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Temporal variation of traffic on highways and the development of accurate temporal allocation factors for air pollution analyses

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Abstract

Traffic activity encompasses the number, mix, speed and acceleration of vehicles on roadways. The temporal pattern and variation of traffic activity reflects vehicle use, congestion and safety issues, and it represents a major influence on emissions and concentrations of traffic-related air pollutants. Accurate characterization of vehicle flows is critical in analyzing and modeling urban and local-scale pollutants, especially in near-road environments and traffic corridors. This study describes methods to improve the characterization of temporal variation of traffic activity. Annual, monthly, daily and hourly temporal allocation factors (TAFs), which describe the expected temporal variation in traffic activity, were developed using four years of hourly traffic activity data recorded at 14 continuous counting stations across the Detroit, Michigan, U.S. region. Five sites also provided vehicle classification. TAF-based models provide a simple means to apportion annual average estimates of traffic volume to hourly estimates. The analysis shows the need to separate TAFs for total and commercial vehicles, and weekdays, Saturdays, Sundays and observed holidays. Using either site-specific or urban-wide TAFs, nearly all of the variation in historical traffic activity at the street scale could be explained; unexplained variation was attributed to adverse weather, traffic accidents and construction. The methods and results presented in this paper can improve air quality dispersion modeling of mobile sources, and can be used to evaluate and model temporal variation in ambient air quality monitoring data and exposure estimates.

Keywords

Classification; Freeways; Highways; Mobile sources; Traffic; Vehicles

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Appendix A. Supplementary data: Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.atmosenv.2015.02.047.

1. Introduction

Traffic activity encompasses the number of vehicles per hour on a road section, vehicle mix (fraction of different types of vehicles), and vehicle speed and acceleration. Traffic activity is dynamic, varying with strong daily, weekly and seasonal patterns. This variation affects on-road vehicle emissions, and, along with changes in meteorological conditions that govern dispersion, can cause dramatic changes in concentration of traffic-related pollutants, especially near major roads (Gokhale, 2011; Kimbrough et al., 2013). Exposure to traffic-related pollutants has been associated with many adverse health effects (Health Effects Institute, 2010), and improved exposure estimates are needed to improve our understanding health impacts (Batterman, 2013; Brauer et al., 2013). Exposures have been estimated, at community to national scales, using geographic metrics (e.g., the proximity of homes to major roads), statistical modeling (e.g., land use regression), simulation modeling (e.g., dispersion models), and hybrid methods (Jerrett et al., 2005; Rioux et al., 2010; Pratt et al., 2014). Most of these methods do not account for temporal variation. In addition, the temporal profiles used to estimate hourly emissions may not reflect the travel patterns of heavy-duty and other vehicles (Lindhjem et al., 2012).

Many factors affect traffic activity, and these need to be considered when modeling on-road emissions. In most US cities, a large or dominant part of vehicle-miles-traveled (VMT) occurs on major roads. If the temporal variation in activity along these major roads can be accurately characterized, then modeling air quality and exposures in urban areas can be greatly improved. This paper presents a methodology for developing temporal allocation factors that account for nearly all variation in traffic activity along major roads in urban regions, and thus can greatly improve the accuracy of air quality modeling at the urban scale. This analysis is motivated by the need to improve exposure estimates of traffic-related air pollutants in epidemiology and other studies (Vette et al., 2013). Results are intended to increase the understanding of temporal variation in traffic-related exposures, and to improve modeling of mobile source emissions.

1.1. Estimating traffic activity

The preferred approach to estimate traffic activity uses continuous and site-specific monitoring of vehicle counts, ideally with additional information to determine vehicle classification. Continuous counting stations used for such measurements employ various technologies, e.g., embedded inductive loops, piezoelectric sensors, magnetic sensors, cameras, and radars (U.S Federal Highway Administration, 2013). Currently, most stations measure vehicle counts and do not provide classification data. Weigh-in-motion sensors, which can determine whether a vehicle is overweight as well as provide classification information, are being increasingly deployed at permanent monitoring sites. Counting stations providing long term data are usually permanent sites. Count and classification data collected at temporary sites are more common. Typically, these short-term counts are collected using tube counters and/or trained observers in field campaigns that last a few weekdays to a few weeks. Seasonal or monthly adjustments may be used to estimate the annual average daily traffic (AADT) volume. Similar approaches are used to estimate commercial annual average daily traffic (CAADT), which applies to vans, buses and trucks.

In addition, traffic activity can be estimated using measurements at other locations, statistical forecasts, and simulation models, e.g., microsimulation (agent-based) and traffic-demand models. Video cameras and cell phone tracking provide additional data, primarily to monitor traffic congestion. While AADT estimates are available in many jurisdictions, continuous measurements are comparatively rare.

Given the AADTor CADT, hourly volumes can be estimated using a “bottom-up” approach by applying temporal allocation factors (TAFs), also called “temporal profiles” (Cook et al., 2008). TAFs are formulated at month-of-year, day-of-week, and hour-of-day levels and derived using historical data collected either locally or nationally. Multiplying the AADT by the TAFs allocates traffic volume to the hour. For example, TAFs reflect commuting patterns, which typically show morning and afternoon volume peaks (and often “rush hour” congestion) and a bimodal diurnal profile, while truck volumes peak during the workday, and some truck drivers may schedule routes and work times to avoid rush hours. The true activity will depend on vehicle type, road type, location, weather and other factors.

In the U.S., TAFs compiled in 1985 for the National Acid Precipitation Assessment Program used four profiles and considered two vehicle classes – light-duty gasoline vehicles, and all vehicle classes; (Fratt et al., 1990; Cook et al., 2008). A single profile was used for seasons (classes combined), two profiles for day-of-week (separating weekends and weekdays), and one profile for hour-of-day (classes combined). Later, a national FHWA database of vehicle activity was used to develop 24 profiles. These profiles were developed for eight vehicle classes by day-of-week (each day of the week), weekday hour-of-day, and weekend hour-of-day (Pollack et al., 2006). Other profiles have been incorporated into the SMOKE modeling system (http://www.cmascenter.org/smoke/), and the current national average profiles provide hourly weekday and weekend profiles for different vehicle classes; work is underway to separate Saturday and Sunday profiles. As shown later, generic profiles can mischaracterize activity on individual roadways or in specific communities.

2. Methods

Data processing and analysis involved obtaining, cleaning and filtering the traffic activity data, calculating monthly and daily volume averages at each counting site, determining TAFs, and determining normalized volumes that represent the volume expected for each day, week and season. We then provide a descriptive analysis of temporal patterns, identify factors that caused volumes to alter from expected values, test for differences between sites, and compare the performance of the TAF-based model using an independent dataset.

2.1. Traffic monitoring sites

Hourly data from 13 permanent counting stations in southeast Michigan for the period of 2009 through 2012 were obtained from the Michigan Department of Transportation (MDOT). These data represent actual vehicle volumes (not weight truck counts or passenger car equivalents, PCEs), and were reviewed and quality checked by MDOT staff. Short-term counts providing classification were obtained for these sites from MDOT from the Traffic Monitoring Information System (http://mdotnetpublic.state.mi.us/tmispublic/Search.aspx). To measure total vehicle counts, nine of the sites used induction loops, which sense the presence of the vehicle by induced eddy currents. Four of the sites used weigh-in-motion sensors, which derive the weight of each axle by measuring the vertical force. The latter data were processed to obtain counts in the 13 FHWA vehicle classes (1 = motor cycles; 2 = passenger cars; 3 = other two-axles, four tire single unit vehicles; 4 = buses; 5 = two axles, six tire, single unit trucks; 6 = three axles, single unit trucks; 7 = four or more axles, single unit trucks; 8 = three or four axles, single trailer trucks; 9 = five axles, single trailer trucks; 11 = five or less axles, multi trailer trucks; 12 = six axles, multi trailer trucks; 13 = seven or more axles, multi trailer trucks). More details are provided in Supplemental information Table S1.

Data for the 14th site (on I-96) from September 29, 2010 through June 19, 2011 were obtained from the Federal Highway Administration (FHWA, personal communication). This site used two radar systems (SS-125, Wavetronix SmartSensorHD, Kansas City, MO, USA), considered the “next generation” traffic instrumentation, installed on opposite sides of the highway. Vehicle counts in six length bins (0–10, 10–20, 20–30, 30–40, 40–50, >50 ft length), along with the average and 85th percentile vehicle speed, were provided on a 5 min basis for each of the 10 lanes at this location. Data quality objectives for this instrumentation were accuracy within 20%, 95% confidence interval within ±20%, and data completeness of >80% (EPA, 2014).

2.2. Data processing

Complete and representative data sets were desired. From the hourly data, 24 valid measurements were required to determine daily volume. Subsequent statistics required most data to be available, e.g., for annual statistics, years with less than 80% of data were excluded. At the weigh-in-motion sites, non-commercial (passenger) vehicle volume was estimated as the sum of FHWA classes 1 to 3 (motorcycles, passenger cars, light duty trucks, pickup trucks, sport utility vehicles), and commercial volume was estimated as the sum of classes 4 through 13. At the I-96 (radar) site, noncommercial volume was estimated using vehicles less than 20 feet in length, and commercial volume as vehicles over 20 feet.

The normalized volume was defined as the ratio of the daily volume to the expected volume, where the expected volume used the AADT. The adjusted normalized volume was similarly defined, but the expected volume used the average of the same day of the week for the three previous and three subsequent weeks, thus accounting for day-of-week and seasonal variation. The ten federal holidays and the days adjacent to both the holiday and the weekend, called “bridge” days, were excluded from these calculations.

2.3. Estimating traffic activity using temporal allocation factors

Hourly class-specific vehicle volumes are estimated as the product of the average daily volume and monthly, daily and hourly TAFs:

$$\mathrm{V_{i,k,t}=AADT_i \times FM_{NFC(i),k} \times MAF_{NFC(i),MON(t)} \times DAF_{NFC(i),k,DAY(t)} \times HAF_{NFC(i),DTYPE(t)}} \quad (1)$$

where $\mathrm{V_{i,k,t}}$ = estimated volume (vehicles $\mathrm{h^{-1}}$); $\mathrm{AADT_i}$ = annual average daily traffic (vehicles $\mathrm{day^{-1}}$); NFC(i) = National Functional Class, which defines the road type;

$FM_{NFC(i),k}$ = fleet mix allocation factor, the fraction of vehicles in vehicle class k (a function of link i and road type NFC(i)); $MAF_{NFC(i),MON(t)}$, $DAF_{NFC(i),k,DAY(t)}$ and $HAF_{NFC(i),t}$ respectively are monthly, daily and hourly temporal allocation factors (dimensionless); DTYPE(t) = day type for the hour, either weekday, Saturday, Sunday or holiday; i = road link; k = vehicle class; and t = time. States and other entities assign road segments to NFCs, providing a designation as either rural or urban, and then into one of eight classes (e.g., NFC 11 = interstate, 12 = other freeways and expressways, 14 = other principal arterial, 15 = minor arterial, 17 = major collector, 19 = minor collector, 21 = local). (In 2010, the NFC system was revised, and NFC 11 and 12 are now designated as Functional Classification Codes 1 and 2, respectively.)

Fleet mix allocation factors can utilize different systems of classifying vehicles. Here the two-class system mentioned earlier is used: non-commercial (e.g., passenger) and commercial (e.g., trucks and buses) vehicles. Summed across vehicle classes, $\Sigma_{k=1 \ldots 2} FM_{NFC(i),k} = 1$ for each road link i. Fleet mix allocation factors were also derived using Table VM-4 in the FHWA Highway Statistics Series (http://www.fhwa.dot.gov/policyinformation/statistics/2010/vm4.cfm) and information from the US EPA Emission Inventory Improvement Program (http://www.epa.gov/ttn/chief/eiip/).

The monthly temporal allocation factor, $MAF_{NFC(i),k,MON(t)}$, typically ranges from 0.9 to about 1.1. Summed across the 12 months, $\Sigma_{t=1..12} MAF_t = 12$. The day-of-week factor, $DAF_{NFC(i),k,DAY(t)}$, has greater variation and potentially strong dependence on vehicle class. Summed across the 7 days in a week, $\Sigma_{t=1..7}$ DAF $NF_{C(i),k,DAY(t)} = 7$ for each vehicle class k and road type $NFC_{(i)}$. The hour-of-day factor, $HAF_{NFC(i),HR(t),DT(t)}$, gives the diurnal pattern, e.g., the bimodal weekday pattern associated with morning and afternoon rush hour periods, and a unimodal pattern on weekends. Summed across the 24 h in a day, $\Sigma_{t=1 \ldots 24} HAF_{NFC(i),DT(t),HR(t)} = 1$ for each road type and day type. Eq. (1) accounts for interactions between the hour-of-day and day-of-week profiles, but otherwise TAFs are assumed to be independent (e.g., HAFs do not depend on month), thus providing a parsimonious set of profiles. Since all sites were located on major freeways, we did not distinguish by road type.

Three sets of TAFs were evaluated (each with monthly, daily and hourly TAFs). The first set included 17 "site-specific" TAFs derived for the total vehicle volume at the 13 Detroit sites and the commercial vehicle volume at the four weigh-in-motion sites. At each site, hourly TAFs for weekdays, Saturdays, Sundays and holidays, along with and daily and monthly TAFs, were calculated by year using normalized volumes, after which the 4-year site average was taken and renormalized (e.g., thus ensuring that $\Sigma_{t=1..7}$ DAF $_{NFC(i),k,DAY(t)} = 7$). The second set of TAFs were "urban" area-wide profiles that averaged TAFs across the Detroit area (again at monthly, daily and hourly levels) for total volume (13-site 4-year average) and commercial volume (4 site 4-year average). The third set used literature estimates from the SMOKE modeling system (http://www.cmascenter.org/smoke/). This compact set used same monthly TAFs for all vehicle classes, daily TAFs for two vehicle classes, and hourly TAFs that depended on road type and day type (weekdays and weekends; Saturday and Sunday profiles were not distinguished). Recent improvements to SMOKE have separated hourly profiles for commercial and non-commercial traffic.

Eq. (1) should approximate the AADT when volumes are summed over vehicle classes and hours of the year:

$$\mathrm{AADT_i} \approx 365^{-1} \sum_{\mathrm{k=1..2}} \sum_{\mathrm{t=1,8760}} \mathrm{V}_{i,\mathrm{k,t}} \quad (2)$$

Eq. (2) is not an equality since AADT generally does not account for holidays, the temporal allocation factors can utilize medians to improve robustness, and missing data can introduce errors. However, differences should be small.

2.4. Evaluation of TAFs and unusually high or low traffic volumes

Descriptive statistics of normalized volumes were computed at annual, monthly, daily and hourly levels stratified by site, year, day-of-week, day-of-week, holiday and bridge day. Separate analyses were performed for total and commercial traffic. Differences between sites were compared using t and Mann–Whitney U tests, and Spearman correlation coefficients.

Adjusted normalized volumes were used to quantify volume changes on holidays and to identify days with unusually high or low volumes, differing by more than 25% from that expected. Days of “abnormal” traffic activity across the study region were identified by first flagging days when the adjusted normalized volume at a site deviated by at least 25% of the norm. Next, to exclude localized events, e.g., accidents or construction, only those days when at least half of the sites had such deviations were considered. The 25% constraint was subsequently relaxed to 10%. This analysis examined total daily volume. Meteorological data on days with unexpectedly low volumes were examined to identify if adverse driving conditions were present. Meteorological data for this purpose were obtained from the National Oceanic and Atmospheric Administration's Quality Controlled Local Climatological Data (http://cdo.ncdc.noaa.gov/qclcd/QCLCD) for four airport sites in the study area (Detroit City Airport, Detroit Metro Airport, Grosse Pointe Farms, St. Clair Shores).

The performance of Eq. (1) was evaluated for the three sets of TAFs using scatter and trend plots, correlation coefficients, and the median relative absolute bias (MRAB, the median of $|P_t – O_t|/O_t$, where P_t and O_t are predicted and observed vehicle counts overall hours t). For diagnostic purposes, these statistics were stratified by day and site. To highlight effects of temporal adjustments, the vehicle mix factor in Eq. (1) was not used. Instead, the measured volume (total or commercial) for the year was used. A final evaluation examined model performance at the I-96 EH site, which represents an independent dataset not used to develop the TAFs.

3. Results

3.1. Data availability

Data availability was high. At the sites recording total vehicle counts, availability averaged over 90% (hours with valid data). Some data were missing-at-random, but more were missing in extended blocks due to equipment malfunction. Traffic interruptions (e.g., from storms or flooding) generally do not cause missing data. Much of 2009 was missing at I-94 site 8839, and about half of 2010 and 2011 was missing at M-10 site 9809. Data from only one direction at the M-24 site 8440 were available during the study period. At the four weigh-in-motion sites, data availability differed by year and site. In 2009, only 15% of data was available at site M-24 site 8440, and no data were available at I-75 site 9799. Excluding these two site-years, over 94% of the hourly data was available. These data gaps had little effect on results since most roads had multiple sites, multiple years were evaluated, and, as shown later, temporal patterns were similar across sites and years.

At the I-96 radar site, data availability was 72.1% for the 9 months the site operated. Given the limited data available, this site was used not used to develop profiles. Instead, it was used as an independent dataset for evaluation purposes.

3.2. Characteristics of study roads and count data

Locations of the 14 counting stations are mapped in Fig. 1, and characteristics of the highways and recorder types are summarized in Table 1. The stations were located on seven different roads that had from 6 to 8 traffic lanes, and all except the US-24 site were on limited access highways (NFC 11 or 12). Based on short-term count and classification data from 2010 to 2011, AADT ranged from 74,000 to 161,000 vehicles/day at the sites. Three of the interstate highway (I-75, I-94, I-275) had considerable (7–11%) commercial traffic. These roads serve many long-haul trucks, e.g., 7000–9000 trucks cross the international border daily from Detroit, Michigan to Windsor, Canada. The fourth interstate, I-96, had a smaller amount of commercial traffic (4%). The other roads (M-10, M-39, US-24) had smaller fractions of commercial traffic (1–4%) and primarily serve commuters. Overall, the 14 sites represent a range of major roads and vehicle mixes.

Based on the continuous counting measurements, vehicle volumes in FHWA classes 1 to 3 (motorcycles, passenger cars, light duty trucks/pickup trucks/sport utility vehicles) constituted an average of 0.44, 78.7, and 13.7% of total vehicle volume on I-94, I-75, I-275 and US-24, respectively (total of 92.9%). Commercial volume, estimated as the sum of FHWA classes 4 through 13, was dominated by classes 9 (5-axle single trailer trucks, 4.27% of total volume) and 5 (2-axle single unit vehicles, 1.11%); the remainder came mostly from classes 6, 10 and 13 (0.36 to 0.49% each). This is fraction is below that reported for Michigan urban interstates (NFC = 11) i n 2000 when FHWA classes 1-3 accounted for 83% of total volume (Lindhjem and Shepard, 2007). Differences may result from inclusion of weekend data in the reported statistics for the weigh-in-motion data, decadal shifts in vehicle mix, and possibly geographic differences in vehicle mix, although vehicle mix was not found to vary by state or region.

Non-commercial and commercial volumes had only moderate correlation (r = 0.61 to 0.68 on an hourly basis; r = 0.73 to 0.83 on a daily basis), indicating different temporal patterns. Across the four roads, trends of noncommercial vehicle volumes were highly correlated (r = 0.82 to 0.97 on an hourly basis; r = 0.77 to 0.91 on a daily basis), as were trends for commercial vehicles (r = 0.81 to 0.96 on an hourly basis; r = 0.86 to 0.97 on a daily basis). These results suggest that temporal variation in traffic activity is similar across the region, but different by vehicle classes.

3.3. Annual, monthly and daily variability

Fig. 2 shows vehicle volumes by year, month and day of total and commercial vehicles. Annual volumes were normalized to the 4-year mean at each site. Volumes of total vehicles (Fig. 2A) were very constant across years. Deviations found at some sites likely result from temporary closures or rerouting. Analyses using only weekend or weekday volumes also showed a lack of trend across the four years (not shown). Somewhat greater variation was found for commercial vehicles, e.g., the decrease in 2010 was larger (Fig. 2D), possibly an impact from the economic recession.

Monthly variation is shown in Fig. 2B and E using normalized volumes (ratio of each month's volume to that year's average). Across all sites, volume decreased by 4–8% in winter (December–January) and increased in summer by 4–5% (June–August). July's increase was smaller than that for the other summer months on most of the study roads, possibly due to the July 4th holiday, summer vacation, and construction activity. Considering only weekends, changes were slightly larger, e.g., December–January volumes decreased by 4–10%, and June–August volumes increased by 4–6%; on weekdays, month-to-month changes were slightly lower. Considering only commercial vehicles, trends were similar but changes were larger, e.g., volume decreased by 12% in January and increased in summer months by 5–8%. To account for monthly effects, this analysis suggests that monthly TAFs might be broken down by vehicle type (commercial vs. non-commercial) and day type (weekend vs. weekday). The monthly TAFs developed in this analysis separate vehicle type, but not day type; the literature TAFs distinguish neither vehicle type nor day type. In the worst case, biases of approximately 5–10% are expected to result from these simplifications.

Fig. 2C and F display day-of-week variation using normalized volumes (ratio of each month's average on a particular day to the month's average volume) that compensate for changes in both annual and seasonal volumes. Holidays used the ten federal holidays plus the day after Thanksgiving (see below). Considering total vehicle volume, activity increased from Monday to Friday (median normalized volumes from 1.05 to 1.15), and then decreased on Saturday and Sunday (normalized volumes of 0.86 and 0.73, respectively). For commercial vehicles, volume was quite constant through the workweek, but dropped on weekends, especially on Sunday (normalized volumes of 0.45 and 0.20 on Saturday and Sunday, respectively). On holidays, volume decreased from annual levels by 21% and 44% for non-commercial and commercial vehicles, respectively. Decreases were much greater on six of the ten holidays, since four are not widely observed, as discussed below.

Both the month-to-month and day-of-week variations were very regular across all sites over the four year period. Commercial and non-commercial (passenger) vehicles showed moderate differences in monthly trends, and larger differences in daily trends. As discussed below, variation can result from highway construction, weather, major accidents, economic trends, and consumer activity.

3.4. Highest and lowest traffic volumes

A total of 37 days across the four years had deviations exceeding 25% from the expected volume at half or more of the counting sites. All were low traffic days, and most fell on six holidays: New Year's, Washington's Birthday, Memorial Day, Independence Day, Thanksgiving, and Christmas, or on bridge days for Thanksgiving or Christmas. Low volume on six additional days were attributed to hazardous road conditions (freezing rain or considerable snow accumulation on 1/17/09, 2/21/09, 2/22/10, 1/9/11, 2/2/11, and 2/5/11). One poor weather day (1/17/09) was also Martin Luther King Jr. Day, a federal holiday that normally experienced only small volume reductions (see below). The last low volume day, Monday 9/24/12, had volumes drop by over 25% at 8 of 11 sites reporting complete data. No holiday, weather condition, or other factor that might explain this decrease was identified, although construction in the Canadian plaza section of the US-Canada tunnel crossing was ongoing (but only minor traffic impacts were expected (http://www.mmdonline.com/trade/construction-begins-at-windsor-detroit-tunnel-78638/).

There were no days when traffic increased 25% or more at most sites. Using a 10% criterion, 26 days over the 4-year period had increased volume. Of these, 15 occurred on weekends, and 9 were in the week before Christmas, suggesting holiday shopping traffic. Given the relatively small increases, these events were not investigated further.

3.5. Traffic volumes on holidays and bridge days

Volume changes over the Thanksgiving week are shown in Fig. 3. This widely-observed holiday always falls on Thursday, and Friday is a bridge day when many workers have a day-off. The dramatic volume reductions on Thanks giving (34 ± 5% and 81 ± 10% for total and commercial vehicles, respectively, overall all sites and years) continued on Friday (30 ± 4%, 59 ± 4%), and to a small extent on Saturday (8 ± 3%, 26 ± 10%). The large drop in commercial traffic is notable. Prior to the holiday, total volume slightly increased (5–6%) from the monthly average, while commercial traffic decreased (Table S2).

Normalized holiday volumes are shown in Fig. 4 and by road in Table 2. For total volumes and the six observed holidays, reductions averaged 38 ± 5% across study roads. Several roads and road sections experienced greater reductions, e.g., M-24 showed over 50% reductions on several holidays. The four other federal holidays had smaller or negligible reductions, e.g., reductions averaged 14 ± 4% on Martin Luther King Jr. Day (but some of this was due to poor weather in 2009), and 9 ± 5% on Washington's Birthday; Columbus and Veterans' days had very small changes. This is not unexpected since these holidays are not widely observed, and many businesses and schools remain open. These patterns were mostly reproducible across the 13 sites and 4 years, although maxima and minima spanned a large range, e.g., normalized volumes for New Year's ranged from 0.41 to 1.21 (left-most bar and whisker plot in Fig. 4). Such observations may be considered “outliers” resulting from construction, weather or other events on the holiday or the comparison periods. Removing those points, e.g., considering only the 5–95th or 25–75th percentile range, considerably tightens the distribution. Since results for each holiday are calculated using 44–54 site-years of data (depending on data completeness), median and average statistics are robust.

Commercial traffic volume fell dramatically on holidays (Fig. 4B), e.g., adjusted normalized volumes dropped by 78 % ± 5% on the six observed federal holidays. This exceeded the typical weekend reduction (Fig. 2F).

Volume changes for bridge days (adjacent to the holiday) were substantial for New Year's (14 ± 2% and 41 ± 9% for total and commercial traffic, respectively), Thanksgiving (30 ± 4%, 59 ± 4%), and Christmas (15 ± 3%, 43 ± 6%) (Table S2). Across the 2009 to 2012 period, New Year's fell on Thursday, Friday, Friday and Monday, respectively; Independence Day fell on Friday, Monday, Monday and Wednesday; and Christmas fell on Friday, Friday, Monday and Tuesday. For these fixed holidays, a “true” bridge day occurred only for New Year's 2009. Results for Christmas and Independence Day bridge days depended, to an extent, on the day-of-week. Since federal holidays other than Thanksgiving always fall on Mondays, most holidays do not have true bridge days. Overall, volume changes on bridge days for New Years', Thanksgiving, and Christmas were significant, especially for commercial vehicles.

Literature TAFs have not been formulated for holidays. Although applicable for only 9–13 days of the year, holidays show large and reproducible changes in activity, especially for commercial vehicles.

3.6. Diurnal trends

Fig. 5 shows hourly activity profiles of total and commercial vehicles. The patterns differed on weekdays, Saturdays, Sundays and holidays, but otherwise were highly reproducible across the 13 sites and 4 years. Considering total vehicle volume, weekday trends were bimodal with modes at 7–8 am and 4–5 pm, reflecting morning and afternoon rush hour periods (Fig. 5A). At these times, normalized hourly volumes approached 10% of the daily volume at some sites and some days. At most sites, the morning peak was shorter in duration and peak volume was lower than the afternoon rush hour peak. (Peak morning and afternoon volumes were similar at I-94 site 9419 and M-24 site 8440.) Saturdays and Sundays had broad unimodal distributions that peaked at 3–5 pm and 2–3 pm, respectively (Fig. 5B and C). Generally similar patterns have been observed on I-440 in Raleigh, NC (Baldauf et al., 2008). Hourly profiles on weekday holidays resembled the weekend profiles, although the variability was greater (Fig. 5D). The lowest traffic activity occurred between 1 and 4 am on weekdays, 2–4 am on Saturdays, and 3–5 am on Sundays. These patterns were consistent, although variability increased during rush hours and late Saturday night.

Hourly profiles of commercial vehicle volume differed from those for total traffic. Weekday profiles were unimodal and relatively uniform from 8 am to 3 pm (Fig. 5E). On weekends, commercial traffic was light (only 36% of the weekday level on Saturday, and only 21% on Sunday), and a new profile is seen: hourly volumes gradually and linearly declined from 9 am Saturday through 3 am Sunday morning (Fig. 5F and G). On Sunday, volumes were similar from 10 am to 7 pm. On holidays (Fig. 5H), trends resembled those seen for total commercial traffic (Fig. 5E). Again, Sunday and holiday patterns for commercial traffic had somewhat greater variability across sites and years than patterns for other days and total traffic. This is also reflected inpoorer performance of the TAF model (discussed below).

The strikingly different trends in Fig. 5 highlight the need to separate hourly profiles by vehicle type and by day type (weekdays, Saturdays, Sundays and holidays).

3.7. Model performance

Observed hourly volumes were compared to predicted volumes calculated using Eq. (1), 4-year site-specific TAFs, and the site- and year-specific AADT or CAADT. As an example, Fig. 6 contrasts estimated and observed hourly volumes at the I-94 weigh-in-motion site in 2012. Given that site-specific parameters were used, estimated and observed volumes were expected to have high agreement, and discrepancies would suggest flaws in the independence assumptions. Fig. 6 shows very good agreement ($r = 0.98$ for total volume, $r = 0.84$ for commercial volume) and small errors (MRAB = 5% for total volume and 7% for commercial vehicles). This performance somewhat exceeds that attained for the other sites and years. Table 3 provides performance statistics at the 4 weigh-in-motion sites across the 4 years. Considering total volume, predictions and observations matched closely (4-site 4-year average: $r = 0.94$; MRAB = 8%; 89% within 25%). Performance was maintained on Saturdays, but degraded slightly on Sundays and further on holidays ($r = 0.92$; MRAB = 18%), reflecting the greater variability of weekend and holiday traffic, which were only partially (though mostly) reflected in the TAFs. Accounting for holidays did not greatly alter overall performance given the relatively few days affected, although it eliminated the noticeable overprediction that occurred on these days. For commercial vehicles, overall performance was very good (4-site 4-year average: $r = 0.94$; MRAB = 13%; 79% within 25%), but fit decreased on Sunday, Saturdays and holidays, and varied across sites. Performance was mediocre for roads with few commercial vehicles, i.e., M-24. While suggesting that more information is needed to estimate commercial traffic on weekends and holidays, the lack of fit may be inconsequential since commercial traffic is very light on these days.

The preceding evaluation used site-specific model parameters and thus represents a “best-case” analysis, although it does not account for all of the monthly dependences in the day-of-week trends discussed earlier. Table 4 shows TAF model performance at all 14 sites using the second set of TAFs, the urban-wide 13-site 4-year average. Again, performance was very good for total volume ($r = 0.93$, 0.92, 0.91 and 0.87 for all, Saturday, Sunday and holiday observations, respectively; MRAB = 13, 14, 14, and 23%). For commercial vehicles, performance was similar to that seen earlier, although the MRAB increased on weekends and holidays.

Table 4 also shows performance at the I-96 EH site, which represents an independent dataset since it was not used to develop the TAFs, and since no other monitoring site was on this road. Agreement was high for the data available (2010–2011; $r = 0.89$, MRAB = 13%). While not comprehensive, this evaluation suggests that TAF-based models can perform well using data from other (potentially similar) roads in the urban area. Overall, the fit achieved using urban-wide TAFs was generally comparable to that using site-specific TAFs. Urban-wide TAFs might be advantageous given increased robustness and spatial representativeness.

Performance with the third set of TAFs, from the literature, is depicted in Fig. 7. For total vehicle volume, correlation was high (4 site, 4-year average: r = 0.89), but many predictions diverged from observations, relative bias increased, and large errors were frequent (MRAB = 40%; 72% within 25%). For commercial vehicles, overall performance was fair (r = 0.76; MRAB = 35%), but poor on weekends (r = 0.59 and 0.31 for Saturdays and Sundays, respectively). These hourly TAFs were based on road type, not vehicle class, and the poor fit for commercial vehicles primarily occurred because both daily and hourly TAFs, derived for total volume, did not match patterns of commercial traffic. The literature profiles also represented a national aggregation, providing a second possible reason for lack of fit, although state and regional differences appear small (Lindhjem and Shepard, 2007). Again, these results demonstrate the need to separate commercial and non-commercial activity. Additional discrepancies, particularly for commercial vehicles, result from failing to distinguish hourly profiles for Saturdays and Sundays, and to a minor extent, not accounting for differences in monthly profiles by vehicle type.

Eight hourly profiles are plotted in Fig. 8. Tabular data for monthly, daily, and hourly TAFs are listed in Tables 5–7. These profiles are suggested as representative for the major roads in metropolitan Detroit.

4. Discussion and conclusion

This paper has quantified the temporal variation in traffic activity for total and commercial vehicles on major roads in the Detroit region using a comprehensive dataset. Results for this large urban region likely reflects the temporal variation and the factors affecting traffic activity in many other U.S. cities. This variation is important for air pollution analyses, air quality modeling and monitoring, exposure estimation, environmental epidemiology, and risk assessment, as described below.

Traffic activity reported as annual estimates, e.g., AADT and CAADT, is easily and accurately apportioned to each hour of the year using temporal allocation factor (TAF) based models. TAFs, the key parameters in these models, describe the expected temporal variation in traffic activity at monthly, daily and hourly levels. We show that separate sets of TAFs are needed for passenger and commercial vehicles, and for weekdays, Saturdays, Sundays and observed holidays. As discussed below, this is highly significant for air quality applications since trucks and other commercial vehicles have far greater emissions rates than passenger vehicles (Watkins and Baldauf, 2012). Both urban-wide and site-specific TAFs developed in this study performed well, explaining nearly all of the variation in traffic activity observed in Detroit with a few exceptions, e.g., low volumes that occur days with adverse weather and poor driving conditions. In contrast, literature TAFs that do not account for differences by day type (e.g., Saturdays vs. Sundays) and vehicle type (e.g., passenger versus commercial vehicles) poorly fitted observed data. In addition to weather, TAFs do not explain variation due to traffic accidents, construction, or other major traffic-altering events, e.g., sports events and presidential motorcades.

4.1. Study limitations

We recognize several limitations. Monitoring sites are subject to faults, full or partial outages (e.g., loss of a lane or direction), and various errors and biases leading to counting or classification errors. While sensors are very reliable and the count data had undergone extensive validation, we experienced multiple and mostly short-term outages; some partial outages also occurred. The use of multiple sites and years of data should minimize such errors. Most of the permanent counting stations were installed on large freeways in Detroit, and trends across sites were generally very similar. Both vehicle mix and temporal patterns can vary on different road types, e.g., arterials and collectors (Lindhjem and Shepard, 2007), and hourly volume on city streets would depend on traffic flow volume, road capacity, the type of intersection, signaling, driver behavior, and other factors. Thus, a greater diversity of roads and urban areas should be evaluated. Traffic activity patterns in the study region do not necessarily pertain to traffic activity elsewhere, including rural areas. Our division of non-commercial and commercial activity is approximate and has limitations. These categories are important since most non-commercial or passenger vehicles in the U.S. use spark ignition (gasoline) engines, while commercial vehicles are larger and predominantly diesel-powered. However, these distinctions are not necessarily reflected in the FHWA classes, which are based on vehicle size and axle counts. Finally, we examined only a subset of factors that constitute vehicle activity, e.g., vehicle speed and acceleration were not evaluated.

4.2. Significance – air quality emissions inventory and modeling

Both annual average and short-term (e.g., 1-h) concentrations must be evaluated to ensure compliance with air quality standards. U.S. EPA suggests the use of an allocation factor to estimate peak-hour volume from AADT values (U.S. Environmental Protection Agency, 2013). Dispersion modeling of traffic-related air pollutants, described elsewhere (Cook et al., 2008; Heist et al., 2013) would benefit by an improved representation of traffic activity since uncertainties in emissions inventories, and hourly emissions estimates in particular, are large, and since temporal patterns of heavy duty and other high-emitting vehicles have not been described accurately (Lindhjem et al., 2012). Our findings support ongoing improvements to SMOKE that separate TAFs for commercial and non-commercial vehicles, and that distinguish weekday, Saturday and Sunday profiles.

In terms of NO_x and PM2.5, each HDDV can represent several or many passenger car equivalents (PCEs). For example, using MOVES2010a, summer fuel, a vehicle speed of 70 miles/h, ambient temperature of 80 °F, and Detroit vehicle fleet parameters, NO_x emissions are 0.685 g/mile for light duty gasoline vehicles (LDDVs) and 8.278 g/mile for HDDVs, thus 1 HDDV = 12 PCEs. Under the same conditions, $PM_{2.5}$ emissions are 0.0072 and 0.3623 g/mile for LDDVs and HDDVs, respectively, giving 50 PCEs. Using these figures and the 14-site average CAADT/AADT ratio of 0.06, the 27 and 72% drop on weekends of total and commercial traffic volumes, respectively, weekend on-road emissions of NO_x and $PM_{2.5}$ decrease by 47 and 61%, respectively, from weekday values. While these calculations are approximate, the combined influence of temporal shifts in vehicle volume and mix is significant. Changes would be larger for roads with a higher fraction of HDDVs.

The weekend/weekday changes in vehicle emissions may help explain the higher levels of ambient ozone (O_3) found on weekends in some areas (Lindhjem et al., 2012). In particular, the higher levels of ambient ozone found on weekends in some areas may result from decreased titration of ozone by NO_x. However, on a regional and certainly on a national scale, NO_x decreases will decrease ozone. In contrast, primary $PM_{2.5}$ emissions associated with vehicles decrease on weekends.

4.3. Air quality monitoring and exposure assessment

Like dispersion modeling applications, monitoring of traffic-related air pollutants often focuses on (worst-case) ‘hotspots’, e.g., locations with the greatest traffic activity. Guidance for the near-road NO_2 monitoring network in the U.S. suggests that locations with the highest hourly (and sometimes 24-h) concentrations be identified along highways with the highest fleet equivalent traffic volume, which heavily weights truck traffic (default PCE = 10) (Watkins and Baldauf, 2012). Since the NO_2 ambient standard is a 1-h average, understanding peak traffic activity is important.

Recently, several urban-scale spatially-resolved link-based traffic networks have been developed and simulated using line source dispersion models, e.g., RLINE (Snyder et al., 2013). Traffic activity information, including temporal variability, is needed at the resolution of the road network. Our results show that temporal variation on major roads was homogeneous across the large Detroit region, indicating that TAFs can be used across an urban area and likely across states and regions (Lindhjem and Shepard, 2007).

Few exposure and epidemiology studies investigating the spatial variation of traffic pollutants have represented temporal variation. (The many time series air pollution epidemiology studies have used daily fluctuations of concentrations at population-oriented sites where traffic impacts are difficult to distinguish and without spatial resolution.) Temporal information is needed to estimate exposures of traffic-related air pollutants, especially for vulnerable populations, e.g., individuals living, working, commuting, or exercising near major roads (Zhang and Batterman, 2008). Additional temporal information is needed to account for the time activity patterns of such individuals, e.g., time spent outdoors and indoors where concentrations may be attenuated. In all cases, temporal information is needed to estimate long- and short-term exposures.

Two additional temporal issues are noted. First, meteorology differentially affects exposures over the day, e.g., mornings are often transitional periods from stable or nocturnal inversion conditions, which can elevate pollutant concentrations, compared to afternoons characterized by unstable conditions with greater dispersion. Such patterns emphasize the importance of early morning exposure and the morning traffic peak. Second, building air exchange rates, which govern indoor concentrations of traffic related pollutants, are driven by indoor/outdoor temperature differences, wind speeds and building factors, also change over the day (Breen et al., 2013). Both issues can affect exposures of traffic-related air pollutants and may cause systematic biases.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights

- Temporal variation in traffic volume affects emissions and pollutant exposures.
- Annual traffic volume can be apportioned to the hour using temporal allocation factors.
- Temporal allocation factors (TAFs) must separate passenger and commercial vehicles.
- TAFs must separate weekdays, Saturdays, Sundays and observed holidays.
- Most variation in traffic flows can be addressed using appropriate TAFs.

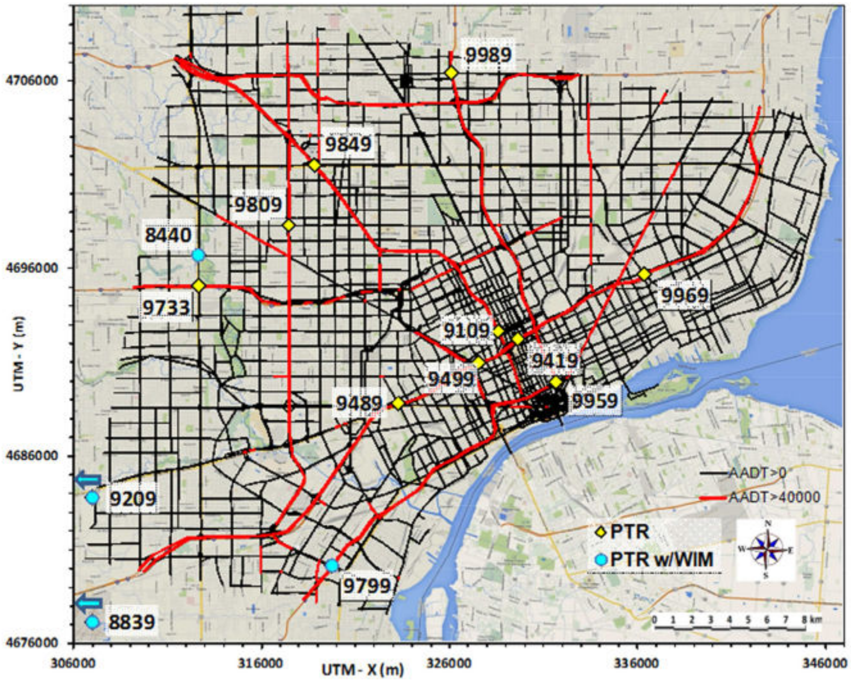

Fig. 1.

Map showing major roads and locations of traffic recorders in the study region. Two of the weigh-in-motion sites (9209 and 8839) are off the map to the west direction as indicated.

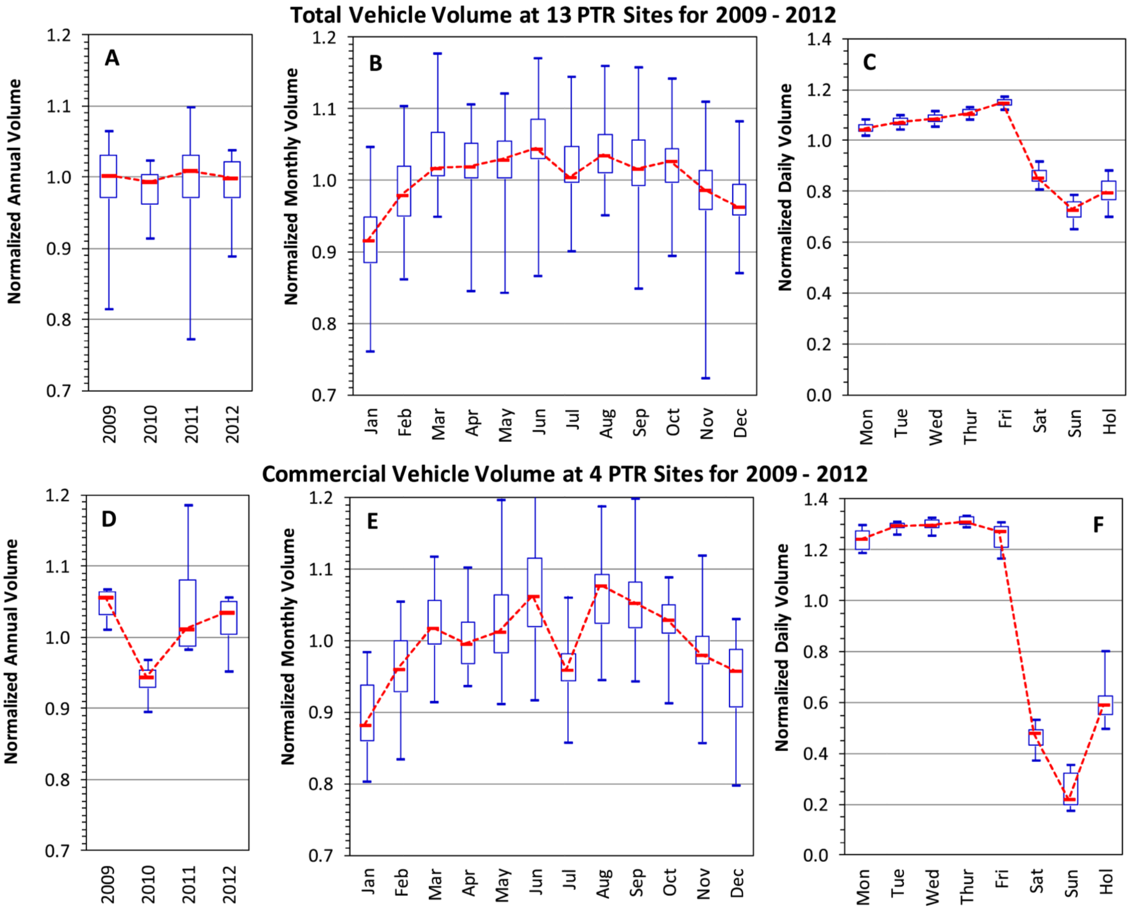

Fig. 2.

Normalized traffic volumes by year, month and day-of-week and holidays for volumes of total vehicles (A–C) and commercial vehicles (D–F). Plots shows 5th, 25th, 50th (red bar), 75th and 95th percentile values. Scales of panels A, B, D and E differ from plots C and F. Panels C and F consider all 10 federal holidays. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

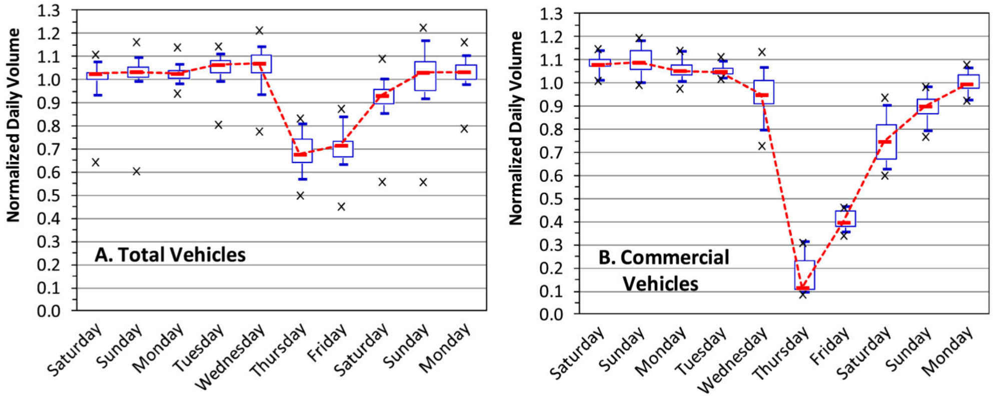

Fig. 3.

Daily normalized volume for Thanksgiving period for total vehicles at 14 sites (A. left panel) and for commercial vehicles at four sites (B. right panel). Plots shows 5th, 25th, 50th (red bar), 75th and 95th percentile values, and minimum and maximum observations as points. Dashed line shows trend of median over the 10-day period. Based on 51 to 54 site-years for each day for total vehicles and 12 to 14 site-years for commercial vehicles. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

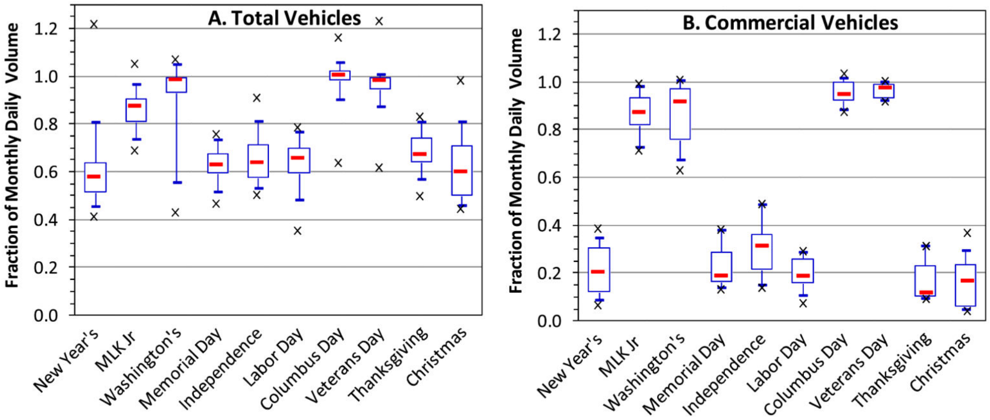

Fig. 4.

Normalized daily traffic volume on federal holidays for total number of vehicles (left panel) and for commercial vehicles (right panel). Normalization to monthly average for same day-of-week on that day. Plot shows 1st, 5th, 25th, 50th (red bar), 75th, 95th and 99th percentile values. Based on 45 to 54 site-days for each federal holiday for total vehicles, and 12 to 14 site-days for each federal highway for commercial vehicles. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

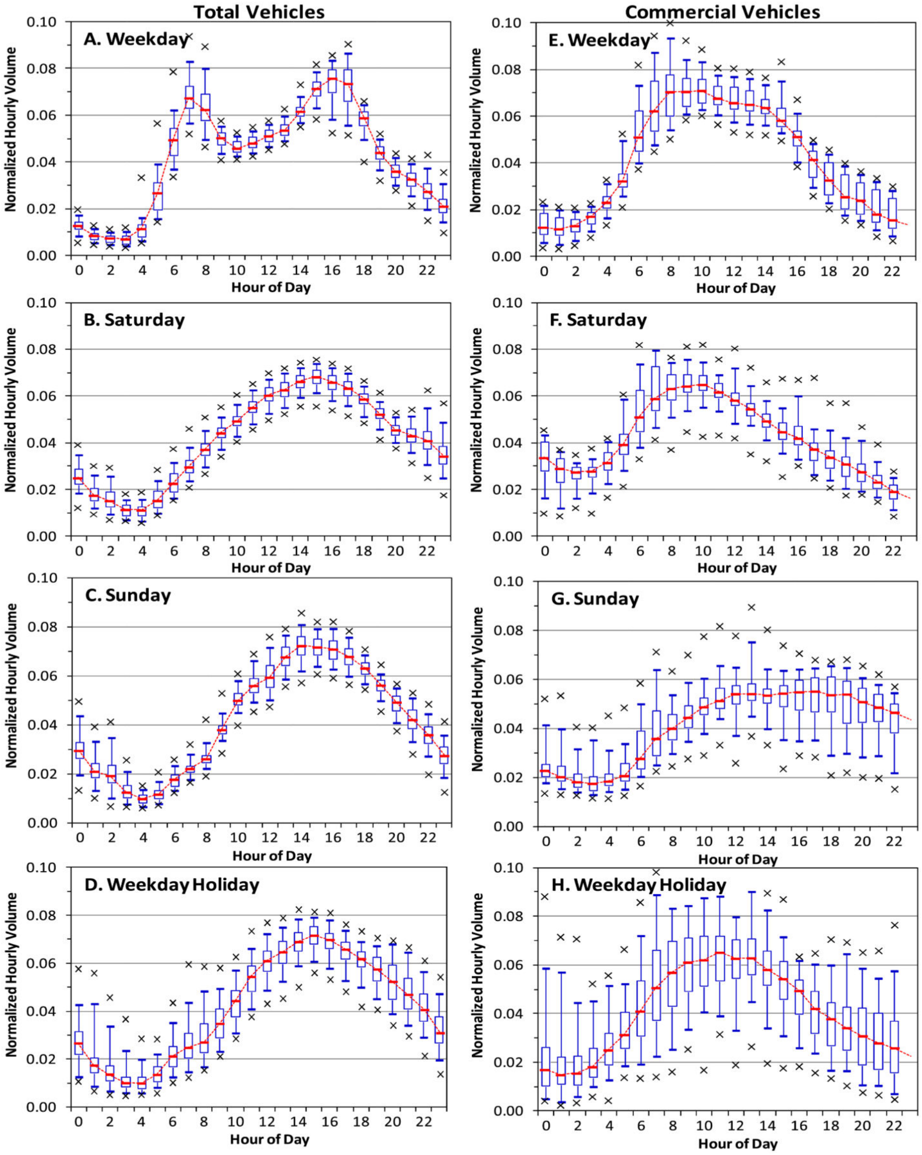

Fig. 5.

Diurnal trends of total volume for total vehicles across the 14 site and 4 years (panels A–D), and commercial vehicles for four weigh-in-motion sites and 4 years (E–H). Hourly volume is normalized to daily traffic for the same day and site. Weekday, Saturday and Sunday excludes ten holidays plus Friday after Thanksgiving. Weekday Holiday includes six federal holidays plus Friday after Thanksgiving. Plot shows 1st, 5th, 25th, 50th (red bar), 75th, 95th and 99th percentiles. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

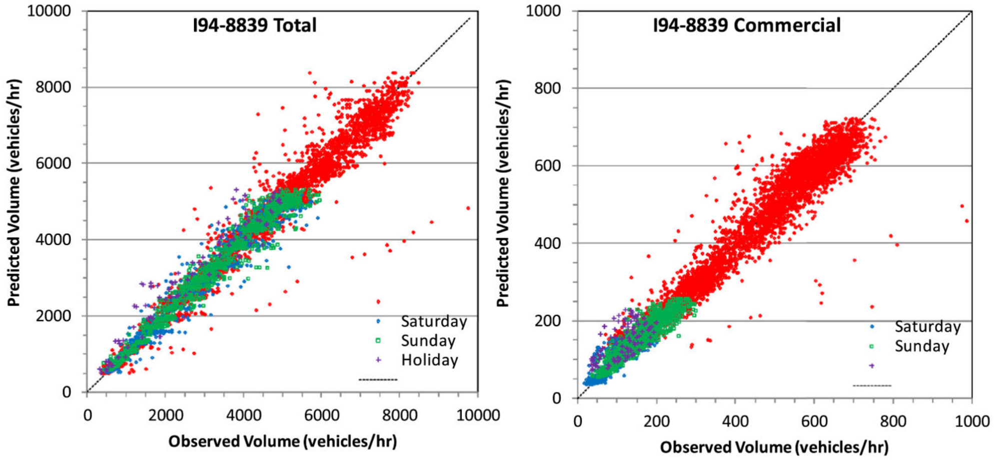

Fig. 6.

Predicted versus observed total (left) and commercial (right) hourly vehicle volumes at the I-94 site for 2012 using site-specific data.

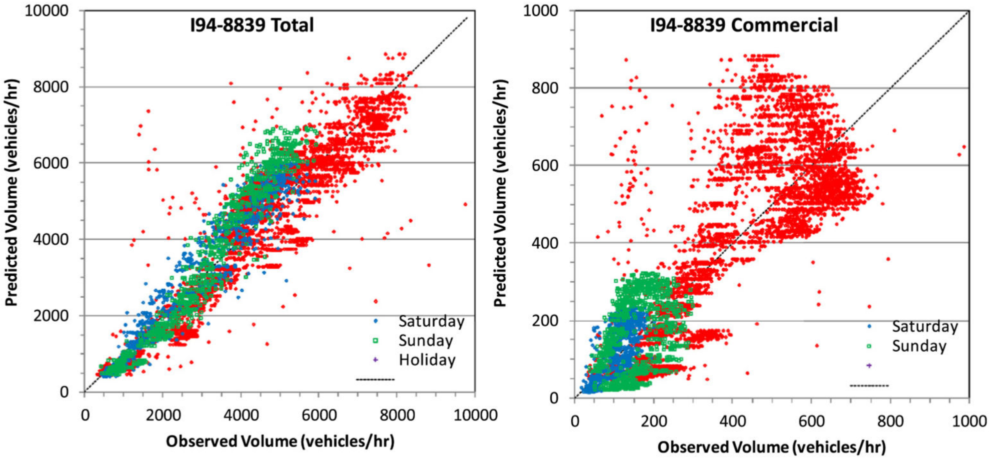

Fig. 7.

Predicted versus observed total (left) and commercial (right) hourly vehicle volumes at the I94 site for 2012 using literature data. Holidays are not modeled.

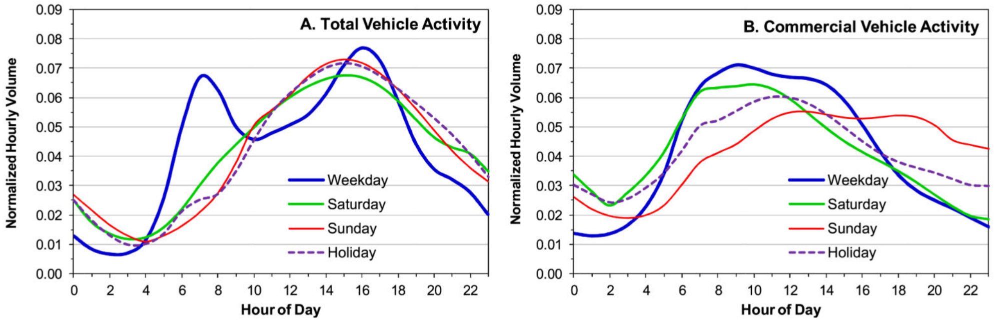

Fig. 8.

A. Total traffic activity for weekdays, Saturdays, Sundays and holidays. B. Commercial vehicle activity for four day types.

Table 1

Locations and descriptions of the traffic-monitoring network. AADT and CADT data taken from short-term vehicle counts. WIM is weight-in-motion.

Station ID	Type	Highway number	Highway name	Cross street	County	Align-ment	No. lanes	AADT (veh/day)	CADT (veh/day)	Coverage (%)	Notes
9799	WIM	I-75	Fisher Fwy	Southfield Hwy (M-39)	Wayne	NE–SW	6	92,558	10,425	98.8	
9959	Induct	I-75	Fisher Fwy	Chrysler Fwy (I-375)	Wayne	E–W	8	100,889	11,106	86.2	
9989	Induct	I-75	Chrysler Fwy	E 11 Mile Rd	Oakland	N–S	6	161,368	5922	95.3	
8839	WIM	I-94	Detroit Industrial Expy	Belleville Rd	Wayne	E–W	6	84,545	7209	73.3	
9489	Induct I-94		Edsel Ford Fwy	Lonyo St	Wayne	E–W	6	118,634	10,475	94.2	
9499	Induct	I-94	Edsel Ford Fwy	Linwood Ave	Wayne	NE–SW	6	137,697	10,764	91.0	
9419	Induct	I-94	Edsel Ford Fwy	Woodward Ave (M-1)	Wayne	NE–SW	6	142,672	10,764	91.0	
9969	Induct	I-94	Edsel Ford Fwy	Conner St	Wayne	E–W	6	126,788	6418	90.1	
9733	Radar	I-96	Jeffries Fwy	Telegraph Rd (US-24)	Wayne	E–W	8	136,600	5157	72.1	*(1)*
9209	WIM	I-275	I-275	US-12	Wayne	N–S	6	95,360	6447	90.5	
9109	Induct	M-10	John C Lodge Fwy	Grand Blvd	Wayne	NW–SE	6	109,947	2074	90.6	
9849	Induct	M-10	John C Lodge Fwy	W 8 Mile Rd (M-102)	Wayne	NW–SE	6	73,650	2074	79.5	
9809	Induct	M-39	Southfield Fwy	6 Mile Rd (McNichols)	Wayne	N–S	6	123,218	4898	93.2	
8440	WIM	US-24	Telegraph Rd	5 Mile Rd	Wayne	N–S	8	63,934	767	97.4	*(2)*

Notes:

*(1)*Site operated from September 29, 2010 through June 19, 2011. Statistics reported for this period only.

*(2)*Continuous count data available for one direction only.

Table 2

Average adjusted normalized volume for ten federal holidays for 2009 through 2012. Shows ratio of volume on holiday to volume onprevious three and subsequent weeks for same day-of-week. Total traffic is average of 13 sites. Commercial traffic is average of 4 site. CCS is number of continuous counting stations on road. Standard deviation in parentheses.

Road	CCS	New Year's	MLK Jr	Washington's	Memorial	Independence	Labor day	Columbus	Veterans	Thanksgiving	Christmas	Average *(1)*
Total traffic												
I-75	3	0.56 (0.08)	0.89 (0.07)	0.86 (0.23)	0.63 (0.04)	0.64 (0.09)	0.68 (0.04)	1.01 (0.03)	0.97 (0.04)	0.72 (0.06)	0.59 (0.15)	0.64 (0.06)
I-94	5	0.64 (0.17)	0.88 (0.07)	0.89 (0.19)	0.67 (0.05)	0.65 (0.11)	0.67 (0.10)	0.98 (0.11)	0.95 (0.12)	0.71 (0.09)	0.65 (0.13)	0.67 (0.03)
I-275	1	0.53 (0.08)	0.90 (0.05)	0.92 (0.20)	0.63 (0.05)	0.66 (0.06)	0.54 (0.08)	1.01 (0.01)	0.98 (0.02)	0.63 (0.02)	0.56 (0.05)	0.59 (0.05)
M-10	2	0.62 (0.10)	0.79 (0.05)	0.96 (0.04)	0.59 (0.03)	0.65 (0.10)	0.61 (0.03)	0.98 (0.03)	0.94 (0.05)	0.66 (0.02)	0.61 (0.12)	0.63 (0.03)
M-24	1	0.49 (0.08)	0.82 (0.05)	0.88 (0.12)	0.50 (0.02)	0.61 (0.10)	0.50 (0.08)	0.96 (0.06)	0.98 (0.01)	0.57 (0.01)	0.53 (0.06)	0.53 (0.05)
M-39	1	0.63 (0.12)	0.87 (0.07)	0.98 (0.02)	0.65 (0.07)	0.66 (0.12)	0.63 (0.05)	1.04 (0.08)	0.98 (0.02)	0.67 (0.01)	0.68 (0.11)	0.65 (0.02)
Average		0.58 (0.06)	0.86 (0.04)	0.91 (0.05)	0.61 (0.06)	0.65 (0.02)	0.61 (0.07)	1.00 (0.03)	0.97 (0.02)	0.66 (0.05)	0.60 (0.06)	0.62 (0.05)
Commercial traffic												
I94-8839	1	0.22 (0.10)	0.92 (0.08)	0.87 (0.15)	0.27 (0.02)	0.27 NA	0.25 (0.00)	0.96 (0.03)	0.97 (0.04)	0.23 (0.01)	0.16 (0.09)	0.23 (0.04)
M24-8440	1	0.22 (0.14)	0.78 (0.09)	0.85 (0.10)	0.15 (0.01)	0.29 (0.16)	0.13 (0.04)	0.95 (0.05)	0.95 (0.04)	0.12 (0.01)	0.18 (0.15)	0.18 (0.07)
I75-9799	1	0.22 (0.10)	0.91 (0.09)	0.87 (0.14)	0.38 (0.01)	0.36 (0.02)	0.28 (0.01)	0.91 (0.03)	0.96 (0.02)	0.31 (0.01)	0.16 (0.09)	0.29 (0.08)
I275-9209	1	0.19 (0.10)	0.88 (0.05)	0.90 (0.18)	0.19 (0.00)	0.29 (0.14)	0.16 (0.03)	1.01 (0.02)	0.99 (0.01)	0.10 (0.01)	0.09 (0.08)	0.17 (0.07)
Average		0.21 (0.02)	0.87 (0.07)	0.87 (0.02)	0.25 (0.10)	0.30 (0.04)	0.21 (0.07)	0.96 (0.04)	0.97 (0.02)	0.19 (0.10)	0.15 (0.04)	0.22 (0.05)

Notes:

(1) Average and standard deviation is for New Years Day, Memorial Day, Independence Day, Labor Day, Thanksgiving Day, and Christmas Day.

(2) NA indicates not enough observations for standard deviation.

Table 3

Performance of the hourly model using site-specific data at the four weigh-in-motion counting stations over 4 years. “Correl.” is correlation coefficient; “MARB” is the median absolute relative bias. “NA” indicates not enough observations for statistic.

Vehicle class	Site	All days		Saturdays		Sundays		Holidays	
		Correl.	MRAB	Correl.	MRAB	Correl.	MRAB	Correl.	MRAB
Total vehicles	I94-8839	0.949	0.053	0.910	0.065	0.964	0.056	0.953	0.139
	M24-8440	0.950	0.091	0.915	0.092	0.958	0.091	0.856	0.236
	I75-9799	0.952	0.055	0.903	0.066	0.947	0.059	0.954	0.126
	I275-9209	0.924	0.121	0.924	0.115	0.947	0.107	0.897	0.230
	Average	0.944	0.080	0.913	0.084	0.954	0.078	0.915	0.183
Commercial vehicles	I94-8839	0.955	0.066	0.802	0.080	0.872	0.084	0.613	0.190
	M24-8440	0.895	0.797	0.363	NA	0.502	NA	0.370	NA
	I75-9799	0.947	0.082	0.827	0.098	0.829	0.095	0.612	0.192
	I275-9209	0.957	0.105	0.769	0.378	0.894	0.125	0.417	0.332
	Average	0.939	0.263	0.690	0.185	0.774	0.101	0.503	0.238

Table 4

Performance of the hourly model using urban-wide TAFs. “Correl.” is correlation coefficient; “MARB” is the median absolute relative bias. “NA” indicates not enough observations for statistic.

Vehicle class	Site	All days		Saturdays		Sundays		Holidays	
		Correl.	MRAB	Correl.	MRAB	Correl.	MRAB	Correl.	MRAB
Total vehicles	I94-8839	0.974	0.083	0.970	0.123	0.966	0.093	0.963	0.129
	I94-9489	0.965	0.089	0.958	0.094	0.928	0.092	0.903	0.212
	I94-9499	0.923	0.111	0.930	0.120	0.892	0.123	0.922	0.134
	I94-9419	0.843	0.191	0.845	0.210	0.810	0.206	0.765	0.258
	I94-9969	0.937	0.124	0.935	0.157	0.921	0.158	0.882	0.177
	I75-9799	0.956	0.112	0.954	0.120	0.946	0.102	0.880	0.179
	I75-9959	0.948	0.108	0.892	0.155	0.887	0.142	0.793	0.259
	I75-9989	0.969	0.103	0.973	0.115	0.970	0.131	0.881	0.226
	M10-9109	0.955	0.101	0.918	0.158	0.917	0.131	0.820	0.254
	M10-9809	0.952	0.108	0.943	0.086	0.907	0.118	0.908	0.186
	M24-8440	0.928	0.145	0.900	0.160	0.951	0.118	0.885	0.301
	M39-9809	0.880	0.165	0.867	0.139	0.820	0.178	0.796	0.249
	I275-9209	0.877	0.191	0.887	0.192	0.890	0.189	0.854	0.245
	I96-EH	0.890	0.177	0.917	0.190	0.942	0.127	0.956	0.406
	Average	0.928	0.129	0.921	0.144	0.911	0.136	0.872	0.230
Commercial vehicles	I94-8839	0.945	0.130	0.775	0.186	0.857	0.115	0.604	0.505
	M24-8440	0.875	0.182	0.278	NA	0.481	NA	0.379	NA
	I75-9799	0.925	0.170	0.788	0.256	0.802	0.139	0.553	0.293
	I275-9209	0.948	0.183	0.741	0.211	0.868	0.241	0.417	0.943
	Average	0.923	0.166	0.646	0.217	0.752	0.165	0.488	0.580

Table 5

Monthly temporal allocation factors for total and commercial (Comm) traffic.

Month	**Detroit metro area**		**US default**
	Total	**Comm**	**All**
1	0.9279	0.8983	0.8748
2	0.9709	0.9564	0.8643
3	1.0322	1.0224	0.9783
4	1.0111	1.0108	0.9852
5	1.0229	1.0347	1.0474
6	1.0393	1.0710	1.0566
7	0.9958	0.9520	1.1051
8	1.0306	1.0617	1.1184
9	1.0082	1.0493	1.0136
10	1.0205	1.0330	1.0356
11	0.9769	0.9625	0.9603
12	0.9639	0.9479	0.9602

Table 6

Daily temporal allocation factors for total and commercial (Comm) traffic.

Day	**Detroit metro area**		**US default**
	Total	**Comm**	**All**
Sun	0.7253	0.2618	0.3536
Mon	1.0384	1.2232	1.2392
Tue	1.0654	1.2679	1.2392
Wed	1.0795	1.2846	1.2392
Thur	1.0989	1.2898	1.2392
Fri	1.1422	1.2211	1.2021
Sat	0.8504	0.4516	0.4873
Obs. Holidays	0.7929	0.5017	NA

Table 7

Hourly temporal allocation factors for total and commercial (“Comm”) traffic.

Hour	Total detroit metro area				Total US default		Commercial detroit metro area				Comm. US default	
	Weekday	**Saturday**	**Sunday**	**Holiday**	**Weekday**	**Weekend**	**Weekday**	**Saturday**	**Sunday**	**Holiday**	**Weekday**	**Weekend**
0	0.0128	0.0251	0.0268	0.0252	0.0081	0.0156	0.0137	0.0338	0.0261	0.0304	0.0081	0.0156
1	0.0084	0.0175	0.0216	0.0183	0.0052	0.0103	0.0129	0.0281	0.0220	0.0272	0.0052	0.0103
2	0.0067	0.0136	0.0165	0.0131	0.0047	0.0079	0.0136	0.0233	0.0196	0.0244	0.0047	0.0079
3	0.0071	0.0118	0.0129	0.0100	0.0057	0.0057	0.0166	0.0277	0.0190	0.0256	0.0057	0.0057
4	0.0115	0.0123	0.0109	0.0102	0.0099	0.0065	0.0229	0.0335	0.0200	0.0293	0.0099	0.0065
5	0.0258	0.0157	0.0129	0.0136	0.0230	0.0106	0.0342	0.0413	0.0233	0.0343	0.0230	0.0106
6	0.0500	0.0219	0.0162	0.0212	0.0489	0.0184	0.0524	0.0526	0.0304	0.0419	0.0489	0.0184
7	0.0668	0.0300	0.0209	0.0252	0.0679	0.0279	0.0637	0.0618	0.0380	0.0504	0.0679	0.0279
8	0.0625	0.0377	0.0274	0.0271	0.0629	0.0400	0.0684	0.0633	0.0413	0.0523	0.0629	0.0400
9	0.0501	0.0439	0.0377	0.0347	0.0531	0.0533	0.0711	0.0638	0.0442	0.0554	0.0531	0.0533
10	0.0457	0.0498	0.0504	0.0454	0.0509	0.0640	0.0700	0.0644	0.0488	0.0586	0.0509	0.0640
11	0.0479	0.0555	0.0558	0.0549	0.0538	0.0723	0.0679	0.0630	0.0529	0.0603	0.0538	0.0723
12	0.0506	0.0602	0.0609	0.0613	0.0560	0.0759	0.0669	0.0594	0.0551	0.0600	0.0560	0.0759
13	0.0541	0.0638	0.0672	0.0662	0.0574	0.0763	0.0664	0.0546	0.0553	0.0580	0.0574	0.0763
14	0.0611	0.0664	0.0714	0.0700	0.0635	0.0770	0.0643	0.0496	0.0543	0.0544	0.0635	0.0770
15	0.0708	0.0676	0.0730	0.0716	0.0733	0.0773	0.0589	0.0452	0.0533	0.0499	0.0733	0.0773
16	0.0768	0.0669	0.0718	0.0705	0.0804	0.0742	0.0506	0.0415	0.0529	0.0452	0.0804	0.0742
17	0.0725	0.0639	0.0683	0.0672	0.0775	0.0677	0.0414	0.0383	0.0534	0.0411	0.0775	0.0677
18	0.0589	0.0589	0.0628	0.0628	0.0579	0.0580	0.0336	0.0350	0.0540	0.0382	0.0579	0.0580
19	0.0442	0.0524	0.0562	0.0579	0.0437	0.0475	0.0283	0.0312	0.0534	0.0362	0.0437	0.0475
20	0.0356	0.0464	0.0489	0.0529	0.0338	0.0388	0.0250	0.0270	0.0506	0.0345	0.0338	0.0388
21	0.0321	0.0430	0.0420	0.0472	0.0280	0.0319	0.0222	0.0230	0.0456	0.0323	0.0280	0.0319
22	0.0277	0.0409	0.0361	0.0406	0.0205	0.0246	0.0190	0.0198	0.0439	0.0303	0.0205	0.0246
23	0.0203	0.0348	0.0314	0.0330	0.0138	0.0184	0.0159	0.0186	0.0426	0.0300	0.0138	0.0184