Final Report

Project 16-010

MOVES-Based NO_x Analyses for Urban Case Studies in Texas

Prepared for

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Executive Summary

Background

Emissions inventories are an important component of air quality planning and a key input to photochemical grid models that support air quality assessments. Findings from recent studies suggest that emissions of nitrogen oxides (NO_x) may be overestimated in the EPA's National Emissions Inventory (NEI), perhaps by as much as a factor of two. This overestimate has generally been attributed to the mobile source sector, for which emission estimates are prepared using EPA's MOVES model (Fujita et al., 2012; Anderson et al., 2014; Canty et al., 2015). A number of potential issues have been identified with MOVES, including reliance on the model's default input data rather than more representative local inputs (Koupal et al., 2014; Warila et al., 2017).

Starting in 2014, the EPA mandated air quality monitoring next to selected major roadways throughout the United States; near-road air quality data for various pollutants, including CO and NO_x, have been collected by monitoring agencies (DeWinter et al., 2015). These routinely collected near-road pollutant concentrations and assessments provide an important resource to support evaluation of mobile source emissions inventories and air quality impacts. This study used near-road monitored concentration data to examine MOVES emissions estimates for NO_x at the local scale and identified which input parameters have the greatest influence on MOVES-based NO_x emissions estimates. Using emissions reconciliation and sensitivity analyses for three case studies in Texas, the results of this work support emissions inventory development and air quality management efforts in Texas by providing information on (1) the accuracy of current MOVES emissions estimates for NO_x, and (2) the MOVES input parameters for which local data collection is most important.

Methods

A CO and NO_x emissions reconciliation analysis was performed at three urban near-road sites in Texas: El Paso, Houston, and Fort Worth. The emissions reconciliation method has been used for more than two decades to identify omissions or inaccuracies in an emissions inventory by comparing emissions data and ambient concentration data (Fujita et al., 1992; Wallace et al., 2012). This method includes selective, quantitative comparisons of emissions-derived (e.g., using MOVES emissions output) and ambient-derived (based on monitored concentrations) metrics, such as carbon monoxide (CO)-to-NO_x (CO/NO_x) molar pollutant ratios (e.g., Chinkin et al., 2005). In this reconciliation analysis, a regression approach was used to derive ambient CO/NO_x ratios, with the data selection process targeting morning commute hours when the monitoring sites were downwind of the adjacent roadway. The MOVES model (MOVES2014a), using national default and county-level local inputs, was used to develop on-road mobile source CO and NO_x emissions and the corresponding emissions-based CO/NO_x ratios on an annual and seasonal basis. The ambient- and emissions-based CO/NO_x ratios were compared.

For each of the three case study sites, a base scenario and 18 MOVES sensitivity testing scenarios were developed to represent various levels of selected input data. Changes in NO_x emissions and CO/NO_x ratios were quantified with respect to fleet mix (truck percentage), vehicle speed (VMT by speed distribution), vehicle age (VMT by age distribution), and meteorology (ambient temperature and relative humidity).

Results

The ambient-based annual CO/NO_x ratios near roadways during morning hours were calculated as 7.76 ± 0.10 at El Paso, 8.56 ± 0.17 at Houston, and 7.04 ± 0.19 at Fort Worth; these ratios are generally within the range of historic values calculated in previous studies. For all cases, CO/NO_x ratios based on MOVES default estimates were much lower than ambient-based ratios, ranging from 2.7 (Houston winter weekday) to 4.7 (Fort Worth summer weekday). Overall, using default inputs in MOVES consistently resulted in underestimation of observed ambient CO/NO_x ratios; this implies that, based on MOVES default input data, emissions estimates for CO or NO_x, or both pollutants, are not modeled correctly and do not reasonably represent on-road mobile sources in the emissions inventory.

When best available local (BAL) data inputs are used in MOVES, the resulting CO/NO_x ratios are in much better agreement with ambient-based ratios, though these ratios differed from the ambient ratios depending on the period and location. The ambient-based ratios are comparable to the MOVES emissions-based ratios for the annual and winter weekdays when local data inputs were used (within the acceptable 25-50% range of agreement): at the El Paso site, on average, the difference between ambient-based and MOVES-based ratios was within 24%; similar mean results were shown at Houston (within 19%) and Fort Worth (within 30%). In general, the comparison indicates the importance of using BAL MOVES inputs to generate more accurate emissions estimates. Both ambient- and emissions-based CO/NO_x ratios were higher in summer than in winter; this is expected given that near-road measurements indicate a larger increase in NO_x than in CO mixing ratios from summer to winter. However, CO/NO_x ratios modeled in MOVES exhibit a larger seasonal variation than ambient-based ratios.

The El Paso, Houston, and Fort Worth case studies in the emissions sensitivity analysis demonstrated the importance of replacing and improving MOVES default inputs with local data to allow a more robust assessment of on-road vehicle emissions. Among the MOVES input parameters tested in the sensitivity study, fleet mix and vehicle age distribution have larger effects than vehicle speed distribution and meteorological data on NO_x emissions estimates. Therefore, these input parameters should be of highest priority for data collection. The results from this study suggest that, when appropriate local data are used, MOVES can reasonably reflect mobile source emissions in the inventory; MOVES emissions-based ratios are comparable to the ratios derived from ambient measurements in reconciliation analyses. However, relying on MOVES default inputs can generate biased ratios and lead to incorrect emissions assessments and conclusions. The evaluation of the mobile source NO_x emissions inventory (e.g., the assessment of NEI in recent studies) should consider how MOVES default inputs are used and what their effect is on emissions estimates.

Recommendations

Further analysis will be useful, based on the existing emissions reconciliation and sensitivity analyses, to improve MOVES-based NO_x emissions estimates. Recommended studies include:

- Revisiting how MOVES emissions were developed and what key assumptions were made (especially related to MOVES default) in recent studies that concluded over-estimation of mobile source NO_x emissions in the NEI. An important practical issue to address is building the connection between EPA's NEI development and local emissions inventory development. Carefully designed assessment is needed to understand how default data were used in MOVES modeling for the NEI, and how the NEI can be improved by ensuring consistency with MOVES emissions inventories developed by state or regional air quality agencies using local data.
- Assessing more temporally and spatially refined MOVES emissions modeling results (e.g., by season, month, weekday vs. weekend, and facility type) to better understand the larger seasonal variation in MOVES emissions-based ratios.

Identifying challenges related to preparation of local MOVES input data, developing potential methods to fill local data gaps, and implementing the methods to improve local data use for the NEI and MOVES-based mobile source emissions inventories.

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Terminology

AADT	Annual average daily traffic
AERR	Air Emissions Reporting Rule
AQRP	Air Quality Research Program
AQS	Air Quality System
AVFT	Alternative Vehicle Fuels and Technologies
BAL	Best Available Local data
BL	Boundary layer
CDB	County Database
CDM	County Data Manager
CEMS	Continuous Emissions Monitoring Systems
CO	carbon monoxide
EP	El Paso (air quality monitoring site)
EPA	Environmental Protection Agency
FHWA	Federal Highway Administration
FW	Fort Worth (air quality monitoring site)
H-GAC	Houston-Galveston Area Council
HPMS	Highway Performance Monitoring System
HT	Houston (air quality monitoring site)
LST	Local Standard Time
MOVES	Motor Vehicle Emission Simulator
NCTCOG	Northern Central Texas Council of Governments
NCEI	National Centers for Environmental Information
NEI	National Emissions Inventory
NO	nitrogen monoxide
NO_2	nitrogen dioxide
NO_x	oxides of nitrogen
RH	Relative humidity
RVP	Reid vapor pressure
SQL	Structured Query Language
TCEQ	Texas Commission on Environmental Quality
TXDOT	Texas Department of Transportation
VMT	Vehicle Miles Traveled

1. Introduction

1.1 Research Background

Emissions inventories are key inputs to photochemical grid models in air quality modeling. Findings from recent studies evaluating ozone concentrations and emissions of ozone precursors suggested that nitrogen oxides (NO_x, the total of nitrogen monoxide, NO, and nitrogen dioxide, NO_2) emissions were overestimated in the U.S. Environmental Protection Agency's (EPA's) National Emissions Inventory (NEI). This overestimate was generally attributed to the mobile source sector (Fujita et al., 2012; Anderson et al., 2014; Canty et al., 2015), as NO_x emissions from power plants were thought to be well-characterized by Continuous Emissions Monitoring Systems (CEMS) data (Frost et al., 2006; Peischl et al., 2010). For example, a research project funded by the Air Quality Research Program (AQRP) used an inverse modeling approach to constrain NO_x emissions over Southeast Texas and estimated that mobile source NO_x emissions in the 2011 NEI should be reduced by a factor of two in Houston for modeling ozone in 2013 (Choi et al., 2015).

Mobile source emissions estimates are primarily developed using EPA's Motor Vehicle Emission Simulator (MOVES) model, which produces emissions and energy consumption estimates at the national, state, county, or project level. A U.S. national default database of input data is included in MOVES for all scales of analysis. However, EPA recommends that, where possible, these default data be updated with local inputs, such as vehicle miles traveled (VMT), VMT distributions by facility type, vehicle fleet age distributions, meteorological data, and fuel specifications (EPA, 2015). Studies evaluating NO_x overestimates in the NEI identified potential issues with MOVES, including the model's treatment of catalytic converter degradation (Anderson et al., 2014), cold-start activity (Wang, 2013), contributions from super-emitters within the fleet (Liu and Frey, 2015), and reliance on MOVES default data rather than more accurate local inputs (Koupal et al., 2014; Warila et al., 2017).

A method typically used to identify omissions or inaccuracies in an emissions inventory is comparing emissions data and ambient concentration data, often referred to as "emissions reconciliation." The basic approaches used to perform emissions reconciliation analyses have been in use for more than two decades (Fujita et al., 1992; Wallace et al., 2012). These approaches include selective, quantitative comparisons of metrics, such as carbon monoxide (CO)-to-NO_x (CO/NO_x) molar pollutant ratios, that are emissions-derived (e.g., using MOVES emissions output) and ambient-derived (based on monitored concentrations). Because of the inherent uncertainties associated with this analysis method, emissions- and ambient-derived ratios that are within approximately 25-50% of each other are usually considered to be in good agreement (California Air Resources Board, 1997). Larger differences may point to inaccuracies or biases in the emissions inventory; for example, emissions-derived CO/NO_x ratios that are lower than corresponding ambient-derived ratios may indicate that, in the emissions inventory, CO is underestimated, NO_x is overestimated, or both. Comparisons across multiple monitoring sites and pollutants can help to identify specific issues with the emissions data.

For mobile source analysis, the comparisons in a reconciliation analysis are typically developed for morning commute periods when vehicle emissions are high and mixing depths are low, minimizing the impact of confounding factors such as transported and chemically changed pollutants (e.g., Chinkin et al., 2005). Previous emissions reconciliation analyses have identified specific issues with on-road mobile source emissions estimates, such as improper characterization of weekend travel activity patterns for heavy-duty vehicles in the Upper Midwest (Reid et al., 2011). In a more recent reconciliation analysis performed in Houston, Texas, an overestimation of MOVES-based CO emissions from light-duty gasoline vehicles was found to contribute to higher CO/NO_x ratios compared to ambient measurements (Rappengluck et al., 2013).

1.2 Motivation and Objectives

Starting in 2014, the EPA mandated air quality monitoring next to selected major roadways throughout the United States; near-road air quality data for various pollutants, including CO and NO_x, have been collected by monitoring agencies in response to this mandate. Using these near-road air pollutant concentrations data, a recent national-scale review and assessment was performed as part of the Near-Road Air Quality Research Transportation Pooled Fund under the U.S. Federal Highway Administration (FHWA) Transportation Pooled Fund Program (DeWinter et al., 2015). These routinely collected near-road pollutant concentrations and assessment provide an important resource to support evaluation of mobile source emissions inventories and air quality impacts.

The objective of this project is to use near-road monitored concentration data to examine MOVES emissions estimates for NO_x at the local scale and identify which input parameters have the greatest influence on MOVES-based NO_x emissions estimates. Using emissions reconciliation and sensitivity analyses for three case studies in Texas, the analysis results of this work will support emissions inventory development and air quality management efforts by providing information on (1) the accuracy of current MOVES emissions estimates for NO_x, and (2) the MOVES input parameters for which local data collection is most important. This information will help planning agencies in Texas identify potential biases in existing on-road mobile source NO_x emissions estimates and prioritize data collection efforts for future MOVES-based emissions inventory development.

1.3 Report Organization

The remainder of this report is organized into three sections. Section 2 presents the method and results for the emissions reconciliation analysis, involving monitoring site selection, near-road air quality data processing, MOVES emissions modeling, and comparison of emission-based and ambient-based CO/NO_x ratios for the case studies in Fort Worth, Houston, and El Paso. Section 3 presents the method and results for the MOVES sensitivity analysis, including the development of MOVES modeling scenarios with different input parameters and changes in MOVES emissions estimates. Section 4 provides conclusions from this project and recommendations for future research on improving mobile source emissions inventories. In addition, the report includes three appendices with supporting information regarding data quality assurance and MOVES modeling scenarios.

2. Emissions Reconciliation

A CO and NO_x emissions reconciliation analysis was performed at three urban near-road sites in Texas: El Paso, Houston, and Fort Worth. In this reconciliation analysis, a regression approach was used to derive ambient CO/NO_x ratios, with the data selection process targeting morning commute hours when the monitoring sites were downwind of the adjacent roadway. The MOVES model (MOVES2014a) was used to model on-road mobile source CO and NO_x emissions on an annual and seasonal basis using national default and county-level local inputs. The ambient- and emissions-based CO/NO_x ratios were compared.

2.1 Case Study Settings

As shown in Table 1 and Figure 1, the three sites selected in this study are located in different counties across the state of Texas and are near major roadways: El Paso (EP), Houston (HT), and Fort Worth (FW). All monitoring sites are operated by the TCEQ.

- The Ascarate Park Southeast monitoring site, located 125 m from the Loop 375 Expressway in central El Paso, was selected for the case study. Although the nearby roadway has a relatively low annual average daily traffic (AADT), this EP site is primarily influenced by on-road emissions sources with simple geometry (a straight transect from northwest to southeast) and surrounding pollutant emission sources other than mobile sources are limited.

- The HT site is part of the U.S. EPA near-road monitoring network and, as required, is sited within 50 meters of the edge of the roadway (EPA, 2012). The HT site is located on the north side of Interstate-610 (I-610), approximately 1 kilometer west of the I-610/I-45 interchange in north Houston. The area is characterized by residential housing, with some low-rise commercial activities to the north and on the south side of I-610.

- The FW site is also part of the U.S. EPA near-road monitoring network and is located on the north side of I-20, approximately 1.5 km west of the I-20/I-35W interchange in south Fort Worth. Land use is mainly residential within 500 meters of this site.

Table 1. Site location information. Longitude is positive East, and latitude is positive North, and d is the distance between the target road and the monitor. AADT values are based on 2015 data provided by EPA (2017) for Houston and Fort Worth, and on 2015 data provided by the Texas Department of Transportation (Texas DOT, 2015).

Site	City	AQS ID	Longitude	Latitude	Local site name	County	Target road	d (m)	AADT
EP	El Paso	481410055	-106.40	31.75	Ascarate Park Southeast	El Paso	Loop 375	125	40,790
HT	Houston	482011052	-95.39	29.81	Houston North Loop	Harris	I-610	15	202,120
FW	Fort Worth	484391053	-97.34	32.66	Fort Worth California Parkway North	Tarrant	I-20	15	184,680

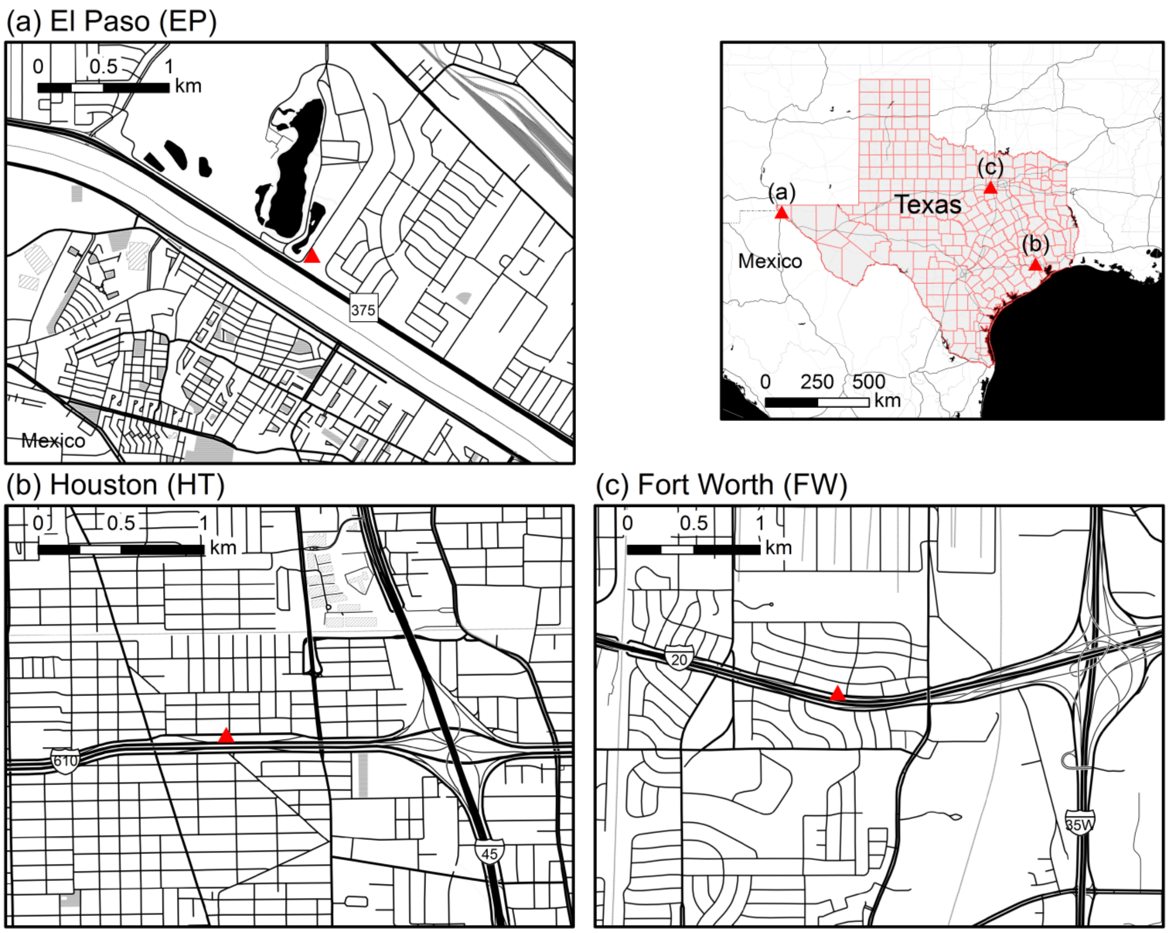

Figure 1. The three case study monitoring site locations (red triangles) in Texas (upper right) and in relation to nearby roads. In subplots (a), (b) and (c), roadways are drawn as black lines, with thicker lines representing larger roadways. Water bodies (black fill), and small park areas (dotted fill), and some larger buildings (hatched fill) are also indicated. Map data provided by Stamen Design and OpenStreetMap. See Figure B-1 for satellite imagery of sites.

2.2 Ambient Measurements

2.2.1 Data Collection

For each monitoring site, hourly CO, NO_x, and NO volume mixing ratios in units of parts per million (ppm) or parts per billion (ppb), wind speed, and wind direction during the period of January 1, 2015, through December 31, 2015, were acquired from the EPA's Air Quality System (AQS). Data from AQS is quality-assured by the submitting managing tribal, state, or local air monitoring agency. In this analysis, additional quality assurance was performed: (a) hourly NO_x was invalidated if NO_x < NO, (b) hourly CO was invalidated if CO < 0 ppb, and (c) periods with perceivable baseline drift of pollutant mixing ratios and/or instrument error were also excluded (see Table A-1). On an annual basis, excluding invalidated hourly data resulted in incomplete data (<75% completeness) for some seasons (see Table A-2). Other pollutants (e.g. $PM_{2.5}$) were not included in this analysis as hourly data were not available from the selected near-road monitoring sites over the observation time period.

The mean annual and mean seasonal diurnal time series of CO and NO_x are presented in Figure 2. In general, annual mean CO and NO_x mixing ratios were higher in the morning (between 06:00 LST and 08:00 LST) and early evening (between 17:00 LST and 21:00 LST). Morning peaks in CO and NO_x are higher in the winter (December, January, and February) than in the summer (June, July, and August). Higher wintertime mixing ratios of NO_x are expected, in part due to slower photochemical reactions and relatively low mixing heights leading to increased lifetime of ambient NO_2. VMT exhibits a similar timing of the morning peak to CO and NO_x on weekdays, but the afternoon peak is usually earlier (at 17:00 LST) at all three sites. On weekends, VMT follows a smooth diurnal profile, reaching a maximum in early afternoon.

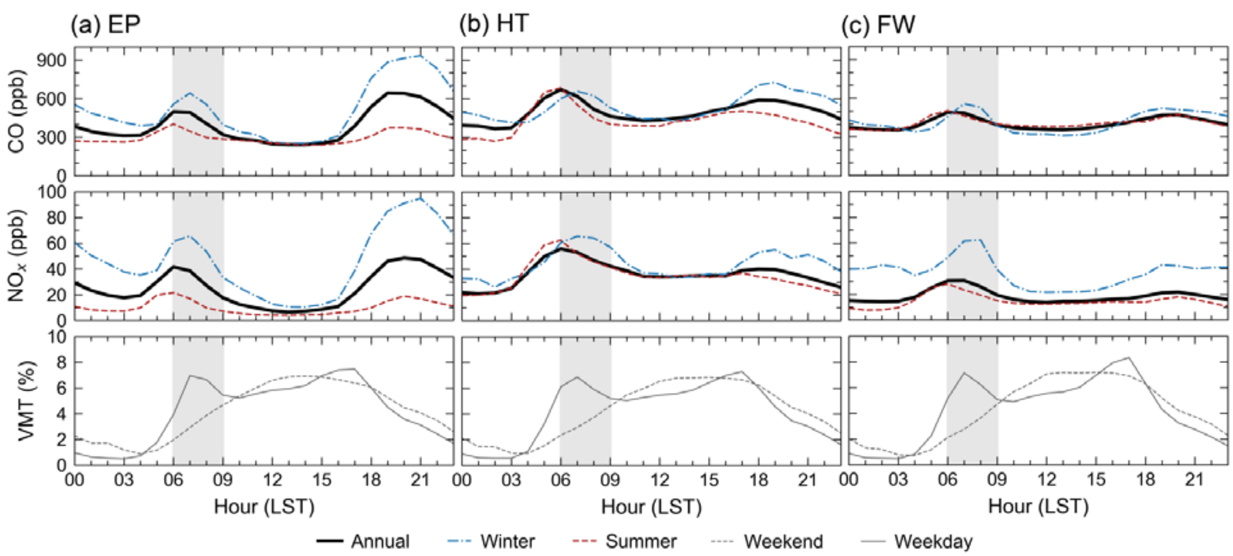

Figure 2. Mean diurnal profile of ambient hourly CO and NO_x and hourly VMT distributions (percentage of passenger cars on urban freeways). VMT data were provided by TCEQ. Shaded background from 06:00 LST to 09:00 LST indicates the range of data used in subsequent analyses in this study.

2.2.2 Data Selection

To compare ambient-based and emissions-based data in a reconciliation analysis, one of the key considerations is to identify ambient measurements that are most representative for the target emission sources. The following data selection approaches were implemented to correlate ambient measurements with the dominating on-road emission sources at the three monitoring sites; these approaches are conceptually similar to previous analyses of ambient mixing ratios (e.g., Parrish et al., 2006).

(1) Using monitoring sites close to the target roadway (<150 m) to ensure that CO and NO_x measurements can largely reflect impact from on-road emissions. Near-road concentrations typically decrease away from the road and may decrease by up to 50% within 150 m of the road (e.g., Karner et al., 2010).

(2) Using CO and NO_x measurements during the morning peak traffic time period (06:00 LST to 09:00 LST) to conduct ratio comparisons. First, the coincidence of peak mean CO and NO_x mixing ratios during this time suggests that on-road emissions are the dominant source. Second, the loss of NO_x (through conversions to ozone, nitric acid, and other nitrates) is limited in this time period due to the minimal influence of photochemistry. Third, as the atmospheric boundary layer (BL) is relatively shallow and generally stable in the morning, the effects of vertical mixing and dilution are constrained, and pollutant concentrations within the BL are relatively high; the impact from non-mobile source emissions (e.g., from industrial stacks with release height above the BL) can be reasonably assumed to be negligible during this period.

(3) Using CO and NO_x measurements obtained when the monitoring sites were downwind of the target roadway (i.e., the on-road mobile source). To classify upwind versus downwind directional ranges for morning hours at the EP, HT, and FW sites, wind speed and direction data were used to construct wind roses and pollution roses, using 22.5° bin ranges (within the range of accuracy of hourly wind direction measurements).

    - Wind directions in EP during morning hours were primarily from the west or had a southeasterly component (Figure 3a). NO_x mixing ratios greater than 100 ppb also occurred when the wind was from the southeasterly sector. Due to the northwest-to-southeast orientation of the target roadway to the EP site, the downwind range was selected such that it encompassed both southeasterly and westerly wind directions (78.75° – 307.75°).
    - At the HT site, wind directions were most prevalent from the eastern sectors in the morning, which corresponded to the largest portion of NO_x mixing ratios over 100 ppb (Figure 3b). As expected, the majority of NO_x mixing ratios when the wind was from the south were relatively high (>50 ppb) due to the proximity of the roadway. The downwind range for the HT site was selected to capture all westerly and southerly directions (348.75° – 191.25°).

- At the FW site, the highest frequency of wind directions occurred from the southeast to southwest (Figure 3c). NO_x mixing ratios measured at FW exceeded 100 ppb from all wind quadrants. Given the slight southerly curvature of the adjacent roadway, wind directions between 78.75° to 281.25° were selected to correspond to downwind directions for pollutant transport at this location.

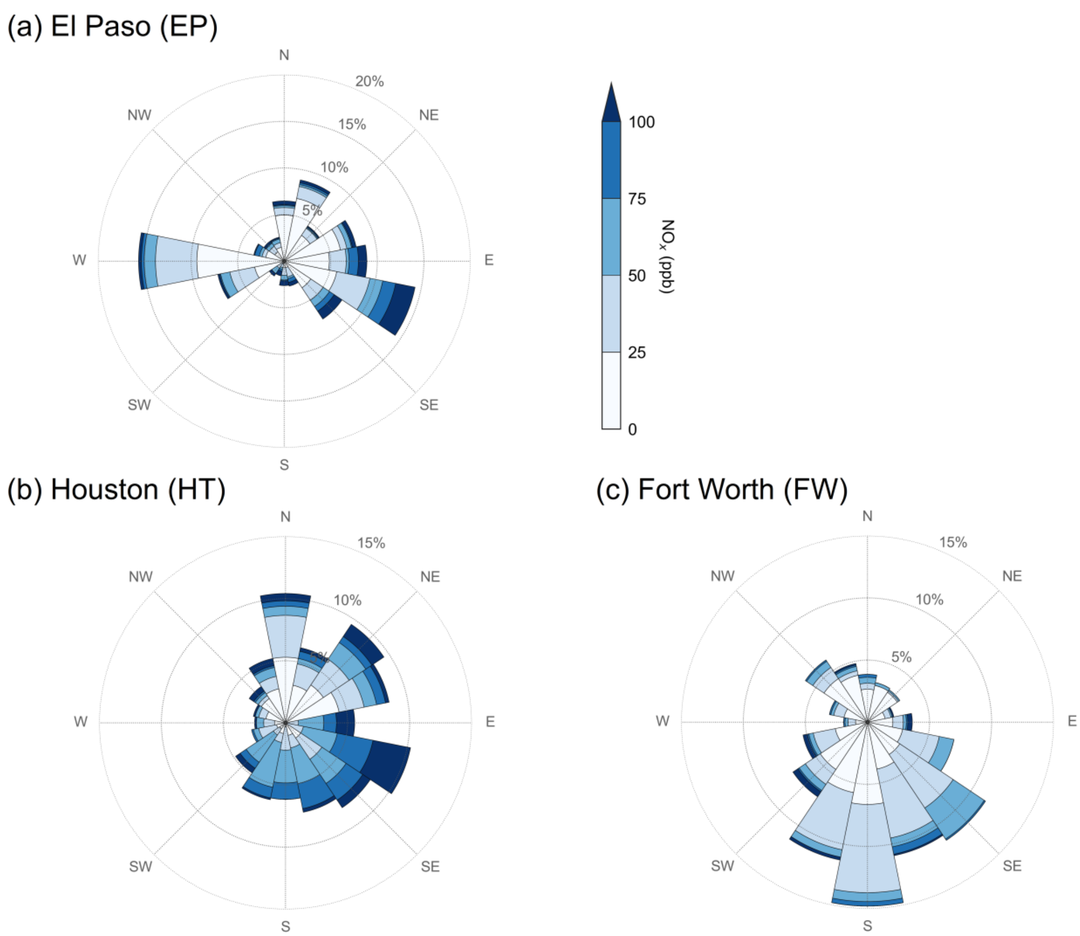

Figure 3. Distribution of NO_x mixing ratios as a function of wind direction for morning hours (06:00 LST to 09:00 LST) in 2015 as a pollution rose. The wind direction is represented as the angular component, the percentage of data records is represented by the radial component, and NO_x mixing ratios are represented by the color scale shown in the upper right.

The downwind ranges were also assessed by examining the distribution of NO_x mixing ratios. The downwind mean NO_x mixing ratios were generally higher than the upwind mean NO_x mixing ratios for each site (Figure 4). The downwind and upwind median NO_x mixing ratios were statistically different at the EP and FW sites; however, the downwind and upwind median NO_x mixing ratios were not statistically different at the HT site, where high NO_x mixing ratios (>100 ppb) occurred when winds were from the northeast and east (likely influenced by another nearby major roadway).

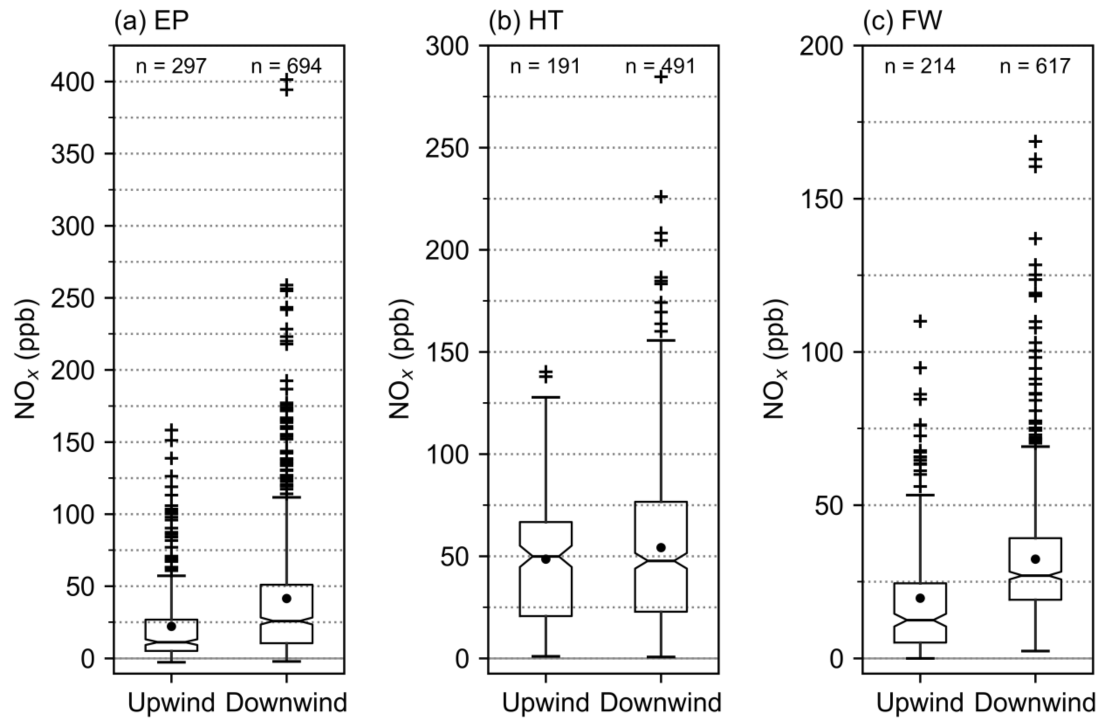

Figure 4. Distribution of NO_x mixing ratios from 06:00 LST to 09:00 LST when the monitor was located upwind and downwind of the target road. Outliers are indicated by crosshairs; the mean NO_x mixing ratio is represented by a black circle. The number of observations (n) used to compute the ambient statistics is shown above each data set.

2.2.3 Inferring Emissions Ratios from Ambient Measurements

The ambient-based CO/NO_x ratios were determined using regression techniques similar to those employed by Parrish et al. (2002) and Luke et al. (2010). The main assumption in this regression technique is that the ambient CO measurements are heavily influenced by background CO levels, since CO is long-lived in the lower atmosphere (~1-3 months). Furthermore, the influence of background NO_x levels on ambient NO_x measurements is minimal, given that the photochemical lifetime of NO_x is short (~2-6 hours), and pollutant concentrations are dominated by on-road emission sources in the morning hours. In this study, a total linear least-squares regression was used, which accounts for errors in both CO and NO_x measurements. The measurements were not weighted, as the uncertainties (which depend on the instruments used) were not quantified. The slope of the fit between the CO and NO_x mixing ratios indicates the ratio of these emissions, and the intercept approximates a regional CO level (see Table B-2).

This regression technique was applied to the annual, summer (June, July, August), and winter (December, January, February) data at each site, where weekend and weekday CO/NO_x ratios were computed separately by season.

2.3 MOVES Modeling

2.3.1 Scenario Configuration and Data Input

The U.S. EPA MOVES2014a model (EPA, 2015) was run at the county scale for each county where the monitoring sites were located. Emissions of CO, NO, and NO_2 were aggregated by hour for all months and days in 2015 from 06:00 LST to 09:00 LST. All vehicle types and road types were included, though only the results from urban restricted-access roads (i.e., freeways as opposed to surface streets) were analyzed (since the monitoring sites are adjacent to freeways). Running exhaust and crankcase running exhaust emissions were modeled, since the air quality at the near-road site is primarily influenced by the running exhaust emissions of vehicles travelling on the freeway (instead of start or idle exhaust emissions from local roads). Further configuration details are provided in Appendix B.

The modeling was performed using MOVES national defaults (the “Default” scenario) and using the best available local (BAL) data (the “Base” scenario). The default scenario was based on the MOVES2014a database (movesdb20161117), which include national default inputs, such as the default meteorological inputs derived from average hourly temperature and relative humidity (RH) data from the National Centers for Environmental Information (NCEI, formerly the National Climatic Data Center) over the period 2001 to 2011. The BAL data inputs were acquired from local planning agencies (see Table A-5). These inputs reflect the best available local data used for the MOVES County Database (CDB), as well as local travel activity data for the target roadways next to the EP, HT, and FW monitoring sites (i.e. on Loop 375, I-610, and I-20, respectively).

Acquiring local data from multiple sources introduced data inconsistency and incompleteness issues. For example, the latest MOVES modeling inputs for Tarrant County (where Fort Worth is located) were 2017 (instead of 2015) data, obtained from the Northern Central Texas Council of Governments (NCTCOG); the 2015 travel activity from the Texas Department of Transportation (TXDOT) contains AADT percentages for combination trucks and single unit trucks, but not for other vehicle types (e.g., passenger cars and passenger trucks). To address these issues, the acquired local data were evaluated, prioritized, and then reconciled to prepare the BAL inputs for MOVES CDBs. The general approach is to use the latest data as much as possible, maintain the integrity of the MOVES CDBs, and apply adjustment to outdated travel activities. Table 2 includes a summary of the MOVES modeling scenarios with data sources for the BAL CDBs. Additional details about compiling MOVES CDBs are provided in Appendix B.

Table 2. Base scenarios and BAL data sources and adjustments for CDBs.

Site	County	MOVES County ID	Season/Day	Data Source	MOVES CDB Preparation
EP	El Paso	48141	Annual, Summer Weekday, Winter Weekday	2014 TCEQ MOVES CDB 2015 TXDOT Roadway Inventory	1. Use 2014 TCEQ CDBs for 2015 modeling scenario. 2. Use TXDOT 2015 Roadway Inventory data to reflect El Paso peak-time truck percentage in MOVES VMT by vehicle class inputs.
HT	Harris	48201	Annual, Summer Weekday	2014 TCEQ CDB 2015 H-GAC CDB	1. Use 2014 TCEQ CDBs for 2015 modeling scenario. 2. Update the MOVES input tables with local data from H-GAC, including source age distribution, I/M coverage, Alternative Vehicle Fuels and Technologies (AVFT), fuel usage fraction, fuel supply, and fuel formulation (summer scenario only). 3. Use TXDOT 2015 Roadway Inventory data to reflect Houston peak-time truck percentage in MOVES VMT by vehicle class inputs.
FW	Tarrant	48439	Annual, Summer Weekday	2015 TXDOT Roadway Inventory 2017 NCTCOG CDB	1. Use 2017 NCTCOG CDBs for 2015 modeling scenario. 2. Update the MOVES input tables with data from TCEQ 2014 CDBs, including fuel supply, fuel formulation, AVFT, fuel usage fraction (summer scenario only), and meteorology. 3. Use TXDOT 2015 Roadway Inventory data to reflect Fort Worth peak-time truck percentage in MOVES VMT by vehicle class inputs.

2.3.2 MOVES-Based Emissions Ratios

The emission-based CO/NO_x ratios were derived from annualized molar CO and NO_x emissions. Mass-based emissions of CO, NO, and NO_2 by source type and fuel type were aggregated for urban restricted-access roads and for running and crankcase exhaust emissions. To compare ambient- and emissions-based data, the MOVES emissions were converted from a mass basis to a molar basis. The molar NO and NO_2 emissions were summed together to derive molar NO_x emissions. Finally, CO/NO_x ratios were calculated by dividing molar CO emissions by molar NO_x emissions.

2.4 Comparison of Ambient- and Emissions-Based CO/NO_x Ratios

Regression results from all time periods are illustrated in Figure 5 and summarized in Table 3. The annual CO/NO_x ratios from vehicle emissions during morning hours were 7.76 ± 0.10 at EP, 8.56 ± 0.17 at HT, and 7.04 ± 0.19 at FW.

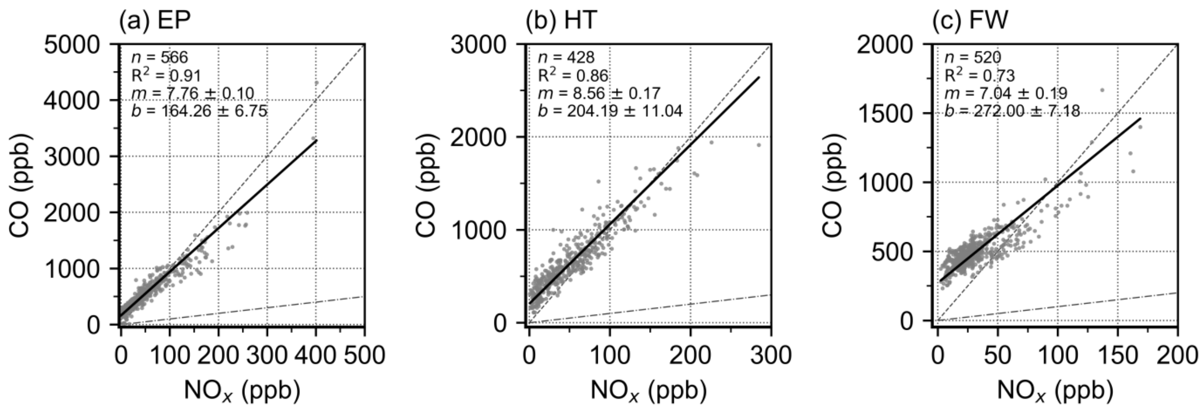

Figure 5. Ambient NO_x and CO mixing ratios from 06:00 LST to 09:00 LST when the monitoring site was downwind of the target road in 2015. The annual regression results are displayed (black line), where *n* is the number of data points, *m* is the slope of the regression, *b* is the intercept, and R^2 is the coefficient of determination from a simple linear regression. The standard error of *m* and *b* are also provided. CO/NO_x ratio lines of 10-to-1 (dotted) and 1-to-1 (dash-dotted) are plotted for reference.

Table 3. Results of regression between ambient CO and NO_x mixing ratios from 06:00 LST to 09:00 LST when the monitoring site was downwind of the target road. Annual ambient results and MOVES output include data from all days of the week; summer and winter data were computed separately for weekdays and weekends. Slopes and intercepts are expressed as the estimated value and standard error of the value. R^2 values are based on simple linear regressions. The mean is the mean $\Delta CO/NO_x$ ratio determined from the regression analysis, where n_m is the number of samples used to calculate the value. MOVES values are CO/NO_x ratio based on molar mass. A hyphen indicates that modeling results were unavailable (BAL input was not provided for weekends).

Site	Season	Day	n	Slope	Intercept	R^2	Mean	n_m	MOVES Default	MOVES BAL Base
EP	Annual	All	566	7.76 ± 0.10	164.3 ± 6.8	0.91	8.6	547	3.3	6.4
	Summer	Weekday	60	8.64 ± 0.32	195.1 ± 10.2	0.93	8.8	60	4.0	7.9
		Weekend	30	11.65 ± 2.19	189.4 ± 22.1	0.50	13.9	30	-	-
	Winter	Weekday	109	7.01 ± 0.19	150.9 ± 20.2	0.92	8.7	106	3.1	5.5
		Weekend	46	9.24 ± 0.26	99.8 ± 26.5	0.97	12.5	45	-	-
HT	Annual	All	428	8.56 ± 0.17	204.2 ± 11.0	0.86	10.6	413	3.3	7.4
	Summer	Weekday	55	8.31 ± 0.58	211.7 ± 42.7	0.79	9.1	55	4.4	9.6
		Weekend	27	9.63 ± 0.69	287.5 ± 28.6	0.88	10.0	27	-	-
	Winter	Weekday	48	7.53 ± 0.23	167.7 ± 20.2	0.96	7.2	47	2.7	5.6
		Weekend	14	10.24 ± 1.34	56.3 ± 80.6	0.83	12.0	14	-	-
FW	Annual	All	520	7.04 ± 0.19	272.0 ± 7.2	0.73	8.2	515	3.5	10.2
	Summer	Weekday	173	9.17 ± 0.39	234.1 ± 11.0	0.77	9.4	173	4.7	15.2
		Weekend	53	12.06 ± 1.13	254.4 ± 19.0	0.69	12.8	53	-	-
	Winter	Weekday	42	7.76 ± 0.51	109.4 ± 42.2	0.85	8.3	42	3.0	8.0
		Weekend	12	4.98 ± 0.72	223.9 ± 24.4	0.82	5.4	12	-	-

The ambient-based annual CO/NO_x ratios derived in this study are generally within the range of historic values developed in previous studies. For example, Parrish et al. (2009) showed that ambient-based CO/NO_x ratios at an El Paso urban site decreased from approximately 12 to 8 from 2000 to 2005; the study also showed the ratios decreased from approximately 7.5 to 6 at a Houston site over the same period. The ambient-based summer CO/NO_x ratios developed in this study (e.g., 8.31 for weekdays and 9.63 for weekends at the HT site) are higher than those in other studies (e.g., 5.81 with morning hour measurements at a Houston site from August to October 2006, and 6.01 with morning hour measurements at a Houston site from July to October 2009 (Luke et al., 2010; Rappengluck et al., 2013). However, a direct comparison of ambient-based CO/NO_x ratios between this study and previous studies is rendered difficult, because no near-road sites were used before and there is a large variation in data processing approaches among different studies (e.g., selection of time periods, calculation of seasonal averages, and regression techniques). In addition, ambient-based CO/NO_x ratios are also changing over time. The ambient total fleet CO/NO_x ratios may slightly increase in the future due to decreasing rates of CO emissions from gasoline vehicles and increased controls on NO_x emissions from diesel vehicles (e.g., McDonald et al., 2013).

From the regression analysis of ambient CO and NO_x data, the intercept was subtracted from CO mixing ratios to obtain ΔCO values, which effectively separates the influence of regional CO levels from on-road vehicle emissions. The arithmetic mean ambient $\Delta CO/NO_x$ ratio is most comparable to MOVES emission-based CO/NO_x ratios, because the MOVES emissions results account only for on-road emissions (i.e., no influence of background values) averaged over the entire fleet and modeling time period (i.e., annual, summer, winter). A comparison between the ambient $\Delta CO/NO_x$ ratios and MOVES-based CO/NO_x ratios for both default and base case modeling scenarios are presented in Figure 6 for annual, summer weekday, and winter weekday periods (BAL data input for MOVES was not provided for weekends).

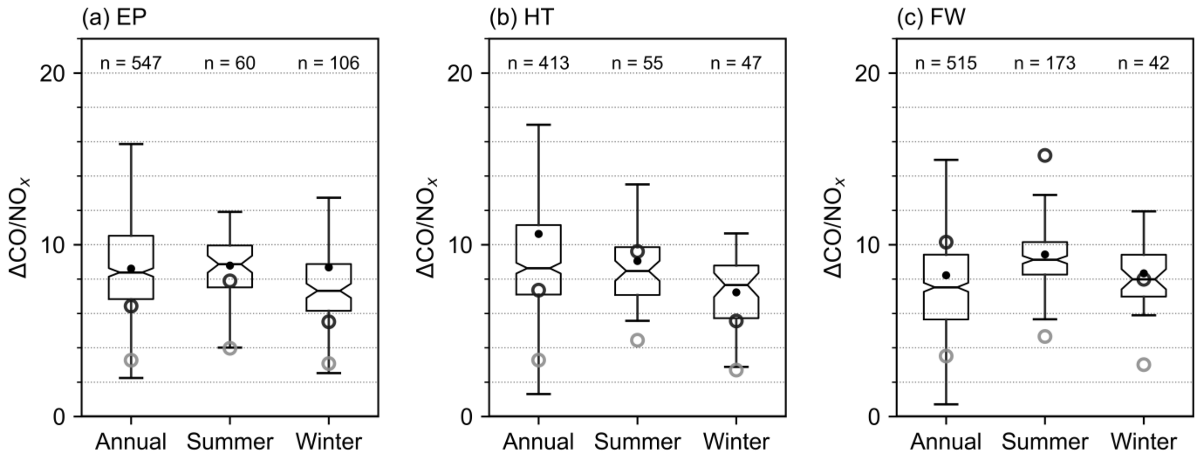

Figure 6. Distribution of $\Delta CO/NO_x$ ratios calculated from ambient data from 06:00 LST to 09:00 LST when the monitoring site was downwind of the target road and when CO mixing ratios exceeded background CO values determined by regression analysis. Median $\Delta CO/NO_x$ ratios are indicated by a horizontal line, and mean $\Delta CO/NO_x$ ratios are indicated by a solid black circle. The extents of the whiskers represent 1.5 times the interquartile range. Outliers are omitted for clarity. The number of observations (n) used to compute the ambient statistics is shown above each data set. MOVES modeling results using default (open gray circle) and base (open black circle) scenario data inputs are also displayed. Annual ambient data and MOVES output include data from weekends and weekdays; summer and winter data are for weekdays only.

For all cases, CO/NO_x ratios based on MOVES default estimates are much lower than ambient-based ratios, ranging from 2.7 (HT winter weekday) to 4.7 (FW summer weekday). More than 75% of ambient $\Delta CO/NO_x$ ratios are higher than MOVES default estimates. The largest difference was between the annual mean $\Delta CO/NO_x$ ratio in HT (10.6) compared to MOVES default CO/NO_x for the same period (3.3). Overall, using default inputs in MOVES consistently results in underestimation of CO/NO_x ratios, implying that CO emissions are underestimated and/or NO_x emissions are overestimated from on-road mobile sources. This finding aligns with inventory evaluations discussed in other studies (e.g. Fujita et al., 2012; Kota et al., 2014).

However, when BAL data inputs are used in MOVES (base scenario), the resulting CO/NO_x ratios are in much better agreement with ambient-based ratios, though these ratios differed from the ambient ratios depending on the period and location. The annual and winter weekday MOVES base ratios are comparable with the respective ambient ratios (within the acceptable 25-50% range of agreement: at the EP site, on average, the difference between ambient-based and MOVES-based ratios was within 24%; similar mean results were shown at HT (within 19%) and FW (within 30%). In general, the comparison indicates the importance of using best available local MOVES inputs to generate more accurate emissions estimates, as discussed in recent studies such as Koupal et al. (2014) and Warila et al. (2017).

Both ambient- and emissions-based CO/NO_x ratios were higher in summer than in winter. This is expected given that near-road measurements indicate a larger increase in NO_x than in CO mixing ratios from summer to winter. However, CO/NO_x ratios modeled in MOVES exhibit a larger seasonal variation than ambient-based ratios. For example, a large discrepancy between ambient- and MOVES-based ratios was found for summer weekdays in FW: the ambient ratio was 9.4 (comparable to the annual and winter weekday ratios, as well as the slope of the regression analysis), while the MOVES base ratio was much higher (15.2). For EP, the differences between the MOVES default and base summer weekday and winter weekday CO/NO_x ratios were approximately 0.90 and 0.24, respectively; the seasonal difference based on mean ambient ratios was only 0.1.

Based on the current analysis, it is difficult to discern which parameters in MOVES may cause this pronounced seasonal variation. As fleet mix and average speed are relatively constant through the year, parameters in MOVES that vary more by season include temperature and RH, which in turn affect other activity- and fuel-related parameters. For running exhaust emissions of CO and NO_x, increased RH reduces NO_x emissions by lowering peak combustion temperature (EPA, 2014). Conversely, the use of air conditioning units (which is more prevalent in warmer months, where the fraction of the fleet with air conditioning units that will be used depends on temperature and RH) also increases NO_x emissions. Based on the BAL data inputs used in this study, gasoline fuel types also vary by season; for example, lower Reid vapor pressure (RVP) in summer months will lead to reductions in running exhaust CO and NO_x emissions. Given these competing factors, further analysis is needed to understand the magnitude of seasonal variation of MOVES CO/NO_x ratios.

3. Emissions Sensitivity Analysis

While results based on BAL data inputs in MOVES suggested good agreement between emissions-based and ambient-based CO/NO_x ratios at all three sites, it is important to further examine the sensitivity of NO_x emissions estimates to various MOVES modeling parameters. In an evaluation of MOVES input data submitted to 2011 NEI, it was found that CO and NO_x emissions of all processes were highly influenced by vehicle age distribution, vehicle population, and combination truck VMT (Koupal et al., 2014). NO_x emissions are also affected by meteorological conditions (EPA, 2014). In this study, fleet mix, vehicle age, average speed, and meteorology were selected as key testing parameters in MOVES. Instead of testing a full range of changes in the selected MOVES input parameters, this analysis focused on changes in NO_x emissions and CO/NO_x ratios against selected levels of MOVES parameter values. For each of the three case study sites, MOVES modeling scenarios were developed and changes in NO_x emissions and CO/NO_x ratios were quantified with respect to fleet mix (truck percentage), vehicle speed (VMT by speed distribution), vehicle age (VMT by age distribution), and meteorology (ambient temperature and relative humidity).

3.1 Sensitivity Testing Scenarios

As shown in Table 4, a base scenario and 18 MOVES sensitivity test scenarios were developed for each of the three analysis areas to represent specific MOVES modeling context with various levels of selected input data. These scenarios include:

- Base: a scenario using BAL data inputs, as described in Section 2.3.
- Base-Default: a reference scenario in which the test input parameter was set as the MOVES default value and the BAL data were used for all other inputs.
- Truck %: scenarios where fleet mix varies by truck percentage (VMT proportions for single unit trucks and combination trucks), from 0% to 30%.
- Speed Distribution: scenarios with different VMT by speed distribution assumptions. The speed distribution data in the TCEQ MOVES CDBs prepared under the 2014 Air Emissions Reporting Rule (AERR) for multiple counties or county groups in Texas were evaluated to construct low (“Speed Low”), medium (“Speed Medium”), and high (“Speed High”) speed distribution categories (see Appendix C for details).
- Age Distribution: scenarios with different VMT by vehicle age distribution assumptions. The age distribution data in the TCEQ MOVES CDBs prepared under 2014 AERR for multiple counties or county groups in Texas were evaluated to construct new (“Age New”), medium (“Age Medium”), and old (“Age Old”) vehicle fleets (see Appendix C for details).

- Seasonal Meteorology: scenarios with temperature and RH data derived from different averaging approaches: half-year season window ("Season Half"; November–April for winter and May–October for summer), 3-month season window ("Season Quarter"; December–February for winter and June–August for summer), and 1-month season representation ("Season Month"; January for winter and July for summer).

Table 4. Summary of MOVES sensitivity testing scenarios.

Scenario	**Truck %**	**Speed Distribution**	**Age Distribution**	Seasonal Meteorology
Base	BAL	BAL	BAL	BAL
Truck Base-Default	Default	BAL	BAL	BAL
Truck 0	0	BAL	BAL	BAL
Truck 5	5	BAL	BAL	BAL
Truck 10	10	BAL	BAL	BAL
Truck 20	20	BAL	BAL	BAL
Truck 30	30	BAL	BAL	BAL
Speed Base-Default	BAL	Default	BAL	BAL
Speed Low	BAL	Low	BAL	BAL
Speed Medium	BAL	Medium	BAL	BAL
Speed High	BAL	High	BAL	BAL
Age Base-Default	BAL	BAL	Default	BAL
Age Old	BAL	BAL	Old	BAL
Age Mid	BAL	BAL	Mid	BAL
Age New	BAL	BAL	New	BAL
Season Base-Default	BAL	BAL	BAL	Default
Season Half	BAL	BAL	BAL	6 month mean
Season Quarter	BAL	BAL	BAL	3 month mean
Season Month	BAL	BAL	BAL	1 month mean

3.2 Sensitivity Testing Results

3.2.1 Fleet Mix

In addition to the base scenario and the scenario with MOVES national default truck percentage, five MOVES modeling scenarios were conducted to examine the impact of varying fleet mix (truck percentage ranging from 0% to 30%) on NO_x emissions during morning hours for each study area. As shown in Figure 7, within the range of truck VMT percentages tested, there is a positive linear relationship between NO_x emissions and fleet average truck percentage. An increase in truck traffic by 1% resulted in an increase in NO_x emissions by approximately 13% at EP, 16% at HT, and 10% at FW. NO_x

emissions from the Base-Default scenario deviate slightly from this relationship; this is because both the truck percentage and the fleet mix of other vehicle types (e.g., passenger cars, passenger trucks, and buses) in the MOVES default inputs are also different from the base scenario and other testing scenarios.

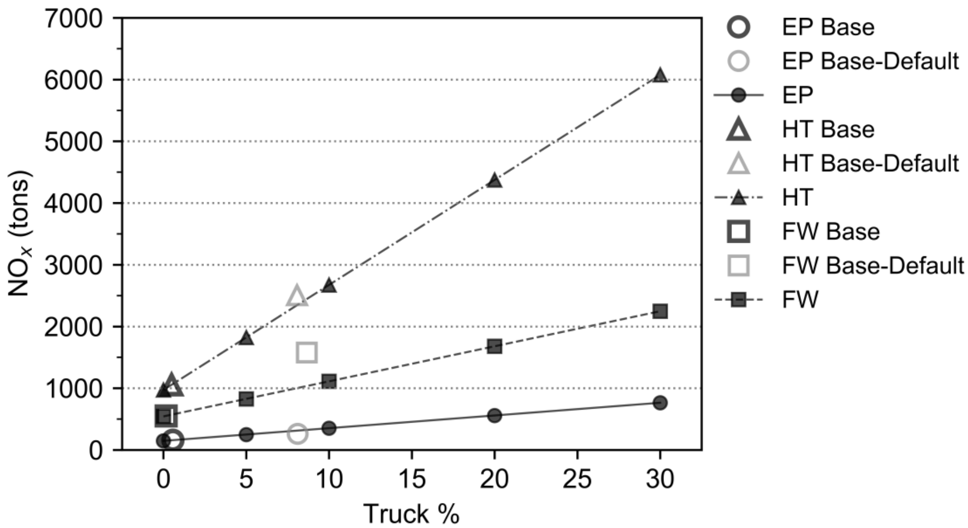

Figure 7. Annual morning peak time NO_x emissions for fleet mix scenarios by fleet average truck percentage. Solid markers indicate the results for each sensitivity run using BAL data inputs for all other parameters examined.

The MOVES emissions-based CO/NO_x ratios decrease with increased truck percentage at a similar rate among the three analysis areas. As shown in Figure 8, the rate of the decrease is larger when truck percentage is low (<10%; see Appendix C), given that NO_x emissions are more sensitive than CO emissions to truck percentage.

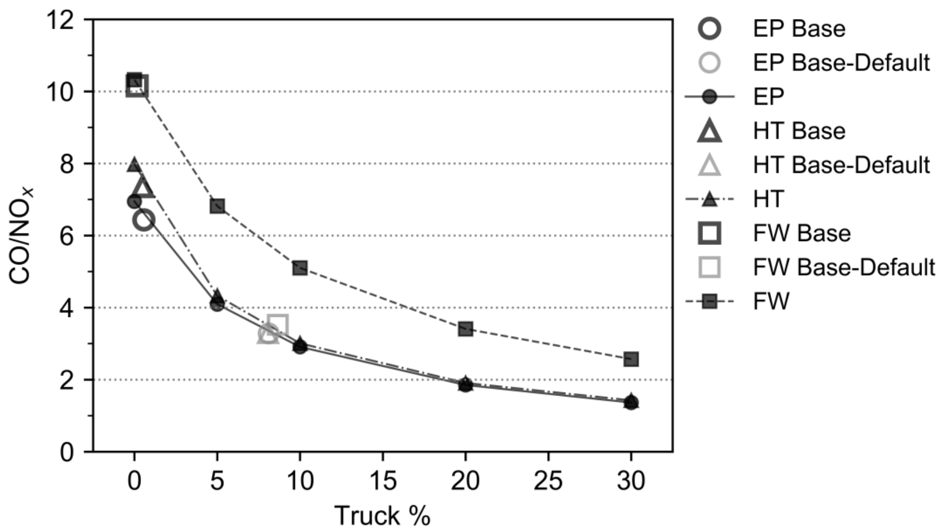

Figure 8. Annual morning peak time CO/NO_x ratios for fleet mix scenarios by fleet average truck percentage. Solid markers indicate the results for each sensitivity run using BAL data inputs for all other parameters examined.

3.2.2 Vehicle Speed

The speed testing scenarios involve different levels of speed between 40 and 70 mph that reflect fleet average (not for individual vehicles). Within the average speed range tested, NO_x emissions are not sensitive to speed change; the emissions increased slightly as fleet average vehicle speed increased (Figure 9), showing that MOVES NO_x emissions are not very sensitive to fleet average speed. The relationship between NO_x emissions and fleet average speed is not linear; this is similar to the relationship between NO_x emissions and speed of individual vehicles, which shows higher NO_x running exhaust emissions at low speeds (e.g., $<$30 mph) and high speeds (e.g., $>$70 mph). The Base-Default scenario had much higher NO_x emissions estimates than other testing scenarios, especially for the HT and FW areas.

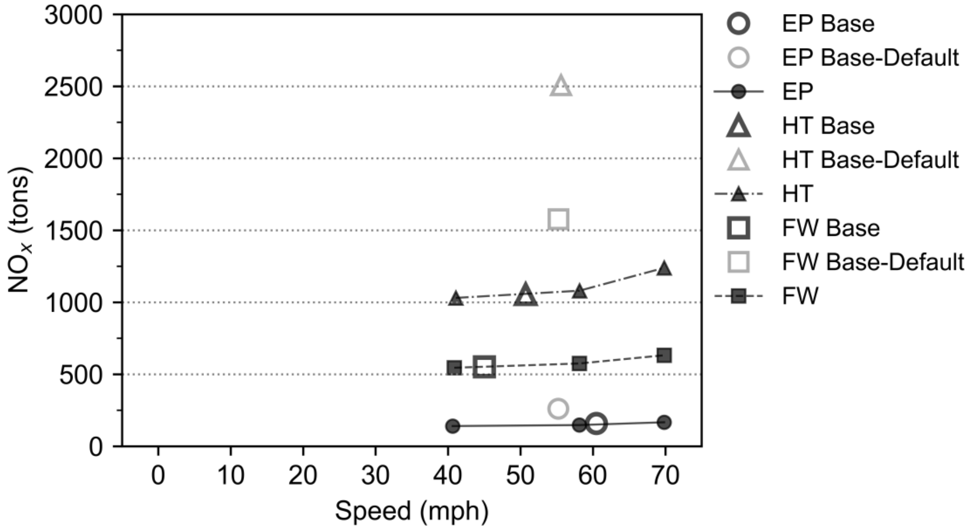

Figure 9. Annual morning peak time NO_x emissions for vehicle speed scenarios by fleet average speed. Solid markers indicate the results for each sensitivity run using BAL data inputs for all other parameters examined.

CO/NO_x ratios showed small variation with respect to changes in fleet average speed within the range examined in the three analysis areas (Figure 10). At EP and HT, CO/NO_x ratios exhibit a slight non-linear relationship, where CO/NO_x ratios decrease from 40 mph to approximately 55 mph, and then increase up to 70 mph. In contrast, CO/NO_x ratios for FW decrease by fleet average speed over this entire range. The CO/NO_x ratios modeled using all BAL data inputs (Base) are within the range of the sensitivity analysis, whereas those modeled under Base-Default inputs are much lower at all three sites.

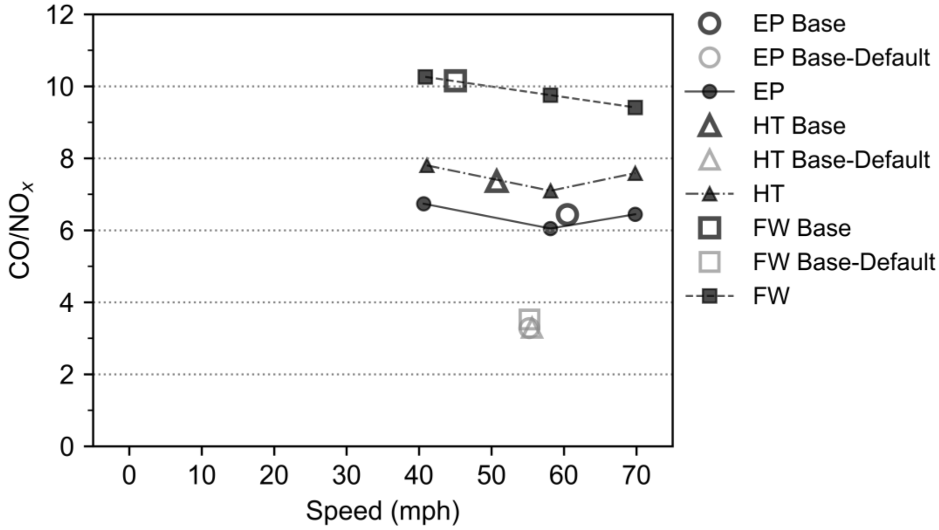

Figure 10. Annual morning peak time CO/NO_x ratios for vehicle speed scenarios by fleet average speed. Solid markers indicate the results for each sensitivity run using BAL data inputs for all other parameters examined.

3.2.3 Vehicle Age

In addition to the Base and Base-Default scenarios, three MOVES modeling scenarios that reflect different levels of fleet average age were modeled. Within the range of tested fleet average ages between 7 and 10 years old, NO_x emissions and fleet average age showed a nearly linear relationship (see Figure 11). The changing rates of NO_x emissions varied by analysis area. For example, an increase in fleet average age by 1 year resulted in up to a 20% increase in NO_x emissions at FW; NO_x emissions changes against fleet age distribution are smaller at EP. NO_x emissions from the Base-Default scenario were much higher than from other scenarios, especially at HT and FW.

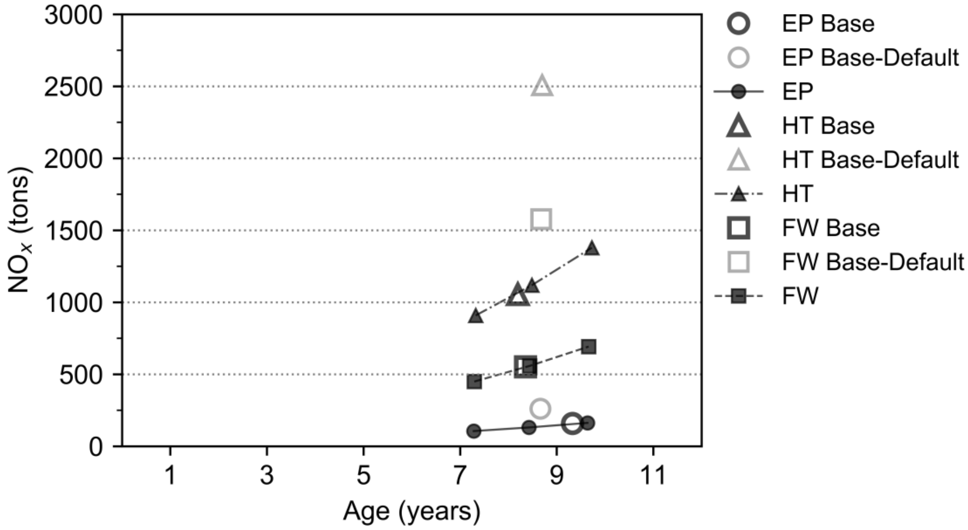

Figure 11. Annual morning peak time NO_x emissions for vehicle age scenarios by fleet average age. Solid markers indicate the results for each sensitivity run using BAL data inputs for all other parameters examined.

The MOVES emissions-based CO/NO_x ratios decrease as average fleet age increases for all three areas (Figure 12). Within the range of average fleet ages examined (7 to 10 years), every 1 year increase in fleet average age was associated with a decrease ranging from 4% to 14% in CO/NO_x ratios.

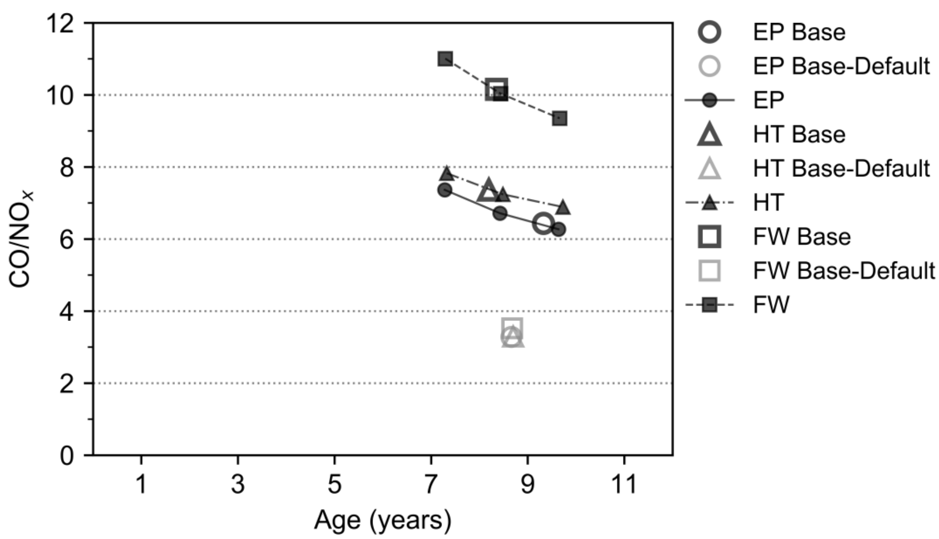

Figure 12. Annual morning peak time CO/NO_x ratios for vehicle age scenarios by fleet average age. Solid markers indicate the results for each sensitivity run using BAL data inputs for all other parameters examined.

3.2.4 *Meteorology*

The five modeling scenarios with different meteorology data include the Base (local data) and Base-Default (MOVES default meteorological data), and three testing cases that reflect different calculation approaches for developing average ambient temperature and RH inputs (see Table C-1). As shown in Figure 13, changes in NO_x emissions with different meteorological inputs were minimal. As with the testing results for other input parameters, higher NO_x emissions were generated for all three analysis areas when the MOVES default inputs for meteorological conditions were used.

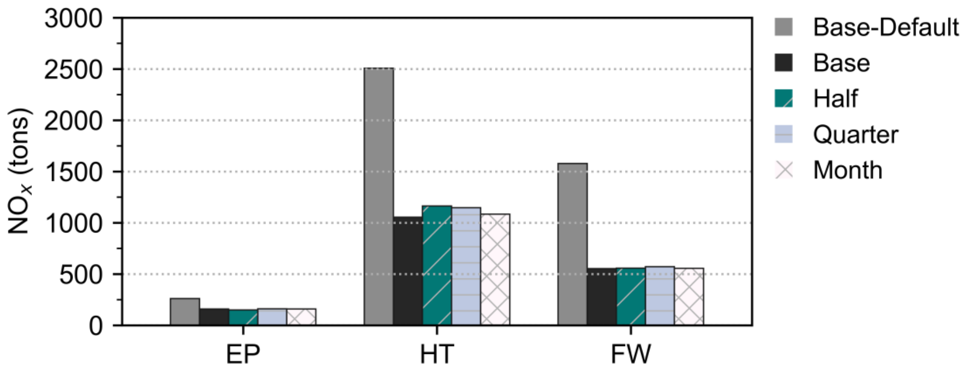

Figure 13. Annual morning peak time NO_x emissions for meteorological scenarios by averaging period used to obtain temperature and RH.

MOVES emissions-based CO/NO_x ratios showed small changes when different averaging approaches were used to prepare meteorological input data (Figure 14). For all three analysis areas, using MOVES default temperature and RH inputs resulted in lower CO/NO_x ratios.

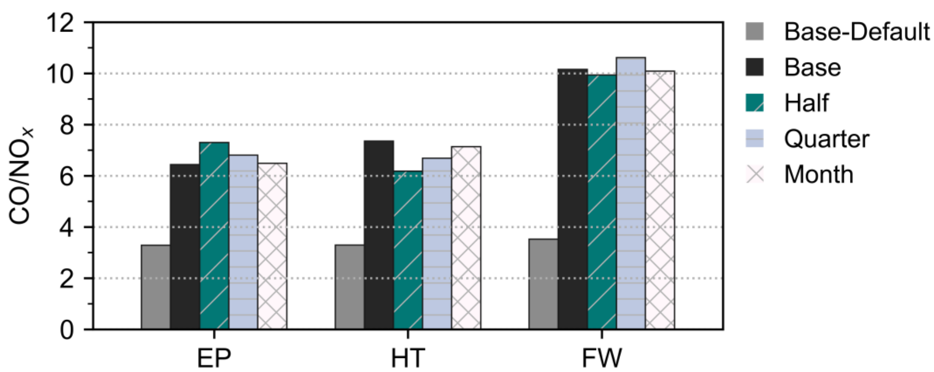

Figure 14. Annual morning peak time CO/NO_x ratios for meteorological scenarios by averaging period used to obtain temperature and RH.

3.3 Discussion of MOVES Input Parameters

In general, MOVES requires three categories of input data to support regional (county-scale) emissions modeling: travel activities, fleet characteristics, and meteorological conditions. MOVES travel activity data mainly include VMT distributions across 13 source types (vehicle classes) by road type, time, and average speed. Fleet data in MOVES include vehicle population by vehicle class and age, fuel information, and Inspection and Maintenance (I/M) program information. Meteorological data used in MOVES include temporal profiles of temperature and relative humidity. The MOVES model includes a MySQL database with default vehicle activity, vehicle fleet, fuel characteristics, control program, and meteorology inputs for each U.S. county, organized in multiple data tables through the County Data Manager (CDM).

The EP, HT, and FW case studies in this emissions sensitivity analysis demonstrated the importance of replacing MOVES model defaults with local data to allow a more robust assessment of on-road vehicle emissions. Local MOVES input data may come from multiple sources, such as conversion of local data from prior MOBILE-based runs, post-processing outputs from local traffic activity estimates and travel models (e.g., temporal and spatial distributions of VMT and speed distributions), and local vehicle fleet registration data (e.g., vehicle population for specific source types).

Among the MOVES input parameters tested in the sensitivity study, fleet mix and vehicle age distribution have a larger effect than vehicle speed distribution and meteorological data on NO_x emissions estimates. Therefore, these input parameters should be of highest priority for data collection. This finding is largely consistent with the discussion in other studies (e.g., Noel and Wayson, 2012; EPA, 2014). The use of local data in MOVES has important emissions consequences; for example, one metropolitan planning organization (MPO) estimated that future-year NO_x and $PM_{2.5}$ emissions increased up to 25% when local information was used for fleet turnover and truck activity (Kirby, 2012).

4. Conclusions and Recommendations for Future Work

Using 2015 ambient concentration measurements from near-road monitoring sites and emissions estimates from MOVES for the El Paso, Houston, and Fort Worth areas during the morning commute period, this study compared ambient- and emissions-derived CO/NO_x ratios to evaluate the quality of on-road mobile source NO_x emissions estimates from MOVES. The analysis of this work indicates that on-road mobile sources are represented reasonably in MOVES-based NO_x emissions when local MOVES inputs are used; there is a generally good agreement (within 30%) between ambient- and emissions-derived pollutant ratios across all three case study sites. The results from this work highlight the importance of using localized modeling input data in developing reasonable MOVES emissions estimates. This is consistent with recent research results (e.g., Warila et al., 2017 and Koupal et al., 2014) that showed issues with on-road NO_x estimates in the NEI resulting from over-reliance on MOVES default data rather than more accurate local inputs. The results from this study suggest that, when appropriate local data are used, MOVES can reasonably reflect mobile source emissions in the inventory; MOVES emissions-based ratios are comparable to the ratios derived from ambient measurements in reconciliation analysis. However, relying on MOVES default inputs can generate biased ratios and lead to incorrect results in the emissions assessment and reconciliation analysis. The evaluation of the mobile source NO_x emissions inventory (e.g., the assessment of the NEI in recent studies) should consider how MOVES default inputs are used and what their effect is on emissions estimates.

The MOVES sensitivity analysis focused on assessing the impact of four selected input parameters (fleet mix, vehicle speed, vehicle age distribution, and meteorological data) on NO_x emissions estimates. In the three regions analyzed, MOVES NO_x emissions estimates for the morning peak hours were shown to be more sensitive to input data for vehicle fleet mix and age distribution and less sensitive to speed distribution and meteorological inputs. The input parameters that MOVES NO_x emissions are more sensitive to should be assigned higher priority for local input preparation and quality assurance, especially when they are used for developing emissions-based pollutant ratios to support reconciliation analysis or air quality photochemical modeling.

The emissions reconciliation analysis provides important feedback for assessment of emissions inventories. However, there are limitations to comparisons of emissions-based and ambient-based ratios. For example, the development of ambient-based CO/NO_x ratios can be sensitive to the measurements data selection (based on wind direction and pollution roses), regression techniques, and identification of background levels. In this study, the MOVES modeling runs focused on NO_x emissions from freeway facilities during morning peak hours; non-running exhaust emissions and diurnal variations in emissions were not included in the analysis. Therefore, the sensitivity analysis may not reflect a complete representation of how the entire NO_x emissions inventory changes against different MOVES input parameters. The analysis results are more suitable for supporting the evaluation of mobile source NO_x emissions in the context of a reconciliation analysis (i.e., how mobile sources are represented in an inventory, given the pattern shown from ambient measurements).

Further analysis will be useful, based on the existing emissions reconciliation and sensitivity analyses, to improve MOVES-based NO_x emissions estimates. Recommended studies include:

- Revisiting how MOVES emissions were developed and what key assumptions were made (especially related to MOVES default) in recent studies that concluded over-estimation of mobile source NO_x emissions in the NEI. An important practical issue to address is building the connection between EPA's NEI development and local emissions inventory development. Carefully designed assessment is needed to understand how default data were used in MOVES modeling for the NEI, and how the NEI can be improved by ensuring consistency with MOVES emissions inventories developed by state or regional air quality agencies using local data.
- Assessing more temporally and spatially refined MOVES emissions modeling results (e.g., by season, month, weekday vs. weekend, and facility type) to better understand the larger seasonal variation in MOVES emissions-based ratios.
- Identifying challenges related to preparation of local MOVES input data, developing potential methods to fill local data gaps, and implementing the methods to improve local data use for the NEI and MOVES-based mobile source emissions inventories.

5. References

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Appendix A. Audits of Data Quality

A.1 Ambient Data

The emissions reconciliation analysis used routine near-road air quality data collected by state and local monitoring agencies in 2015 at three monitoring sites in Texas (Fort Worth, Houston, and El Paso). Specific quality requirements for ambient air quality monitoring programs are provided in the EPA's *Quality Assurance Handbook for Air Pollution Measurement Systems*.[1] The monitored air quality data used in this study have been previously quality-assured by each air monitoring and reporting agency and meet EPA's quality requirements. Additional quality assurance were also applied to all ambient monitored data used in this study (100% of data were audited), such as excluding data during the periods with perceivable baseline drift of pollutant mixing ratios and excluding data showing potential instrument errors. The additional periods of data manually removed from the analysis are summarized in Table A-1.

Table A-1. Periods of data by site and pollutant excluded from air quality analysis due to baseline drift and/or instrument error.

Site	Pollutant	Start time	End time
EP	CO	2015-05-20 00:00	2015-07-15 23:00
HT	CO	2015-05-29 00:00	2015-07-03 14:00
FW	CO	2015-03-13 06:00	2015-04-30 23:00

The resulting seasonal completeness of data after all quality-assurance procedures were applied to the ambient data (based on all hours of data), is summarized in Table A-2.

[1] Available at https://www3.epa.gov/ttn/amtic/qalist.html.

Table A-2. Completeness (%) of hourly CO and NO_x data by season in 2015 (for all hours of day). Winter is defined as January, December, February; spring is defined as March, April, May; summer is defined as June, July, August; and fall is defined as September, October, November.

Site	Season	CO	NO_x
EP	Winter	95.7	87.8
	Spring	86.4	90.0
	Summer	50.3	82.7
	Fall	97.4	82.1
HT	Winter	34.1	29.6
	Spring	47.8	47.0
	Summer	63.7	90.7
	Fall	98.6	93.0
FW	Winter	34.2	26.6
	Spring	33.8	78.7
	Summer	98.9	85.3
	Fall	99.0	92.8

A.2 MOVES Data

In this project, the MOVES model was applied to generate emissions estimates for the reconciliation and sensitivity analyses; no additional model verification for MOVES is needed. The MOVES modeling data in this project included default and local inputs for case studies. The project team obtained MOVES data from the TCEQ and local planning agencies (e.g., H-GAC and NCTCOG) and reviewed all local vehicle activity data, vehicle age distribution, fleet mix information, and other modeling input parameters. All MOVES modeling inputs were reviewed for quality-assurance purposes (i.e., 100% of data were audited). The log data generated from MOVES modeling (i.e., moveserror table in output MySQL database) were checked to ensure there were no errors in emissions modeling due to data issues or runtime interruption. The MOVES output files with emissions data and analysis results (data tables and graphics) were assessed through the planned emissions reconciliation and sensitivity analyses, with temporal and spatial variations of modeled emissions evaluated through data tables and graphics.

Quantitative assessment of local MOVES input data was also conducted for quality assurance purposes; examples of statistical metrics include VMT-weighted average fleet age (Equation 1) and annual average VMT per vehicle by vehicle type (Equation 2); these metrics were compared between the local data and MOVES default data to quantify percent differences (e.g., Table C-4) and evaluate data variation (e.g., Table A-3). For example, the average annual VMT per vehicle from the base scenario and the 2014 TCEQ MOVES CDBs are consistent for all vehicle types. The variation among the three study areas, as well as the difference between local data (i.e, Base and TCEQ) and

MOVES national averages (i.e., MOVES default and 2015 Highway Statistics), indicates the significant regional variations.

$$WAFA_i = \sum_{j=1}^{30} \left(VAF_{i,j} \times j\right) \qquad \text{Equation (1)}$$

Where, WAFA = weighted average fleet age
i = vehicle type (source type defined in MOVES)
j = vehicle age (0, 1, 2..., 30)
VAF = vehicle age fraction

$$AAV_i = {}^{AVMT_i}/_{P_i} \qquad \text{Equation (2)}$$

Where, AAV = average annual VMT per vehicle
i = vehicle type (Highway Performance Monitoring System [HPMS] type in MOVES)
AVMT = annual vehicle miles traveled
P = HPMS vehicle type population (aggregated from source type population in MOVES)

Table A-3. Average annual VMT per vehicle by HPMS vehicle type. Data were prepared for each study area and were summarized from BAL scenario, 2014 TCEQ MOVES CDBs, MOVES national default, and 2015 Highway Statistics.

HPMS	**Base**			**TCEQ**			**MOVES Default**	**Highway Statistics**
Vehicle Type	**EP**	**HT**	**FW**	**EP**	**HT**	**FW**	**National**	**National[a]**
Motorcycles	379	662	1,018	347	643	976	2,191	2,280
Light Duty Vehicles	11,057	13,896	30,137	10,118	13,496	28,905	11,367	11,443
Buses	51,856	23,352	82,323	47,452	22,679	78,959	18,996	18,258
Single Unit Trucks	39,831	21,241	82,157	36,448	20,629	78,799	12,599	12,960
Combination Trucks	128,550	39,483	145,002	117,634	38,345	139,076	63,689	61,978

[a] Data retrieved from 2015 Highway Statistics Table VM-1 (see https://www.fhwa.dot.gov/policyinformation/statistics/2015/vm1.cfm)

Appendix B. Additional Materials for Emissions Reconciliation Analysis

B.1 Case Study Setting

Satellite imagery of the three sites selected in this study is shown in Figure B-1.

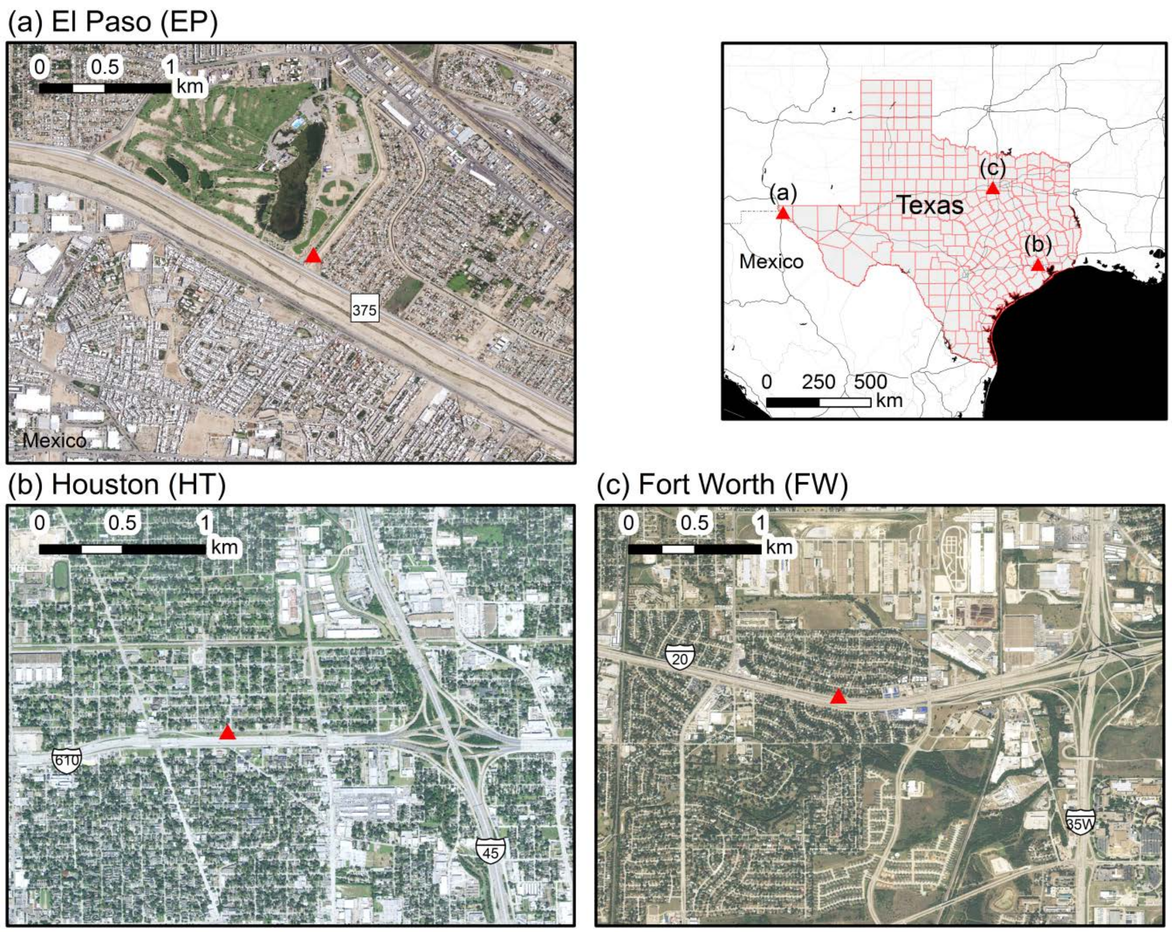

Figure B-1. Satellite imagery of the three case study monitoring site locations (red triangles) in Texas (upper right). Map data provided by Stamen Design and OpenStreetMap.

B.2 Regional Background Monitors

For each case study site, a regional monitoring site was selected to reflect the general regional background CO concentration levels (Table B-1). The regional CO values were computed as the mean of the CO mixing ratios measured from 06:00 LST to 09:00 LST by period (Table B-2). The purpose of these regional CO levels is to provide a basis for comparison that would ensure a reasonable regression approach in the reconciliation analysis. The main selection criteria include (1) location within the same urban area (either upwind or downwind) as the study site, and (2) no major roadways or other large sources of CO emissions nearby. The intercepts from the annual regression at EP, HT, and FW were generally comparable to annual mean morning hour regional CO mixing ratios at the selected regional monitoring sites (Table B-2). At all sites, summertime intercepts are higher than mean summer regional CO mixing ratios, and wintertime intercepts are lower than mean winter regional CO mixing ratios.

Table B-1. Monitoring sites used to calculate regional background CO mixing ratios. Longitude is positive East, and latitude is positive North. The distance is the approximate distance between the study site and the background monitoring location.

	Regional Background Monitor			Distance
Site	AQS ID	Longitude	Latitude	(km)
EP	481410037	-106.50	31.77	9.6
HT	482011039	-95.13	29.67	29.8
FW	484391002	-97.36	32.81	15.7

Table B-2. Morning peak (6:00 to 9:00 LST) mean CO mixing ratio from the selected regional sites. The intercept of the regression between CO and NO_x mixing ratios is provided for comparison; the summer and winter intercepts are for weekdays only.

Site	Season	Regional CO (ppb)	Intercept
EP	Annual	171.0	164.3 ± 6.8
	Summer	73.2	195.1 ± 10.2
	Winter	198.5	150.9 ± 20.2
HT	Annual	208.7	204.2 ± 11.0
	Summer	133.5	211.7 ± 42.7
	Winter	281.1	167.7 ± 20.2
FW	Annual	271.3	272.0 ± 7.2
	Summer	231.2	234.1 ± 11.0
	Winter	312.7	109.4 ± 42.2

B.3 MOVES Modeling

For each MOVES model run, a run script file was created with the general modeling configurations, as shown in Table B-3. Approximately 50% of the run script files were reviewed and audited for quality assurance purposes. All modeling scenarios were executed in a MOVES batch mode using a Run Specification (*runspec*) list file; the output data were written to the same database to facilitate post-processing and calculating emission-based CO/NO_x ratios. The *moveserror* and *movesrun* tables in the output database were reviewed and quality-checked to ensure no errors or exceptions occurred during the MOVES modeling process.

Table B-3. General modeling configuration used for MOVES emissions modeling.

Section	Settings
Scale	
Domain/Scale	County
Calculation Type	Inventory
Time Span	
Aggregation Level	Hour
Year	2015
Months	All
Days	Weekend, Weekdays
Hours	Start Hour: 6, End Hour: 9
Geographic Bounds	Texas Counties: El Paso, Harris, Tarrant
Vehicles/Equipment	All
Road Type	All
Pollutants and Processes	
Species	CO, NO, NO_2
Processes	Running Exhaust, Crankcase Running Exhaust

Local input data for MOVES modeling were obtained from the agencies listed in Table B-4. The local MOVES input data were reviewed, compared, and prioritized to compile the input CDBs for base scenarios as discussed in following section. SQL scripts in conjunction with MOVES CDM Interface were used to create CDBs. Table B-5 documents the steps for preparing CDBs for each scenario.

Table B-4. Sources and brief descriptions of data collected.

Agency	CDB Data
TCEQ	Readily available 2014 MOVES CDBs prepared under 2014 AERR including: - CDBs representing annual days, winter weekdays, and summer weekdays for El Paso - CDBs representing annual days, and summer weekdays for Houston - CDBs representing annual days, and summer weekdays for Fort Worth
TXDOT	2015 Texas Roadway Inventory containing AADT, daily truck percentage, and truck percentage during peak time periods for the roadway segments of interest
H-GAC	2015 MOVES CDB input tables for Harris County, including: - Source age distribution - I/M coverage - Fuel supply, fuel formulation, AVFT, fuel usage fraction - Meteorology
NCTCOG	2017 MOVES CDB for Tarrant County representing annual average days

Table B-5. Procedures to create MOVES BAL CDBs

Site	Season/Day	BAL CDB Name	Revisions
EP	Annual	Original c48141_tceq_trk_pk_2015_ann_in Revised mvs14_aerr14_elp_48141_2014ann_ei_cdb_in	1. Update yearID, fuelYearID from 2014 to 2015. 2. Import annual VMT by HPMS vehicle class adjusted to reflect road-specific, peak-time truck percentage in 2015 Roadway Inventory from TXDOT via MOVES2014a CDM.
	Summer Weekday	Original c48141_tceq_trk_pk_2015_sum_in Revised mvs14_aerr14_elp_48141_2014sumwkd_ei_cdb_in	1. Update yearID, fuelYearID from 2014 to 2015. 2. Import summer weekday VMT by HPMS vehicle class adjusted to reflect road-specific, peak-time truck percentage in 2015 Roadway Inventory from TXDOT via MOVES2014a CDM.
	Winter Weekday	Original c48141_tceq_trk_pk_2015_win_in Revised mvs14_aerr14_elp_48141_2014winwkd_ei_cdb_in	1. Update yearID, fuelYearID from 2014 to 2015. 2. Import winter weekday VMT by HPMS vehicle class adjusted to reflect road-specific, peak-time truck percentage in 2015 Roadway Inventory from TXDOT via MOVES2014a CDM.
HT	Annual	Original c48201_hgac_tceq_pk_2015_ann_in Revised mvs14_aerr14_hgb_48201_2014ann_ei_cdb_in	1. Update yearID, fuelYearID from 2014 to 2015. 2. Import the following tables from H-GAC via MOVES2014a CDM: source age distribution (SourceTypeAgeDistribution), I/M coverage (IMCoverage), AVFT (avft), fuel usage fraction (FuelUsageFraction), and annual VMT by HPMS vehicle class (HPMSVtypeYear) adjusted to reflect road-specific, peak-time truck percentage in 2015 Roadway Inventory from TXDOT.
	Summer Weekday	Original c48201_hgac_tceq_pk_2015_sum_in Revised mvs14_aerr14_hgb_48201_2014sumwkd_ei_cdb_in	1. Update yearID, fuelYearID from 2014 to 2015. 2. Import the following tables from H-GAC via MOVES2014a CDM: Source age distribution (SourceAgeDistribution), I/M coverage (IMCoverage), AVFT (avft), fuel usage fraction (FuelUsageFraction), fuel supply (FuelSupply), fuel formulation (FuelFormulation), and summer weekday VMT by HPMS vehicle class adjusted to reflect road-specific,

Site	Season/Day	BAL CDB Name	Revisions
			peak-time truck percentage in 2015 Roadway Inventory from TXDOT.
FW	Annual	Original c48439_nctcog_tceq_trk_pk_2015_in Revised 17tarrant_conf_in	1. Update the following tables with that from TCEQ CDBs via SQL scripts: fuel supply (FuelSupply), fuel formulation (FuelFormulation), meteorology (ZoneMonthHour). 2. Update yearID, fuelYearID from 2017/2014 to 2015. 3. Import annual VMT by HPMS vehicle class adjusted to reflect road-specific, peak-time truck percentage in 2015 Roadway Inventory from TXDOT via MOVES2014a CDM.
	Summer Weekday	Original c48439_nctcog_tceq_trk_pk_2015_sum_in Revised 17tarrant_conf_in	1. Update the AVFT table with that from TCEQ CDBs. 2. Update yearID, fuelYearID from 2017 to 2015. 3. Import summer weekday VMT by HPMS vehicle class adjusted to reflect road-specific, peak-time truck percentage in 2015 Roadway Inventory from TXDOT via MOVES2014a CDM.

Appendix C. Additional Materials for Emissions Sensitivity Analysis

C.1 Scenario Design

For selected MOVES input parameters in the sensitivity analysis, different levels were chosen to represent a reasonable range of input changes. The methods and data sources used to set the range of MOVES inputs are presented below, as well as the specific procedures used to prepare MOVES CDBs for the sensitivity modeling runs.

Fleet Mix (Truck Percentage)

Five sensitivity scenarios for each study area were designed with the truck VMT percentages of 0%, 5%, 10%, 20%, and 30%. These values cover a reasonable range of truck percentage on urban freeways. The VMT by HPMS vehicle class were adjusted to reflect the assumed truck VMT percentages.

Speed Distribution

For urban freeways (limited access roads), the average speed distribution data were selected on the basis of fleet average speed in conjunction with the ranges of the cumulative speed curves. The average speed distribution data prepared by TCEQ under the 2014 AERR for each county in Texas were considered an appropriate data pool. Using these data to select speed distribution is a reasonable approach, because the data (1) are readily available and represent an analysis year close to the target modeling year; (2) are most complete and have good quality; and (3) represent a reasonable range of speed levels in Texas. These data were plotted by season, source type, road type, day of week (weekday vs. weekend), and hour of the day. The plot displays a range of cumulative speed curves (i.e., cumulative VMT fractions vs. average speed) across all Texas counties (see Figure C-1 for example). Three levels of speed distribution data were then chosen to represent low, medium, and high vehicle fleet average speeds (see Figure C-2).

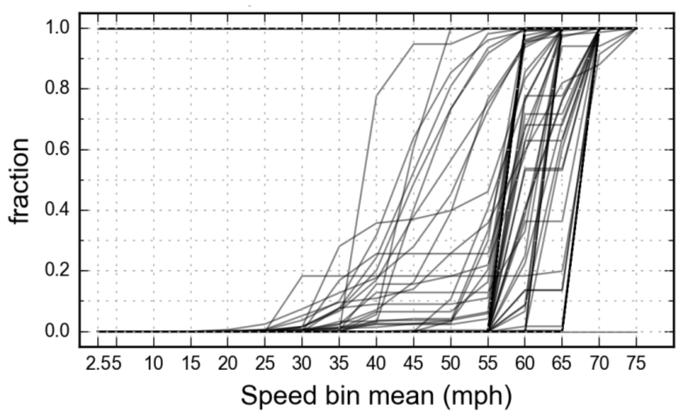

Figure C-1. Cumulative speed distribution curve (annual, passenger cars, urban restricted-access roads, weekdays at 07:00 LST, individual lines by county).

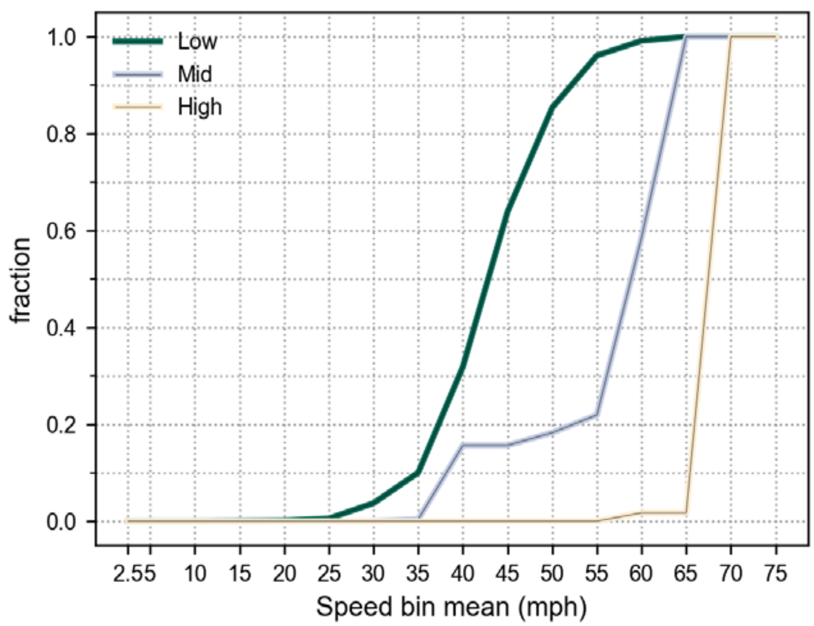

Figure C-2. Cumulative speed distribution curve for the selected low, mid, and high fleet average speeds (annual, passenger cars, urban restricted-access roads, weekdays at 07:00 LST).

Age Distribution

In an approach similar to that used for speed distribution, cumulative vehicle age curves were developed to represent VMT by age distributions by county (see Table C-3). The fleet average ages were also calculated for each county. Three levels of age distribution data were chosen to represent low, medium, and high vehicle fleet average age levels (see Table C-4).

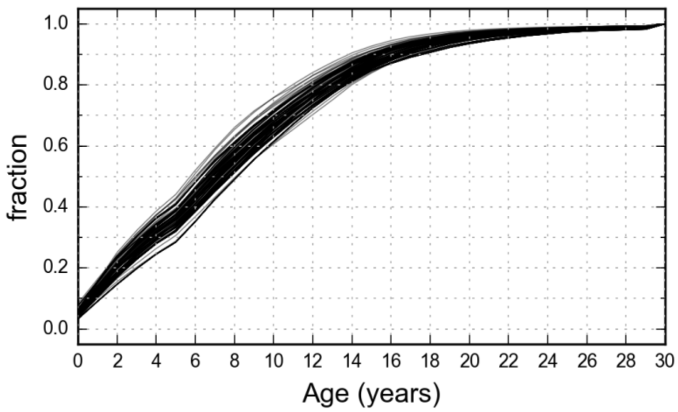

Figure C-3. Cumulative vehicle age distribution curve (2014 annual, passenger cars, individual lines by county).

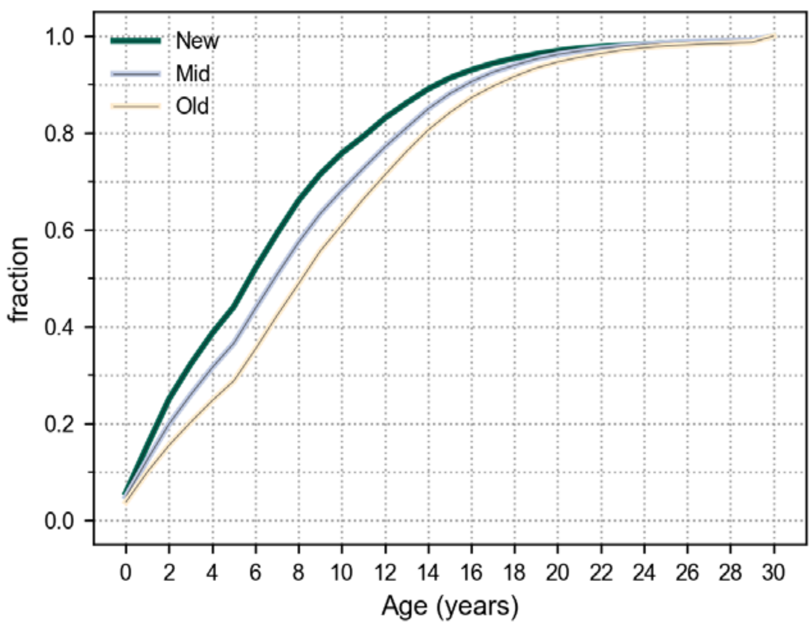

Figure C-4. Cumulative vehicle age distribution curve for the selected low, medium, and high fleet average age levels (2014 annual, passenger cars).

Meteorology

The meteorological data obtained from local agencies represent the condition of the entire county, not just the area surrounding the near-road monitoring sites and roadway segments modeled. Therefore, to obtain meteorology data for the MOVES sensitivity analysis, hourly temperature and RH data were retrieved from EPA's AQS for year 2015 at the three near-road sites in the study areas. For Houston, RH data were not available at the near-road site (AQS ID 482011052); meteorological data from a nearby site (AQS

ID 482010024) were used as a surrogate. A set of monthly 24-hour temperature and RH profiles was then derived from these data using different averaging time windows, by month, three-month season (e.g., June to August for summer), and half-year season (e.g., April to September for summer). To illustrate the range of variation the averaging techniques have on the meteorological data, the mean temperature and RH for each modeling scenario are shown in Table C-1.

Table C-1. Mean temperature and relative humidity used in MOVES modeling scenarios for emissions sensitivity analysis.

Site	County	Scenario	Mean Temperature (°F)	Mean Relative Humidity (%)
EP	El Paso	Base	59.7	48.4
		Season Base-Default	54.4	47.3
		Season Half	64.9	60.9
		Season Quarter	62.1	49.5
		Season Month	63.2	46.3
HT	Harris	Base	65.3	83.1
		Season Base-Default	62.6	84.6
		Season Half	66.5	57.3
		Season Quarter	65.1	64.4
		Season Month	68.3	72.1
FW	Tarrant	Base	61.8	72.5
		Season Base-Default	57.9	76.4
		Season Half	63.8	70.0
		Season Quarter	63.1	67.3
		Season Month	64.1	69.9

C.2 MOVES CDB Development

For each sensitivity scenario, an input CDB was created in two steps: (1) create a CDB with a name consistent with the scenario name by cloning the CDB for the base scenario; and (2) replace the target input parameter to test with scenario-specific input data, while holding other inputs constant. SQL scripts were used to automate and streamline the process, including construction of a MySQL database to host all testing data. The CDBs were created for all testing scenarios and then reviewed in MySQL Workbench (v6.3) to ensure accuracy.

C.3 Impact on MOVES NO_x Emissions

The following tables (Table C-2 through Table C-5) present the MOVES sensitivity analysis results in terms of the impact of selected input parameters on NO_x emissions estimates.

Table C-2. Percentage changes of NO_x emissions with every 1% of increase in truck percentage in the fleet compared to the base scenario, associated with truck percentage for the three study areas.

Scenario	Truck %	EP	HT	FW
Truck 0	0	13%	16%	10%
Truck 5	5	13%	16%	10%
Truck 10	10	13%	16%	10%
Truck 20	20	13%	16%	10%
Truck 30	30	13%	16%	10%

Table C-3. Changes of NO_x emissions with every 1 mph increase in fleet average speed compared to the base scenario, associated with speed bins for the three study areas.

Scenario	Speed (mph)	EP	HT	FW
Speed Low	41	0.6%	0.2%	0.3%
Speed Medium	58	3.0%	0.3%	0.3%
Speed High	70	0.5%	0.9%	0.6%

Table C-4. Changes of NO_x emissions with every 1 year increase in fleet average age compared to the base scenario, associated with fleet age bins for the three study areas.

Scenario	Age Range	EP	HT	FW
Age New	7	16%	16%	18%
Age Mid	8	20%	21%	13%
Age Old	10	7%	20%	20%

Table C-5. Change (%) in average temperature, relative humidity, and NO_x emissions compared to the base scenario.

Site	Scenario	T	RH	NO_x
EP	Season Half	9%	26%	-5%
	Season Quarter	4%	2%	1%
	Season Month	6%	-4%	0%
HT	Season Half	2%	-31%	10%
	Season Quarter	0%	-22%	9%
	Season Month	4%	-13%	3%
FW	Season Half	3%	-4%	1%
	Season Quarter	2%	-7%	3%
	Season Month	4%	-4%	1%

C.4 Impact on MOVES Emissions-Based CO/NOx Ratios

The following tables (Table C-6 through Table C-9) present the MOVES sensitivity analysis results in terms of the impact of selected input parameters on CO/NO_x ratios.

Table C-6. Percentage changes of CO/NO_x ratios with every 1% of increase in truck percentage in the fleet compared to the base scenario, associated with truck percentage for the three study areas.

Scenario	EP	HT	FW
Truck 0	-14%	-17%	-10%
Truck 5	-8%	-9%	-7%
Truck 10	-6%	-6%	-5%
Truck 20	-4%	-4%	-3%
Truck 30	-3%	-3%	-3%

Table C-7. Changes of CO/NO_x ratios with every 1 mph increase in fleet average speed compared to the base scenario, associated with speed bins for the three study areas.

Scenario	Speed (mph)	EP	HT	FW
Speed Low	41	-0.2%	-0.6%	-0.2%
Speed Medium	58	2.6%	-0.5%	-0.3%
Speed High	70	0.0%	0.2%	-0.3%

Table C-8. Changes of CO/NO_x ratios with every 1 year increase in fleet average age compared to the base scenario, associated with fleet age bins for the three study areas.

Scenario	Age Range	EP	HT	FW
Age New	7	-7%	-7%	-8%
Age Mid	8	-5%	-6%	-14%
Age Old	10	-8%	-4%	-6%

Table C-9. Change (%) in average temperature, relative humidity, and CO/NO_x ratios compared to the base scenario.

Site	Scenario	T	RH	CO/NO_x
EP	Season Half	9%	26%	13%
	Season Quarter	4%	2%	6%
	Season Month	6%	-4%	1%
HT	Season Half	2%	-31%	-16%
	Season Quarter	0%	-22%	-9%
	Season Month	4%	-13%	-3%
FW	Season Half	3%	-4%	-2%
	Season Quarter	2%	-7%	5%
	Season Month	4%	-4%	-1%