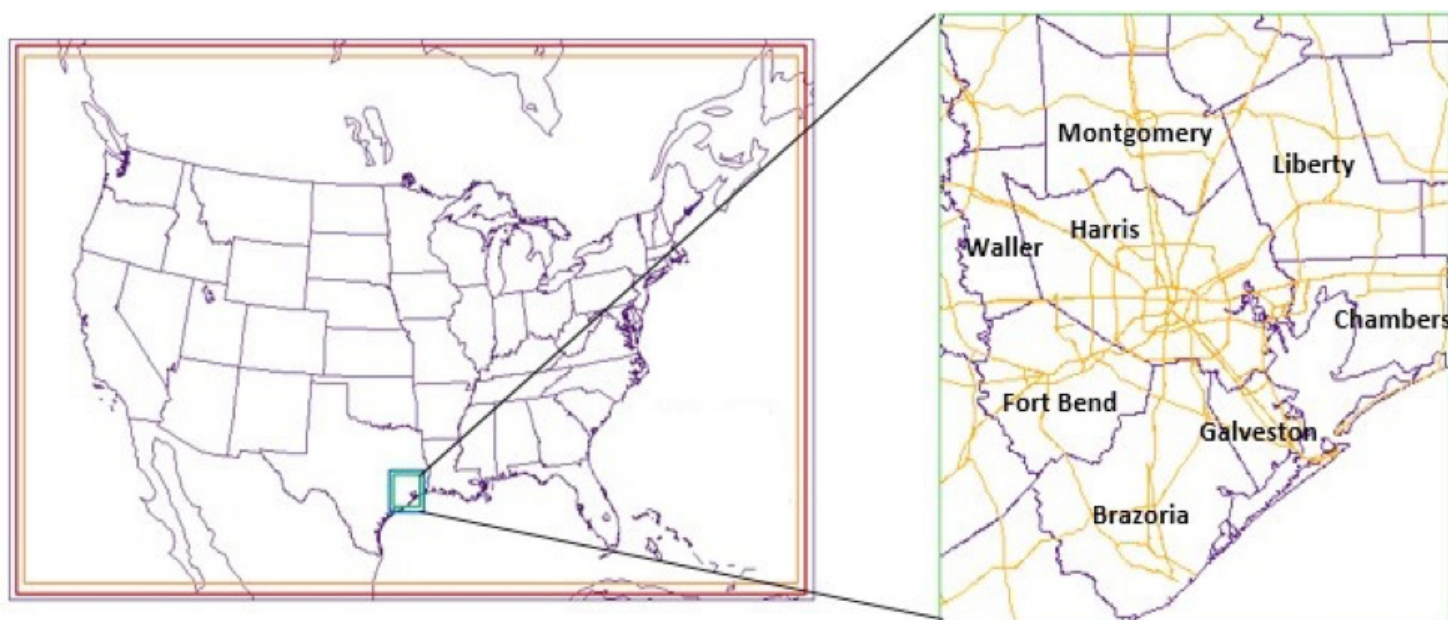


Figure 5: Horizontal domains of WRF and CMAQ at different grid resolution; the HGB 1 km is used in this study while the US 12 km is used to provide boundary conditions. For the zoomed-in plot on the right, roadways are represented in orange and county boundaries in purple.

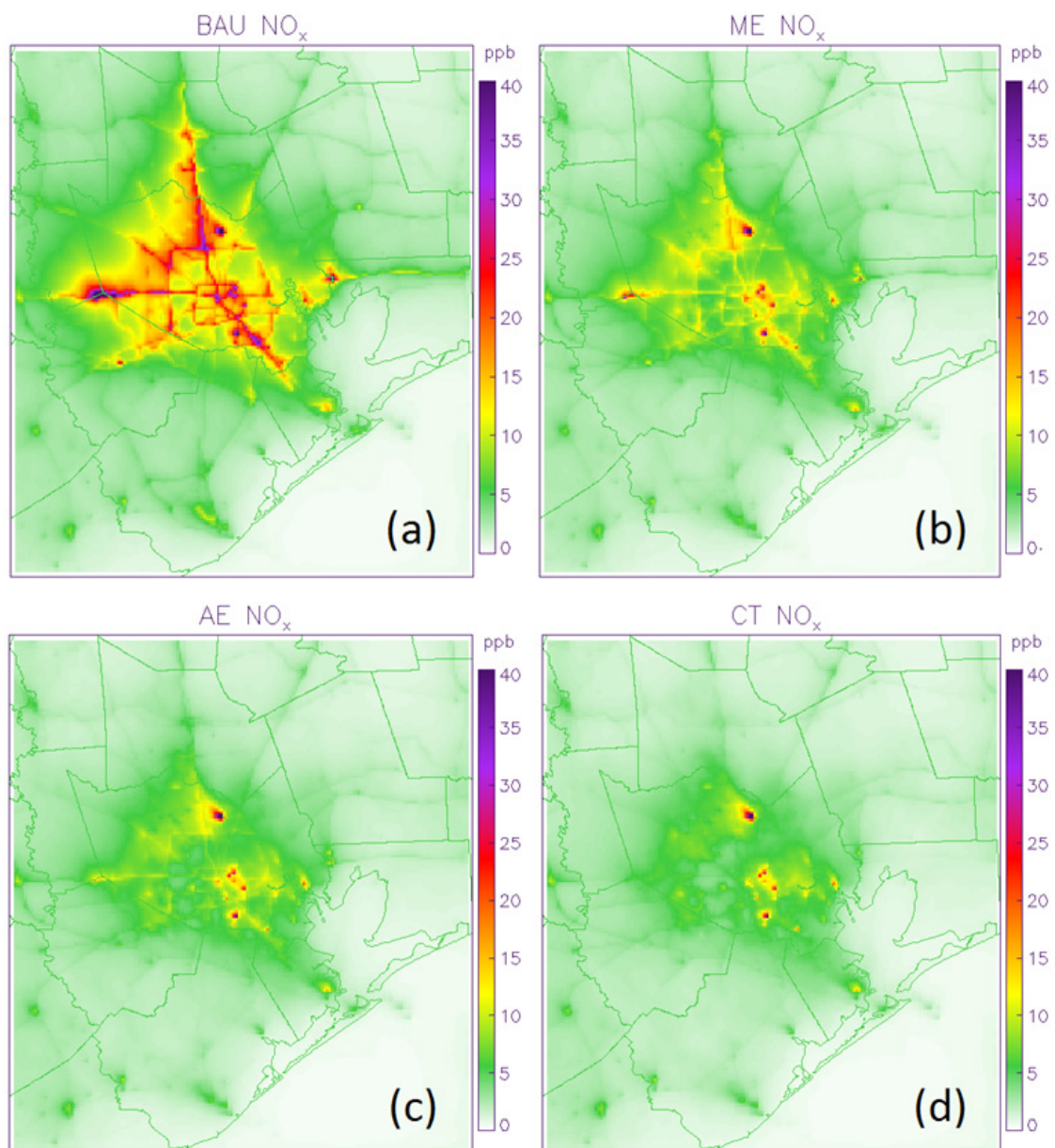


Figure 6: Simulated total NO_x concentrations (parts per billion, ppb) for the year 2040 in each case: (a) BAU-Business As Usual, (b) ME – Moderate Electrification, (c) AE- Aggressive Electrification, and (d) CT – Complete Turnover.

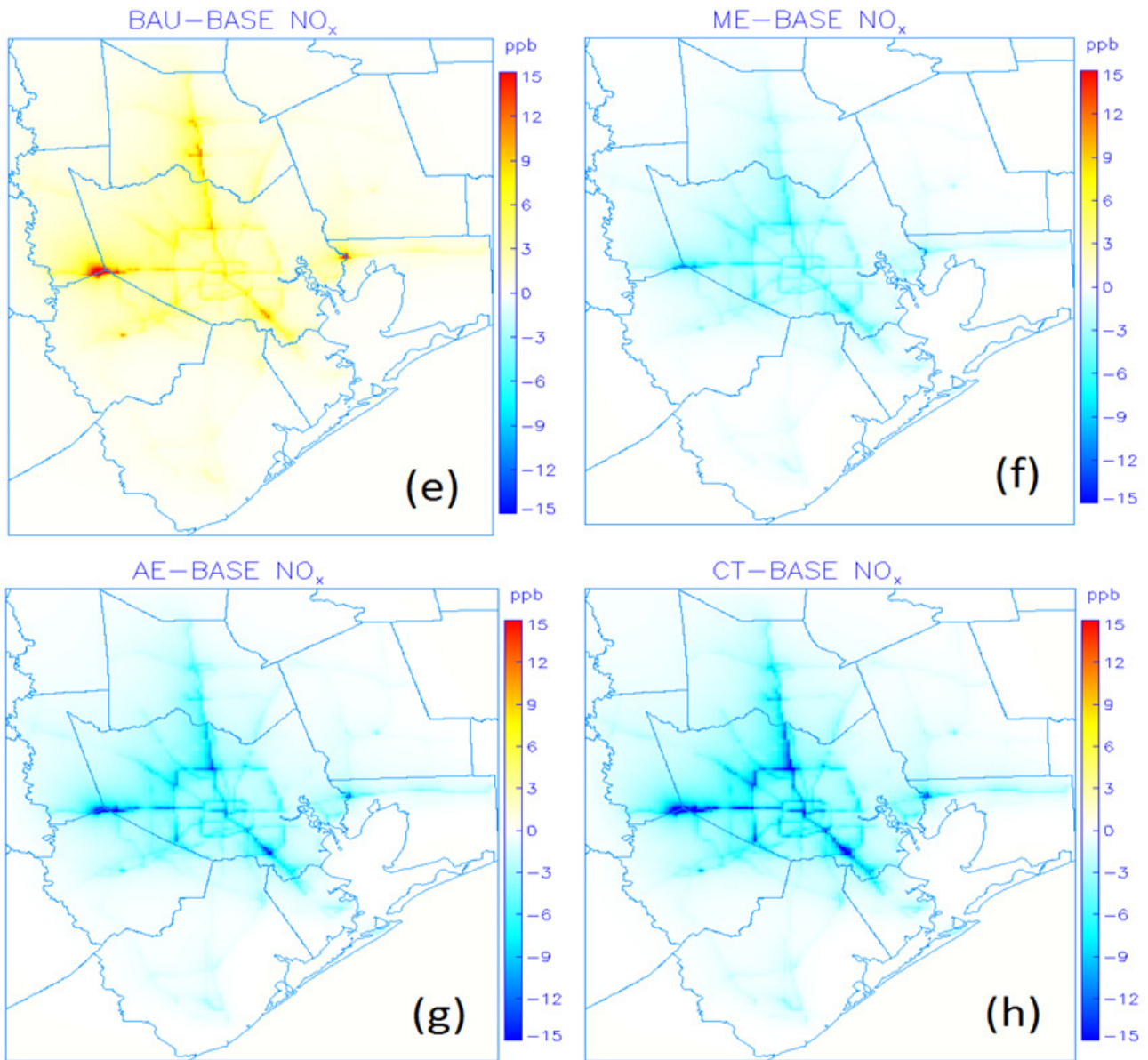


Figure 6: Simulated NO_x concentration differences (parts per billion, ppb) from 2013 baseline to each 2040 case: (e) BAU-Business As Usual, (f) ME – Moderate Electrification, (g) AE- Aggressive Electrification, and (h) CT – Complete Turnover.

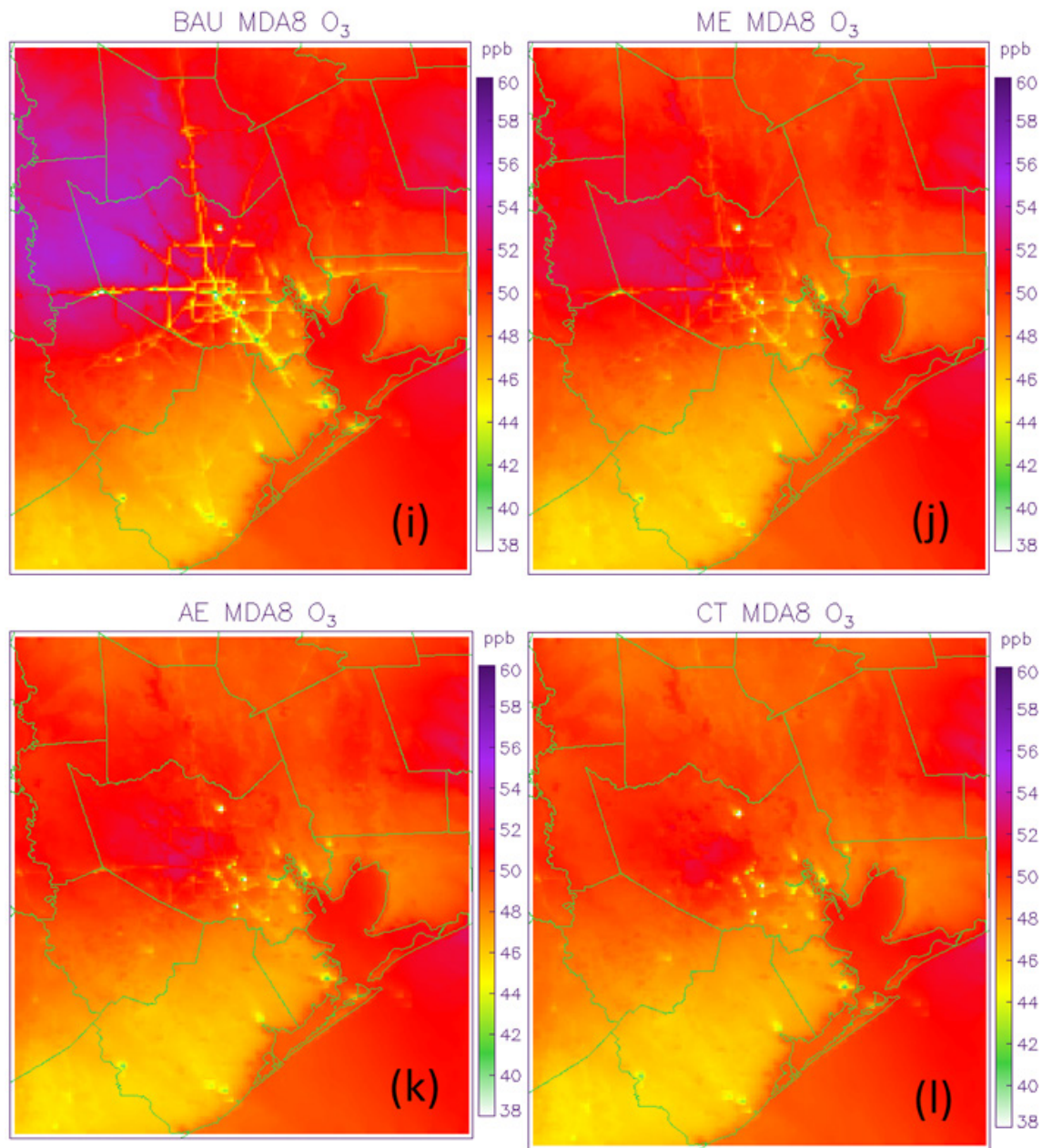


Figure 6: Simulated total Maximum Daily 8-hr Average (MDA8) ozone concentrations (parts per billion, ppb) for the year 2040 in each case: (i) BAU-Business As Usual, (j) ME – Moderate Electrification, (k) AE- Aggressive Electrification, and (l) CT – Complete Turnover.

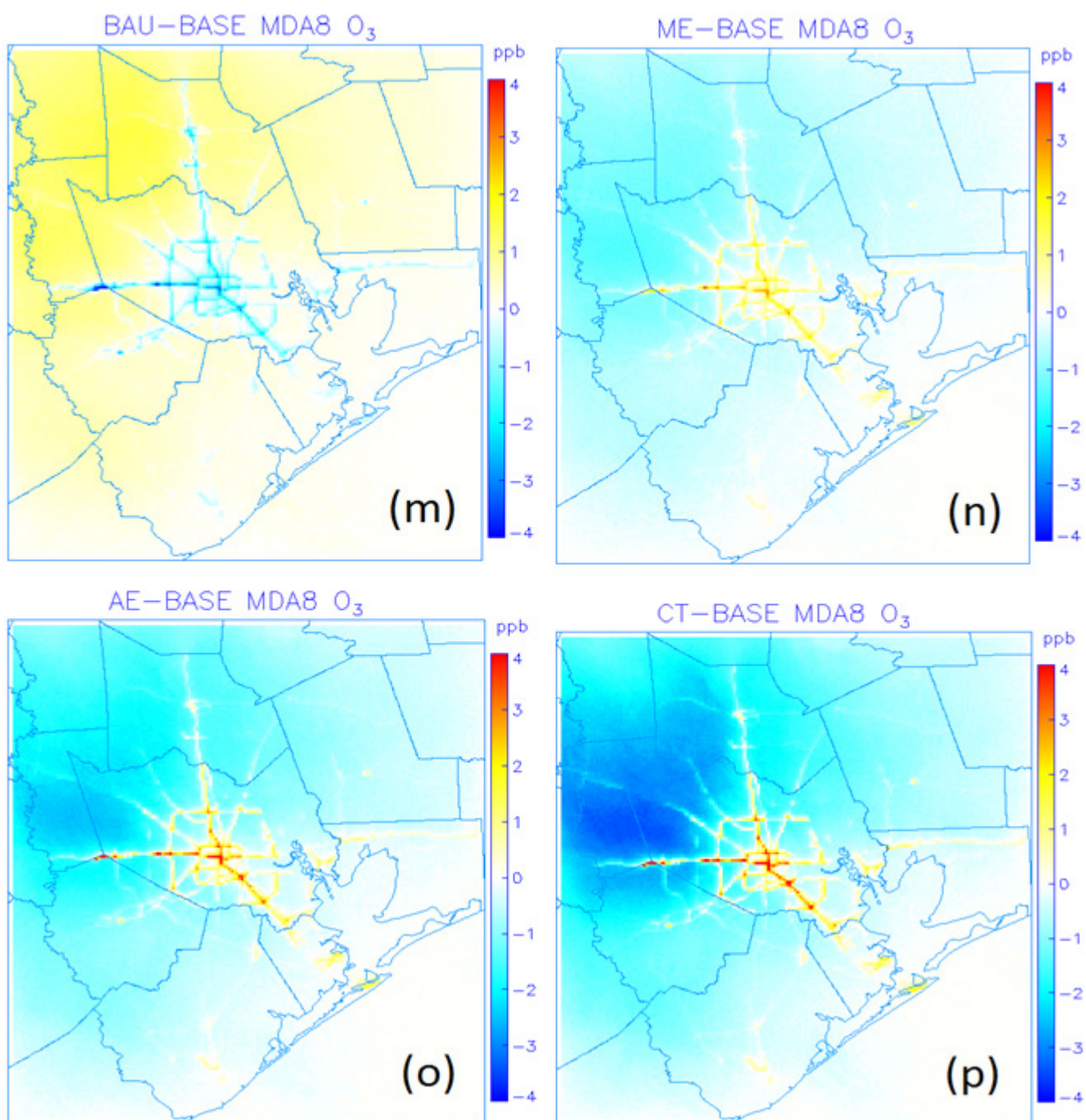


Figure 6: Simulated Maximum Daily 8-hr Average (MDA8) ozone concentration differences (parts per billion, ppb) from 2013 baseline to each 2040 case. (m) BAU-Business As Usual, (n) ME – Moderate Electrification, (o) AE- Aggressive Electrification, and (p) CT – Complete Turnover.

CMAQ SIMULATION RESULTS:

OZONE AND NITROGEN OXIDES

Figure 6 plots CMAQ-simulated NO_x and Maximum Daily 8-hr Average (MDA8) ozone concentrations for the different scenarios. Figures 6(a)-(d) plot absolute NO_x concentrations, 6(e)-(h) differences of the future scenarios from base case, 6(i)-(l) absolute MDA8 O₃ and 6(m)-(p) differences with respect to the 2013 base case.

As expected, it is predicted in figures 6(a)-(d) that absolute NO_x concentrations decrease with increasing fleet turnover, electrification, and emissions control.

For example, concentrations hotspots are predicted all over the highway loops over Houston for the BAU case which significantly decrease as we move towards the CT case. In other words, stringent emissions controls/retrofits accompanied with complete fleet turnover result in lower NO_x emissions and consequently, lower NO_x concentrations. However, figures 6(i)-(l) which plot ozone concentrations convey a different message. The Business as Usual case shows lowered MDA8 O₃ concentrations over the highway loops, and higher concentrations elsewhere. This can be explained by the fact that highways have significant NO_x emissions and are therefore NO_x-saturated. In such areas, O₃ and NO_x concentrations are inversely correlated as illustrated by previous studies (e.g. Choi et al., 2012). Another interesting point in panel 6(i) illustrates increased ozone concentrations over regions northwest to the loop, due to ozone formation in the outflow of NO_x-saturated areas. The outflow regions are NO_x-limited and provide favorable conditions for ozone formation, as illustrated by Pan et al. (2015). With decreasing tighter controls, increased fleet turnover, and decreasing NO_x concentrations, O₃ concentrations increase along the highway loop and decrease over the outflow. Similar facts are corroborated in figures 6(m)-(p), which show the effects of ozone impacts vis-à-vis the base 2013 case. It is predicted that ozone concentrations due to increased motor vehicle emissions decrease for the BAU case over the NO_x-saturated areas by 1-3 ppb while increasing 1-2 ppb over the outflow. With increasing controls/turnover/retrofit and lower NO_x emissions, O₃ concentrations increase by 1-2 ppb over the highways but decrease over the entire outflow surrounding the highway loop, as well as the areas enclosed by the loop. Of note is the CT case where there is a decrease of 3-4 ppb over the northwestern outflow, the same region where significant ozone increase was predicted for the BAU case.

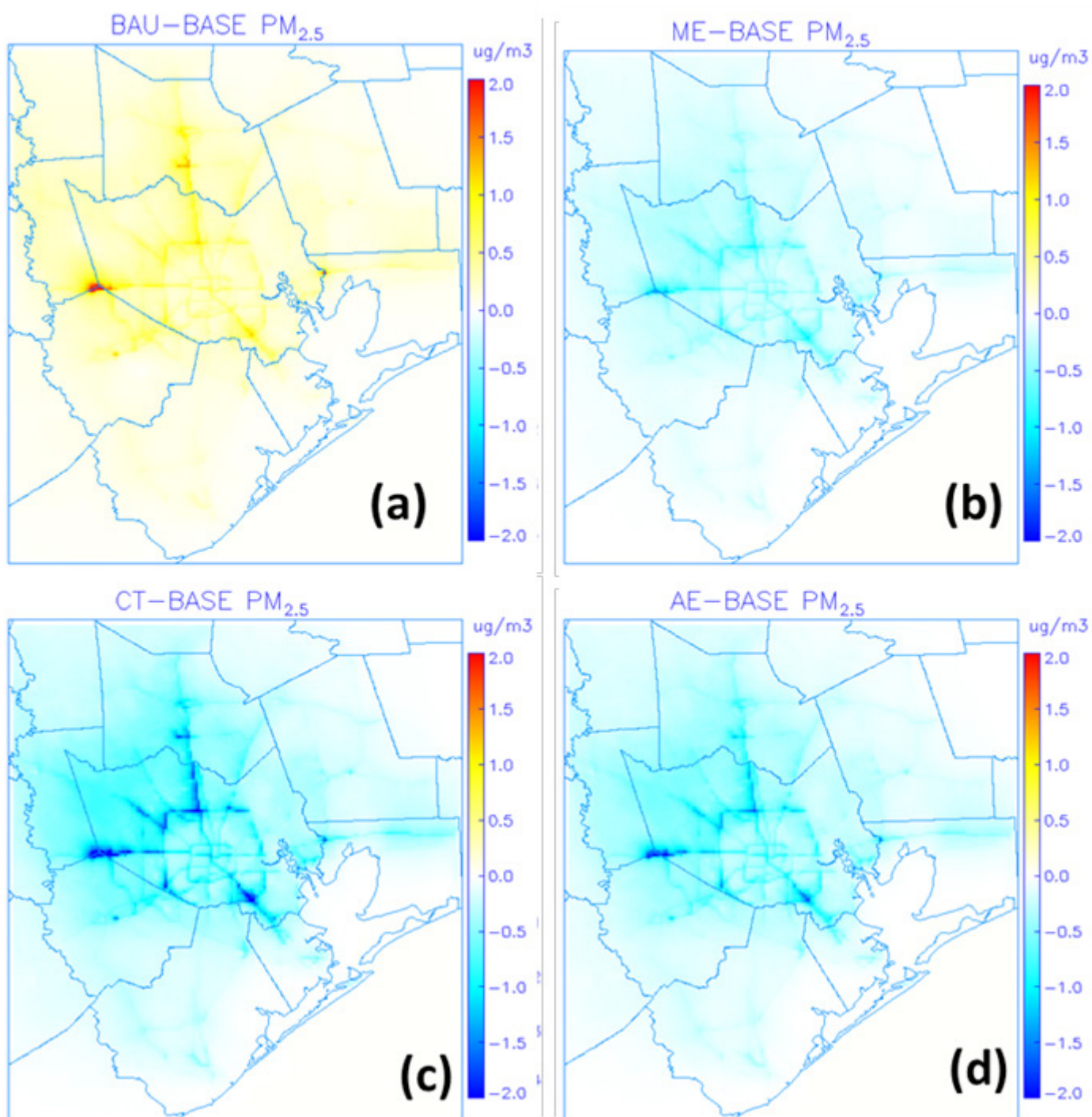


Figure 7: Spatial differences of monthly average PM_{2.5} surface concentrations, micrograms per meter cubed ($\mu\text{g}/\text{m}^3$). (a) BAU-Business As Usual, (b) ME – Moderate Electrification, (c) AE- Aggressive Electrification, and (d) CT – Complete Turnover.

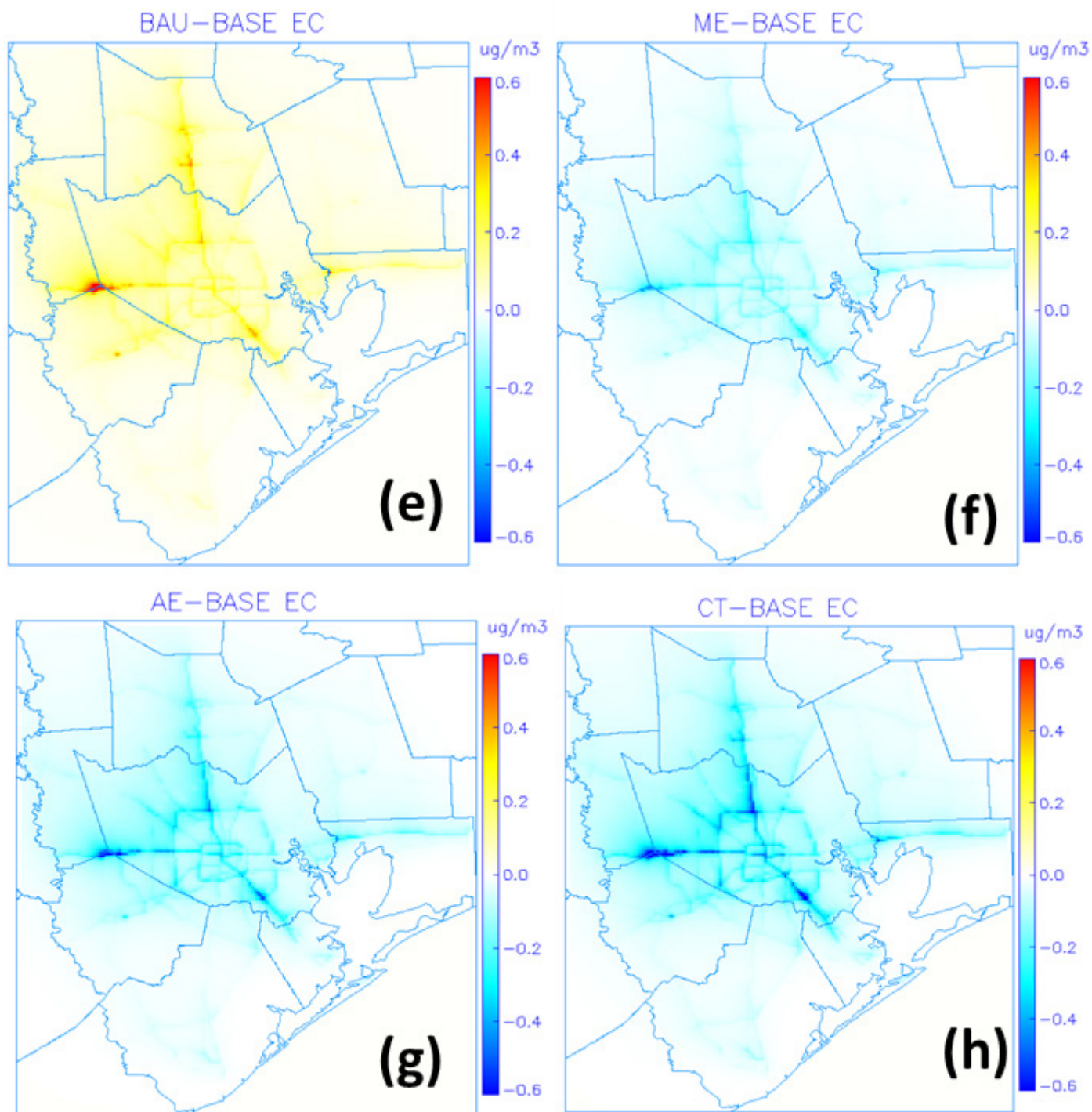


Figure 7: Spatial differences of monthly average elemental carbon surface concentrations, micrograms per meter cubed ($\mu\text{g}/\text{m}^3$). (e) BAU-Business As Usual, (f) ME – Moderate Electrification, (g) AE- Aggressive Electrification, and (h) CT – Complete Turnover.

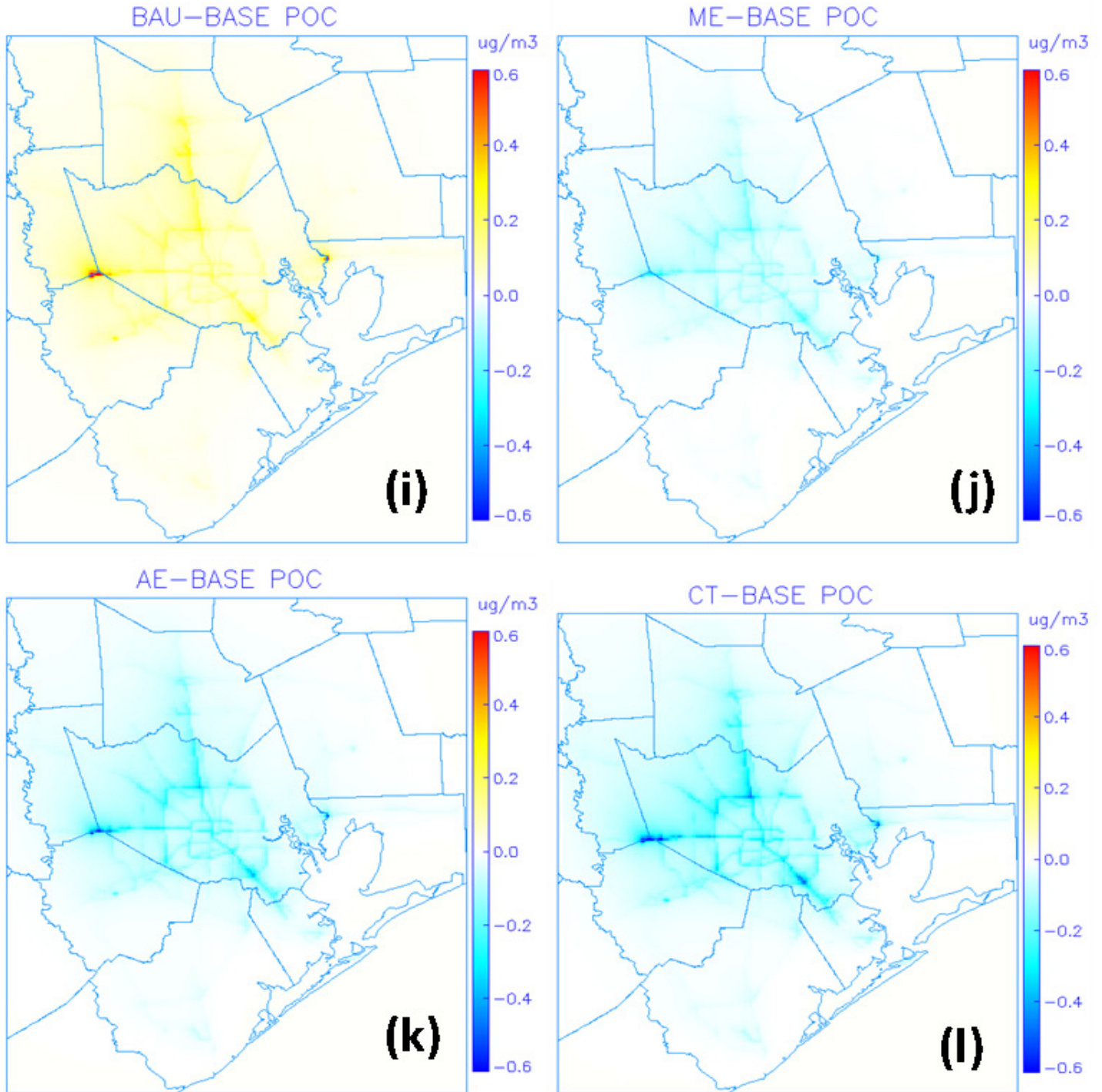


Figure 7: Spatial differences of monthly average particulate organic carbon surface concentrations, micrograms per meter cubed ($\mu\text{g}/\text{m}^3$). (i) BAU-Business As Usual, (j) ME – Moderate Electrification, (k) AE- Aggressive Electrification, and (l) CT – Complete Turnover.

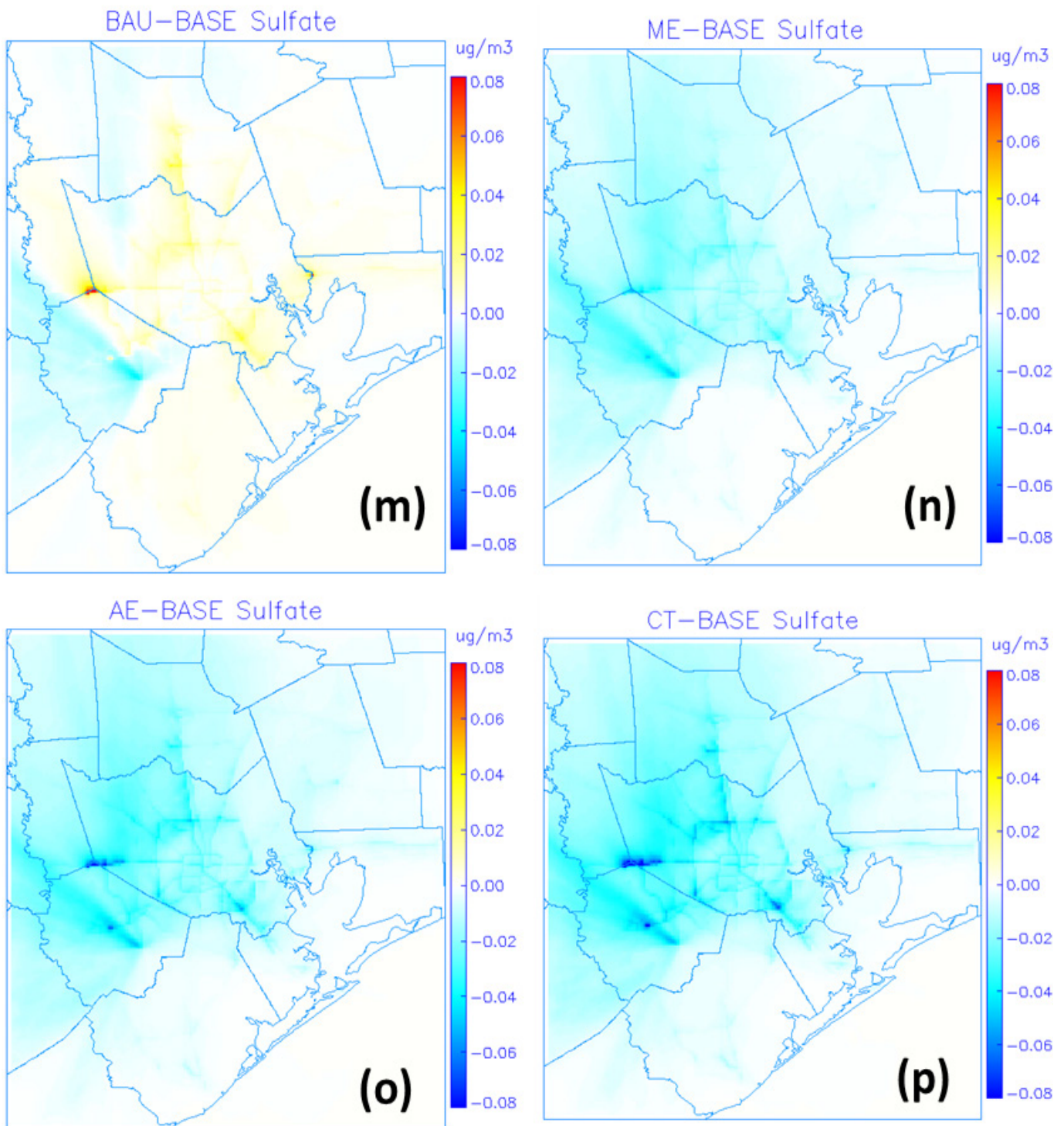


Figure 7: Spatial differences of monthly average sulfate surface concentrations, micrograms per meter cubed ($\mu\text{g}/\text{m}^3$). (m) BAU-Business As Usual, (n) ME – Moderate Electrification, (o) AE- Aggressive Electrification, and (p) CT – Complete Turnover.

SPECIATED FINE PARTICULATE MATTER



Figure 7 plots the spatial differences between the projected control scenarios and the base 2013 case. The BAU case results in increasing PM_{2.5} concentrations by 1-2 $\mu\text{g}/\text{m}^3$ (figures 7(a)-7(d)), while the control scenarios bring about changes between 0.5-2 $\mu\text{g}/\text{m}^3$. The most dramatic changes occur on the highways, due to a reduction in motor vehicle emissions, as is corroborated in the plots for EC (figures 7 (e-h)) and OC (figures 7(i-l)). The changes in sulfate (figures 7 (m-p)) also mirror EC and OC, but one additional important point is the reduction in sulfate hotspots over areas with EGU emissions. This could be explained by the reduction in coal capacity over these areas.



HEALTH IMPACTS

This section presents health impacts related to the BAU, ME, AE and CT. Pollutant metrics include Maximum Daily 8-hr Average (D8HourMax) for O₃ and daily 24-hr mean (D24HourMean) for PM_{2.5}, respectively. The USEPA's PopGrid program (U.S. EPA, 2017b) was implemented to allocate 2010 block-level U.S. Census population data to our BenMAP domain. Population information is classed into groups of race, ethnicity, genders, and age range. The BenMAP model contains county-level population growth rates for each year from 2000 through 2050.

We evaluated the health endpoint of "Mortality, All Cause" in this study. For O₃, we chose health impact functions based on the epidemiological studies by Bell et al. (2005), Zanobetti and Schwartz (2008), and Levy et al. (2005), and for PM_{2.5}, we chose a study by Krewski et al. (2009). These studies were chosen as their analyses were based on a large geographic area (e.g., 116 U.S. cities in Krewski et al. (2009)). Hence, they are likely to be more representative and applicable to our analysis in the Houston area. Moreover, we also examined several O₃-induced morbidities (e.g., asthma exacerbation, emergency room visits) and associated benefits. Because the health impact functions for morbidities were derived from fewer cities or smaller time-scale sample sizes, the functions from several epidemiological studies were used to estimate the risk outcome.

We predict that the BAU case will result in an increased number of premature deaths with respect to 2013, but all of the control scenarios will result in prevented mortality with respect to the 2013, as illustrated in Figure 8. For PM_{2.5}, the results indicate about 121 more premature deaths in the BAU case, and 109, 177, and 229 prevented premature deaths in the ME, AE, and CT cases, respectively. These findings coincide with trends in PM_{2.5} concentration, as depicted in panels (a)-(d) in Figure 7. The findings also roughly correspond to 61% enhancement of PM_{2.5} emissions in the BAU case, and 46%, 75%, and 95% reductions in emissions in the ME, AE, and CT cases. An interpretation of the results for O₃, however, is more complicated because the trends of O₃ change vary spatially (panels (m)-(p) of Figure 6). For instance, in the BAU case, BenMAP would predict an increase in adverse health effects in the downwind area because of increase in O₃ concentrations, while predicting a decrease of damage in the urban and major highways. In contrast, for the other scenarios with emissions reductions (i.e., the ME, AE, and CT cases), the gains in health endpoints in downwind areas are all greater than the losses over the urban highways, resulting in about 5, 11, and 17 prevented premature deaths, respectively. We may expect more health benefits if we extend the simulation domain to cover more places downwind. It should be noted that even in the case of an increase in O₃ concentrations over the urban highways, the reductions in air toxics emissions would occur, so their concentrations would lead to more health benefits. However, the health impact functions for these air toxics are not available in the current BenMAP model. The economic cost (benefit) values generally coincide with premature mortality results. Table 4 shows similar trends in O₃-induced morbidities and associated benefits. Thus, the emissions reductions scenarios would significantly reduce asthma exacerbation and school loss days, benefiting younger individuals.

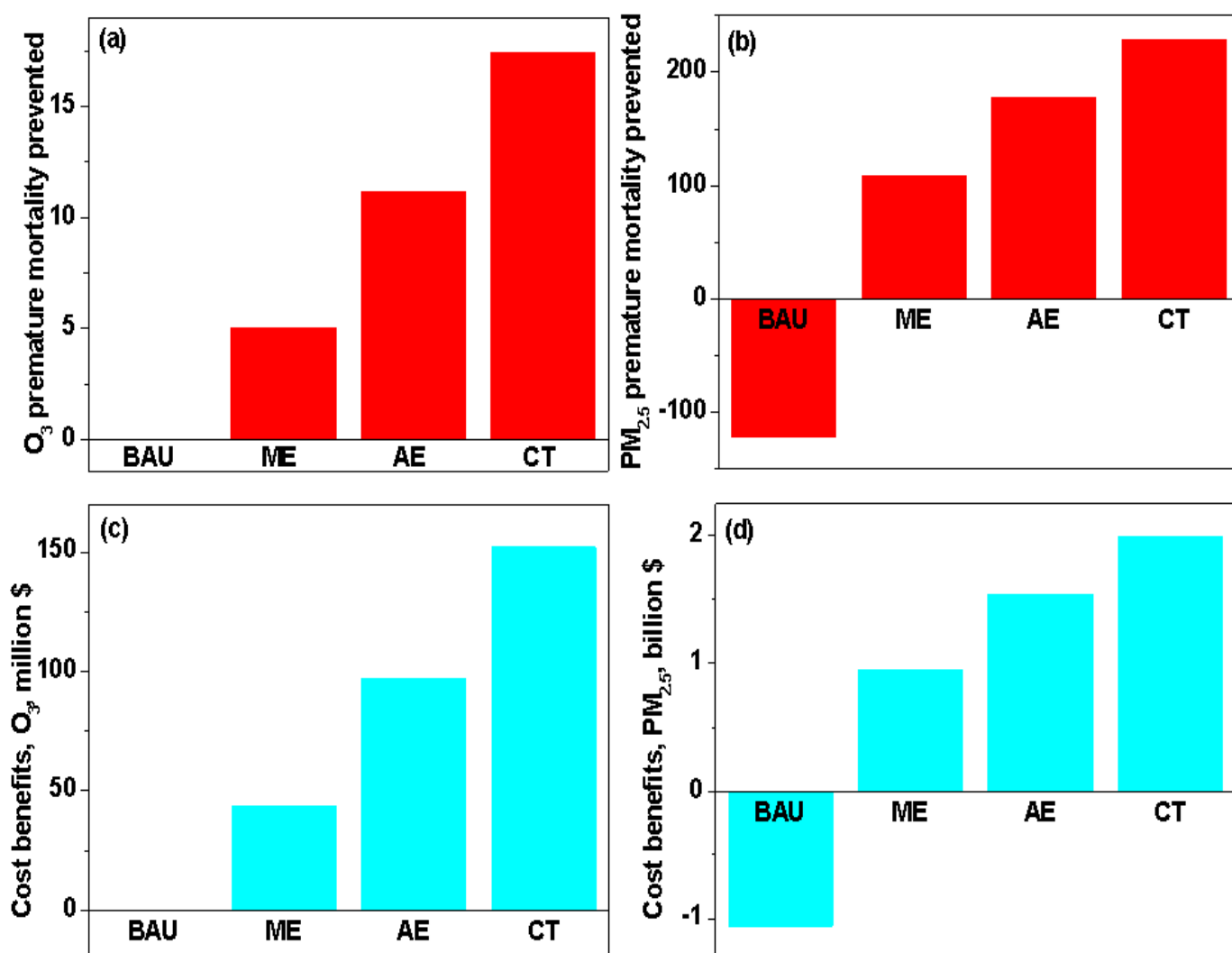


Figure 8. Estimates of avoided mortality and benefits from the changes in O_3 and $PM_{2.5}$ concentrations in the 2040 scenarios. The age range is 0 to 99 for O_3 and 30 to 99 for $PM_{2.5}$. In each plot, positive values indicate the number of premature deaths prevented because of control strategies and the associated benefits achieved, while the negative values in the BAU case indicate an increase in the number of premature deaths and economic losses.

Table 3: Estimates of avoided mortality and benefits from the changes in O₃ and PM_{2.5} concentrations in the future year scenarios. The age range is 0 to 99 for O₃ and 30 to 99 for PM_{2.5}. Note: The BASE scenario is the baseline case (2013) in the BenMAP model, and the future year scenarios are the different control cases. Positive values indicate the number of premature deaths prevented because of control strategies and the associated benefits achieved, while the negative values in the BAU case indicate an increase in the number of premature deaths and economic losses.

Species	Scenarios	Premature Mortality Prevented	Benefits [Million Dollars, in 2015 currency year]
Ozone	Business As Usual	0	-0.33
	Moderate Electrification	5	43.57
	Aggressive Electrification	11	97.19
	Complete Turnover	17	151.99
PM 2.5	Business As Usual	-122	-1057.69
	Moderate Electrification	109	947.99
	Aggressive Electrification	177	1542.27
	Complete Turnover	229	1993.07

Table 4. Estimates of prevented O₃-induced morbidities and benefits in the future year scenarios.

Scenarios	Prevented Cases of Asthma exacerbation, one or more symptoms	Benefits [Million Dollars, in 2015 currency year]
Business As Usual	-1213	-0.076
Moderate Electrification	7534	0.475
Aggressive Electrification	16119	1.016
Complete Turnover	24652	1.554
	Prevented Emergency room visits, Asthma	
Business As Usual	-1	-0.001
Moderate Electrification	20	0.01
Aggressive Electrification	43	0.023
Complete Turnover	67	0.036
	School loss days, Prevented	
Business As Usual	-833	-0.088
Moderate Electrification	5,518	0.585
Aggressive Electrification	11,844	1.255
Complete Turnover	18,153	1.924
	Prevented Hospital admissions, All respiratory	
Business As Usual	0	-0.002
Moderate Electrification	4	0.133
Aggressive Electrification	8	0.294
Complete Turnover	13	0.459

SUMMARY, CONCLUSIONS, AND FUTURE WORK

Four emissions scenarios were considered to understand the effects of future control technologies, fleet turnover and electrification for both gasoline and diesel vehicles on air quality and health impacts over the 8-county area surrounding Houston, which is in nonattainment for ozone with respect to the new EPA standard of 70 ppb. For each case, the vehicular activities (Vehicle Miles Traveled, Vehicle Population and Hoteling hours) were scaled to reflect future population increases and vehicle usage. The cases considered included Business as Usual (projected increased activity with no new controls/retrofits/fleet turnover), Moderate Electrification (35% of the fleet assumed to be electric, 33% clean combustion technologies/retrofitted and 32% current vehicles), Aggressive Electrification (70% electric, 15% clean combustion technologies and 15% current) and Complete Turnover (65% clean combustion technologies, 35% electric). These turnover assumptions were applied to aggregate emissions from both gasoline and diesel vehicles. The emissions were modeled and speciated using the Motor Vehicle Emissions Simulator and the USEPA's SPECIATE database. They were temporally and spatially allocated to a 1-km grid using the Sparse Matrix Operator Kernel Emissions model. Using a fine resolution of 1-km helped to identify NO_x-saturated and NO_x-sensitive areas over the simulation domain.

The Business As Usual Case represented increased emissions with no controls. Consequently, ozone concentrations along highways decreased due to NO_x-titration for this case. However, it resulted in significant ozone formation in the NO_x-limited outflow over the regions bordering the I-610 highway loop in Houston. The emissions control cases all resulted in ozone increases along the highways, due to decreasing saturation. However, the emissions control cases resulted in ozone reduction both in the regions enclosed by the highways as well as the outflow. Simulated PM_{2.5} concentrations showed elemental and organic carbon hotspots along the highways, which decreased with increasing control and fleet turnover. One important point was the removal of sulfate hotspots in 2040 due to fossil fuel retirement.

Our health impact assessments indicated that while the Business As Usual case would lead to 122 additional premature deaths, the Moderate Electrification, Aggressive Electrification, and Complete Turnover scenarios prevented 114, 188, and 246 premature deaths, respectively. Further, the prevented morbidities and economic costs (benefits) generally mirrored premature mortality. These findings can potentially shed light on the effects of mobile emissions control strategies in other urban environments. Large urban cities can benefit significantly from reductions in PM_{2.5} pollution if local emissions from the transportation sector are controlled, while efficient O₃ pollution reductions primarily occur in downwind areas.

One advantage over the 8-county area is the significant retirement of fossil capacity and consequent replacement by renewables as indicated by Borkar et al. (2016). This can provide an impetus to clean electrification in Texas, but these efforts might not be replicable everywhere. For example, a significant fraction of the generation in states such as Pennsylvania and Ohio is by coal, and the added load due to electrification could exacerbate an existing nonattainment problem. Hence, several scenarios need to be investigated over the continental United States to understand the overall effects of fleet electrification and long-range transport of emissions.

This study assumes the added load because of motor vehicle electrification will be borne by the upcoming renewable electricity generating capacity. This is a bounding estimate as the renewable capacity might not be adequate to meet electrification demands, a fraction of which would then be needed to transfer to the fossil capacity. Hence, electricity demand needs to be wisely allocated to minimize emissions. Another uncertainty not considered in this study is changing climate in 2040, which would invariably affect emissions and future EGU load. Further modeling and analyses needs to be conducted on these points to get a clearer picture of motor vehicle electrification with load on residual fossil capacity in the light of changing climate.

This is a pilot study to show how the combined effects of a greening grid, emissions control, and fleet electrification can improve air quality and health indicators over the 8-county area surrounding Houston. There are several studies which can offshoot from this – one being the effects of truck stop electrification being studied in detail to identify the candidate stops for electrification, which can be extended to buses (especially school buses) to reduce idling hours and hence improve fuel consumption. The additional investigation can also be done to understand expenses per mile for newer gasoline and diesel vehicle vis-à-vis electric vehicles for different combustion, emissions control and battery technologies, and amalgamated with a change in health costs due to cleaner air, to understand the total monetary benefits/disadvantages of fleet electrification for vehicle owners.

AUTHOR BIOS



Dr. Yunsoo Choi received a Ph.D. in Atmospheric Chemistry (2007) from Georgia Institute of Technology, and B.S. in Chemistry (1994) from Hanyang University (in Korea) and M.S. in Physical Chemistry from Hanyang University (1996) and in Biophysical Chemistry (1999) from University of California in Irvine (1999). His Ph.D. topic is about the Spring and Summer transitions of ozone and its precursors over North America and photochemistry over Antarctica using Regional chEmical trAnsport Model (REAM: developed by Dr. Choi and his supervisor). After graduation, he worked as a Postdoctoral Research Scientist at California Institute of Technology/Jet Propulsion Laboratory, where he worked on the evaluation of satellite retrieval products. In February 2010, he joined NOAA Air Resource Laboratory as a staff scientist, where he worked on developing chemical and physical modules of Air Quality Forecasting system. After he shortly worked for NASA OMI satellite team for April-August of 2012 and joined the University of Houston as an assistant professor since the fall semester of 2012 and is an associate professor at the Department of Earth and Atmospheric Sciences of UH now. Over the period at UH, with his group members, he has established UH Air Quality Forecasting (UH-AQF) system to provide 48 hour forecasting results for ozone and particulate matters (PM) and their ingredients for local users, atmospheric scientists and air pollution policymakers including diverse end-users of the forecasting system (see the details, <http://spock.geosc.uh.edu>). He also initiated several Artificial Intelligence machine learning projects for diverse atmospheric sciences such as air quality forecasting, climate change (and future energy usage) and air pollution, energy land mapping for renewable energy, extracting surface air pollution data from remote sensing, and forecasting Hurricane's track and strength. His UH research group was/is working on diverse projects on atmospheric chemistry, air pollution, climate change, and disaster relief funded by the university, non-governmental, state, federal and overseas organizations.



Dr. Anirban Roy is currently working as an Air Resource Engineer with the California Air Resources Board headquarters in Sacramento. He holds a PhD in Mechanical Engineering from Carnegie Mellon University. His research broadly focuses on sustainable energy and transportation. He has looked at understanding the bias in receptor models for our current understanding of the gasoline-diesel split in contributions to organic carbon and evaluated the effects of control technologies and strategies on unconventional gas development emissions and subsequent air quality in the Marcellus Shale. During his postdoctoral stint at the University of Houston, he has evaluated the effects of temperature and driving conditions on gasoline exhaust VOC speciation, and briefly worked on using machine learning to fill in missing data in an air quality time series.



Ebrahim Eslami received his BSc in Civil Engineering from the Sharif University of Technology in Iran in 2008. He continued his research as a research flow at SINTEF in Norway in 2009 and 2010. Then he worked as an Engineer-in-Training in several construction companies in Iran between 2011 and 2014. He received his Master's in Environmental Engineering from the University of Tehran in 2016. Since 2016, he is a PhD candidate of Atmospheric Sciences at the University of Houston. His main interests are deep learning, health and cost impact of air pollution and advanced environmental data analysis.



Dr. Shuai Pan is currently a postdoctoral associate at Cornell University. He is working on assessing the impact of energy transitions on transportation emissions, air quality, and community health. He completed his Ph.D. in atmospheric science from the University of Houston. His Ph.D. work includes the investigation of ozone sensitivity to precursors' emissions and meteorology, deciphering ozone exceedance formation at coastal urban environment, and fine resolution (1 km) modeling. He received B.S. and M.S. in atmospheric science from Nanjing University of Information Science and Technology (NUIST), China, where he designed circuit boards for a flight mill and processed radar signals to study insect flight patterns.

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