

Acquisition and Utilization of Real-Time District-Wide Truck Traffic Volume Data from Single Loop Detectors

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ABSTRACT

We deployed a recently proposed single loop detector based, real-time freeway truck traffic volume estimation algorithm to a County-level traffic database. The scale-up of the algorithm is achieved by adding an extra layer, consisting of a spatial filtering component for removing noise and an aggregation component for efficient analysis. All calculations could be done in real-time to produce a real-time, district-wide snapshot of the spatial distribution of truck traffic volume. Quantitative comparison with an independent truck volume data shows 31% discrepancy, which is decent considering the limited nature of the latter [??] data source. Qualitatively, the map of the estimated truck traffic volume enables us to instantly identify known freight truck rich routes and capture interesting temporal patterns in truck traffic. We also show that the output of the algorithm can be used as an input for a simplified emission factor model. In another application, the study of the relationship between the estimated truck traffic volume and freeway crash rate shows that the former significantly affects crash rate. As illustrated by these applications, the proposed algorithm and visualization scheme could provide valuable tool and data source for transportation planners and practitioners in diverse fields.

Keywords: truck traffic; vehicle volume; vehicle classification; single loop detectors; emission study; freeway accident risk analysis

1. INTRODUCTION

Accurate knowledge of freight or heavy truck traffic is critical for various highway-related planning, design, and policy analyses. It is necessary to have estimates of such quantities as Truck Annual Average Daily Traffic (TAADT) for different sections of a freeway (1,2). Various methods exist for acquiring such data, including manual counting and Automatic Vehicle Classifier (AVC). The latter is based on technologies like Weigh-In-Motion (WIM), video imaging, laser, night vision systems, or acoustic signal analysis, or inductance signature from double loops. Most of these methods suffer either from large margin of error or high cost of hardware and/or operation, and it is difficult to balance the margin of error and cost.

We recently proposed an algorithm for real-time estimation of truck traffic volume from single loop detectors (3). It incurs virtually no extra cost when single loop detectors are already installed, which is typically the case for most urban freeways in the US. Also, the algorithm showed remarkable accuracy (~6% margin of error) in the pilot study. Furthermore, it estimated the significant drop in truck traffic volume during October 2003 port lockout, validating it as an effective surveillance tool for detecting shifts in truck traffic volume. The algorithm achieves balance between the low cost of implementation and reasonable accuracy.

But the previous study looked at only a few locations and we could not see location-to-location or freeway-to-freeway variability. Given the low cost and reasonable accuracy of the algorithm, we address this issue by large-scale deployment of the algorithm to a County level. In particular, data from Los Angeles County, California (Caltrans District 7) is used in this paper. Such large-scale deployment presents new challenges in terms of data quality and presentation of the results. We address the first issue by spatial smoothing and the latter by segment-based maps.

The output of such large-scale implementation provides a rich source of information for planners and practitioners, helping decision-making process in applications like pavement control, emission study, and freeway accident analysis. We illustrate the potential usefulness of the data by two studies: highway mobile source emission estimation and freeway accident analysis.

The paper is organized as follows. Section 2 briefly reviews the original algorithm and presents the method for spatial filtering and aggregation. The details about the data source and application are given in Section 3. Section 4 illustrates the application of the algorithm to emission and accident analyses. Section 5 summarizes the results.

2. METHODS

Figure 1 shows the data flow of the proposed system. Truck volume for individual detector location is estimated by the algorithm proposed in (3), smoothed over neighborhood locations to reduce noise and aggregated to produce segment truck volumes. They are explained below in turn.

Truck traffic volume estimation at an individual detector location

We briefly review the original real-time truck volume estimation algorithm of (3). A single loop detector measures flow (the number of vehicles that pass over the loop) and occupancy (the proportion of time that the loop is covered by a vehicle). Let $q_a(i, j)$ and $O_a(i, j)$ be the flow and occupancy measured at detector in lane i (lane 1 is closest to the median) of location a at time j . We make the following assumptions: for multi-lane freeways, 1) vehicle speed over different lanes tend to be synchronized (lane-to-lane speed correlation), 2) the inner lane is truck-free, 3) passenger cars and trucks have representative lengths \bar{l}_c and \bar{l}_t respectively.

Then for an outer lane i' at time j , the average vehicle length is estimated as

$$L_a(i', j) = \beta(i, i') \frac{q_a(i, j)/O_a(i, j)}{q_a(i', j)/O_a(i', j)} \bar{l}_c, \quad (1)$$

and the truck proportion as

$$p_a(i', j) = \frac{L_a(i', j) - \bar{l}_c}{\bar{l}_t - \bar{l}_c}. \quad (2)$$

Here, $\beta(i, i')$ is the ratio of average speed in lane i' to that in lane i , which is typically less than 1 since lane 1 is usually the fastest lane. The truck proportion is truncated to have a value inside [0,1]. Then the truck traffic volume is estimated by

$$m_a(i, j) = p_a(i, j)n_a(i, j). \quad (3)$$

The lane-total truck volume at location a is given by

$$m_a(j) = \sum_i m_a(i, j). \quad (4)$$

By summing $m_a(i)$ over a day, we get a daily truck traffic volume m_a for location a . See (3) for further details of the algorithm.

AADT and TAADT are estimated by averaging the daily volume over a study period. The study period needs to balance weekdays and weekends for unbiased estimation of these quantities.

Spatial filtering over freeway locations

The truck volume estimates m_a are noisy. The main source of the noise and error is violation in assumption (1) that happens usually near on and off-ramps, and/or ill-specified β parameters. When the former happens, it typically results in over-estimation of truck traffic volume, since the traffic in outer lanes is a lot slower than expected due to heavy weaving and huge $O(i', j)$ results.

We reduce the effect of this error as follows. Consider individual truck volume estimates m_a for multiple locations along the freeway. Though the truck traffic volume changes along the freeway due to entrance and exit at on- and off-ramps, we expect it to be nearly conserved for most segments. More formally, we expect

$$m_a \approx m_{a'} \text{ if } a \text{ is close to } a'. \quad (5)$$

This motivates the spatial filtering

$$\bar{m}_a = \text{median}(m_a, : |a'-a| < A), \quad (6)$$

in which $|a'-a|$ denotes the distance between the locations a and a' , and A is a user-specified neighborhood size.

In the current application, we use Tukey's running median smoother of length 3 (4) for each freeway. This is similar to (6), but instead of fixing the distance parameter A , it uses two nearest locations and takes the median of estimates from those two and the self. It not only simplifies the calculation but also enables us to adapt to variable spatial density of detectors.

Aggregation of the estimates into segments

We divide all freeways in the study area into approximately 1-mile long *segments*, each containing at least one loop detector location. We aggregate measurements from detectors in the segment in obvious way to calculate traffic parameters for the segment.

3. ANALYSIS

We apply the algorithm to the whole district of Los Angeles, California for one-week period from Monday, May 19th, 2003 to Sunday, May 25th 2003. Figure 2 shows the freeway map of the district. As a data source, we use 5-minute volume and occupancy measurements archived in Freeway Performance Measurement System (PeMS) (5).

We use only mainline detector locations that report more than 280 samples out of 288 (5-minute) samples in each day. The number of such detector locations range from 633 to 738 for each day, or 48% to 56% of all 1,324 detectors. Truck volume estimates m_a are computed for all locations for each day. In this application, we set parameter values as in Table 1. The β values are equivalent to 5% decrease of average speed for each increase of the lane number, inspired by the study in (3) and an informal study conducted on double loop speed data from San Francisco Bay Area (Caltrans District 4).

In the generic workstation that runs the PeMS website, the computation took less than 2 hours to process the whole district for each day, including data retrieval from database (which takes most of the time). We expect the computation will add negligible overhead once included in TMC software.

District-wide spatial distribution of daily truck traffic volume

Figures 3 and 4 show spatial distribution of the total daily traffic volumes n_a , total truck traffic volume m_a , and the ratio $r_a = m_a / n_a$ for Tuesday and Sunday in the study period. Let's consider Figure 3 first. The distribution of the total traffic volume doesn't reveal much except that a few locations exhibit lighter traffic than other locations. But the map of truck traffic volume reveals a lot more: there is substantial spatial and freeway-to-freeway variability. Among others, I-710, I-605 and I-60 show significantly more truck traffic volume than other freeways, say I-405. Median m_a for those freeways are close to 150,000 trucks/day while other freeways exhibit

median between 50,000 and 100,000 trucks/day. The same pattern is observed in the distribution of the truck volume ratio r_a .

Compared to this, the Sunday estimates shown in Figure 4 don't exhibit such distinction between those three freeways and the others. All freeways exhibit median truck traffic volume of about 50,000 trucks/day. This is a natural phenomenon since commercial freight trucks travel a lot less during weekends, and this confirms that our algorithm captures the shift in truck traffic pattern over day-of-week well.

Day-of-week trend of daily truck volume

In Figure 5, we show the day-of-week trend of daily volume and daily truck volume for locations in two freeways, I-710 and I-10. The former route is well known for heavy freight truck traffic to and from Long Beach Port in southern LA County. According to Caltrans data (*I*), I-710 has the median (over the freeway locations) TAADT of 10,339(veh/day) while that of I-5 is only 6,314 (veh/day), or 61% of I-710. Note that AADT are 86,000 and 119,000 (veh/day) for two freeways, with I-5 having 40% more average traffic flow than I-710.

Figure 5 shows that our estimates detect these features clearly. The estimated AADT and TAADT for each freeway clearly approximate the Caltrans quantities. The estimated TAADT is 12,252 and 7,238, with 18.5% and 14.6% relative errors if one consider Caltrans values as a ground truth. Estimated AADT are 83,583 and 104,922 for two freeways, with 2.8% and 11.8% relative errors.

In addition to the close match with Caltrans quantities, the proposed algorithm detects the day-of-week trend in truck traffic volume. For I-710, there is a sharp drop in daily truck volume during Saturday and Sunday, confirming the hypothesis of reduced commercial freight truck traffic volume during weekends. That pattern is not as visible in I-5. There is decrease in truck traffic volume over weekend but that is not more significant than the drop in total daily volume.

Two classes of truck traffic

The proposed algorithm is based on the estimated length distribution and assumes the car consists mostly of short passenger cars and very long trucks like 18-wheelers with 5 axles or more. In reality, the traffic consists of other vehicle classes as well, whose lengths fall between the lengths of these two extreme classes. Light and medium-duty trucks as well as many SUVs, which are simply trucks in terms of their lengths, are such examples. From empirical analysis, the truck volume estimates from our algorithm seems to match the total truck counts aggregated over all truck classes, including light-duty trucks as well as freight trucks. For many applications though, one wants only the volume of freight trucks that have 5 or more axles.

The relationship between total truck volumes ($TAADT_{total}$ or simply TAADT) and those of trucks with 5-axles or more ($TAADT_{5-axle}$) can be studied using Caltrans data (*I*), which is shown in Figure 6. To our advantage, the two variables are highly correlated with $R^2=0.932$. Linear regression models with and without intercept terms are fitted to the data by the least squares method and the fitted models are

$$TAADT_{5-axle} = -822 + 0.540 \times TAADT_{total} \quad (7)$$

with the intercept and

$$TAADT_{5-axle} = 0.486 \times TAADT_{total} \quad (8)$$

without. Thus, we treat our estimates m_a as an estimator of TAADT and use the simpler model (8) to derive estimate of $TAADT_{5-axle}$.

Comparison with Caltrans estimates

To quantitatively evaluate the validity of the outputs from our algorithm, we compare the output of our algorithms to AADT and TAADT reported in (1). For each segment, we compute both quantities from our algorithm as well as from (1). There are 164 links for which estimates from both sources are available. Figure 7 shows the relationship between the proposed estimates and Caltrans estimates.

Table 2 shows the results of the quantitative comparison. The median relative error for AADT is 18.7% while that of TAADT is 30.8%. This is not an impressive result but we have to take into account the limitations of both estimates in interpreting results. Even though we treat Caltrans estimates as the ground truth, it is not based on census-type data but based on sampling in a short time period, corrected for time-of-day and seasonal effect (1). Even the sampling is not done annually and only 156 entries out of 438 entries (36%) are verified or estimated in year 2001, while most of other entries are verified/estimated around 1990, some as old as 1980's. Note also that the mean relative error of total AADT, though smaller than TAADT, is substantial at 18.7% as well. Considering these factors, we view the observed discrepancy of 30.8% for truck traffic volume as acceptable. More accurate, extensive and up-to-date ground truth from another sources would be beneficial for validating the performance of the proposed algorithm.

4. USING TRUCK VOLUME ESTIMATES FOR EMISSION AND ACCIDENT ANALYSIS

Since the proposed system produces detailed district-wide spatial distribution of truck traffic volume in real-time, it has many potential applications. As an illustration, we implement two applications: estimation of highway mobile source emission and the study of the relationship between freeway crash rate and truck volume.

Emission estimation

Study of emission from mobile source is a critical component in air quality management, and is reported and studied extensively at various state and federal organizations. Most freight trucks belong to the Environmental Protection Agency (EPA) class of heavy-duty diesel trucks and their traffic volume is a significant factor affecting air quality, especially now when many passenger cars produce very little emission due to strict emission standards. Table 3 shows emission level of four pollutants hydrocarbons (HC), Carbon Monoxide (CO), Nitrogen Oxides (NO_x), and Particulate Matter (PM) for two representative vehicle classes (6,7). We can observe significant differences between the two vehicle classes in emission level, implying it is crucial to have heavy truck volume information for estimation of emission.

We compute daily total highway mobile source emission for each pollutant by a simplified model:

$$\begin{aligned} emission &= \sum_i (EF_{1,i} \times v_{1,i} + EF_{2,i} \times v_{2,i}) \\ &= EF_{1,i} \times V_1 + EF_{2,i} \times V_2 \end{aligned} \quad (9)$$

in which the sum is taken over 24 hours of the day, $EF_{1,i}, EF_{2,i}$ are emission factors for two vehicle classes in Table 3, $v_{1,i}, v_{2,i}$ are estimated hourly total passenger car and freight truck VMT and V_1, V_2 are daily total VMT of each classes. The last identity implies that we only need to take the weighted sum of total daily passenger car volume and truck volume with correct weights to derive total daily emission.

Note that this analysis is for an illustration purposes only and we have made a lot of simplifications. Not only do we simplify vehicle classes, but we also omit various ingredients like model year distribution, altitude, ambient conditions, fuel ingredients etc. Speed correction factor is another important factor, which could be provided in real-time from the same data source we estimate truck volume from. If we incorporate these factors, which change over time-of-day, we cannot simply take the weighted sum of V_1 and V_2 as above, but need to calculate the hourly summand in (9) individually. But even such complicated approach is feasible because of the real-time nature of our truck volume estimates.

Figure 7 shows the spatial distribution of the amount of pollutants estimated from the algorithm. Total length of all the segments is 803.8 miles and the estimated total mobile source emission can be estimated from the above estimates and the segment information. They are shown in the last column of Table 3.

Freeway accident analysis

Accidents, especially crashes, on freeways are not only a safety issue but also create congestion and reduce freeway productivity as well. Active researches are still going on to investigate the relationship between factors like (real-time) traffic conditions, ambient condition and road geometry and the type and rate of crash. The truck traffic volume can be treated as an ambient condition as well as traffic condition, due to different driving characteristics of heavy-duty trucks.

We inspect the relationship between truck volume and crash occurrences as another application of the truck volume estimates from our algorithm. For each of 636 segments, we compile crash frequencies observed during 2001. The crash data is obtained from the Traffic Accident Surveillance and Analysis System (TASAS) maintained by the California Department of Transportation (8). The database contains those collisions that occur on the California State Highway System for which there are police reports.

There are 127,335 crashes reported to TASAS in 2001 and we could match 34,609 of them to our segments. We calculate crash rate in crashes/mile for each segment. Since crash occurrences

occur as a Poisson process, we take its log to stabilize the variance. Then we fit the log crash rate on three sets of variables in turn: 1) AADT, 2) AADT and TAADT, and 3) AADT, TAADT and the interaction of the two. They are hierarchical models with increasing complexity. If the truck traffic volume does not affect the crash rate, the models 2) and 3) would not be significantly better than previous model in explaining the crash rate. Plot 8 shows the marginal relationship between the log crash rate and AADT and TAADT. It is clear that AADT explains the variability of the crash rate much better than TAADT. But ANOVA results shown in Table 4 support that adding TAADT variable indeed helps. There is a significant (at 5% and 1% significance level each) gain in explanation power as one adds TAADT and the interaction of AADT and TAADT.

Even though we used only annual averages like AADT and TAADT in the current analysis, a similar analysis can be done using real-time data. Truck volume and proportion changes over time of day and day of week, and investigation of the relationship between crash occurrence and the truck volume at the time of the occurrence can reveal the real relationship between the two variables. One could even develop real-time crash prediction models incorporating the current truck volume as one of “crash precursors” (10).

Pavement management

Heavy vehicles affect pavement significantly due to their weights. Various computer models for pavement management require truck traffic volume estimates as an input and our algorithm can provide it.

5. CONCLUSION

We deployed a single loop detectors based, real-time freeway truck traffic volume estimation algorithm to the whole LA County, comprising 1,324 detector locations. The scale-up of the algorithm is achieved by adding an extra layer, consisting of spatial filtering and aggregation components. All calculation could be done in real-time to produce real-time district-wide snapshot of the spatial distribution of truck traffic volume.

Quantitative comparison with an independent TAADT data from Caltrans shows 30.8% discrepancy while that for AADT was 18.7%. Since the Caltrans data is outdated as well as indirectly estimated, more study is needed to properly evaluate the accuracy of the proposed algorithm.

Qualitative feature of the output of the algorithm is promising and informative. Inspection of the “map” of the truck traffic volume instantly identifies Interstates 60, 605 and 705 as “truck rich” routes, which is confirmed by a separate data source. The algorithm captures sharp drops in truck traffic volume over weekends in those routes, which is consistent with other studies. Drop in truck traffic volume in other routes without commercial freight truck traffic is not as severe.

The output of the algorithm has many potential applications. Its utilization for mobile source emission estimation, even though in a very simplified setup, shows the possibility of real-time estimation of spatial concentration of pollutants purely from single-loop detector data sources.

We also relate the output of our algorithm to the freeway crash data. It is shown that TAADT variable is a statistically significant factor affecting the crash rate, controlling for AADT. As in emission application, real-time truck volume data feed from the proposed algorithm could enable more detailed research and development of crash management system.

As is illustrated by these applications, the proposed algorithm and visualization scheme could provide valuable tool and data source for transportation planners and practitioners in various fields.

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TABLE 1 Parameters used in the district-wide implementation

Parameter	Values
$\beta(i, i')$	1, 0.95, 0.9, 0.85, 0.8, 0.75 for $i'=1, \dots, 6$ (5% decrease for each increase)
\bar{l}_c and \bar{l}_t	16.6 (ft) and 60 (ft)

TABLE 2 Comparison between the Proposed Estimates and Caltrans Estimates

	<i>Mean</i> (veh/day)	<i>Mean Absolute</i> <i>Error (veh/day)</i>	<i>Median¹ Absolute</i> <i>Relative Error</i> (Percent)
<i>AADT</i>	222,627	54,309	18.7%
<i>TAADT</i>	13,871	4,787	30.8%

1. The median, instead of the mean, is used here because Caltrans TAADT estimates can be very small and dividing by them makes the distribution of relative error unstable

TABLE 3 Emission Rates for Representative Vehicle Classes¹

<i>Pollutants</i>	<i>Emission rate (g/mile)</i>		<i>Ratio of HDDV and LDGV factors</i>	<i>Estimated total daily emission during Tuesday, May 20th, 2003³ (kg)</i>
	<i>Light duty gasoline powered vehicle (LDGV)</i>	<i>Heavy duty diesel vehicles (HDDV)</i>		
HC	1.2	2.0	167 %	297
CO	14.6	10.9	75 %	3,332
NO _x	1.0	6.5	650 %	349
PM	0.0043	0.0836 ²	1,944 %	2.67

1. The entries correspond to Current year 2003, Model year 1998 (5 year old vehicles), and low altitude.
2. We use conversion factor 1 to convert g/BHP-hr to g/mi. (7)
3. This values are for illustration purposes only.

TABLE 4 Analysis of the Relationship between Crash Rate and AADT and TAADT

<i>Factors</i>	<i>Fitted model</i> <i>Log(accident rate)=...</i>	<i>Adjusted</i> <i>R²</i>	<i>F-statistic¹</i>	<i>p-value¹</i>
AADT (10 ⁶ vehicles/day)	2.52+5.81×AADT	0.144	-	-
AADT + TAADT	2.40+5.31×AADT+14.3×TAADT	0.153	5.3796	0.02
AADT+TAADT+AADT:T AADT	1.55+9.81×AADT+79.0×TAADT- 331×AADT:TAADT	0.168	8.4645	0.004

1. Statistics for analysis of variance (ANOVA) test of the significance of the current model compared with the one in the above row; can be interpreted as the statistical significance of the added variable

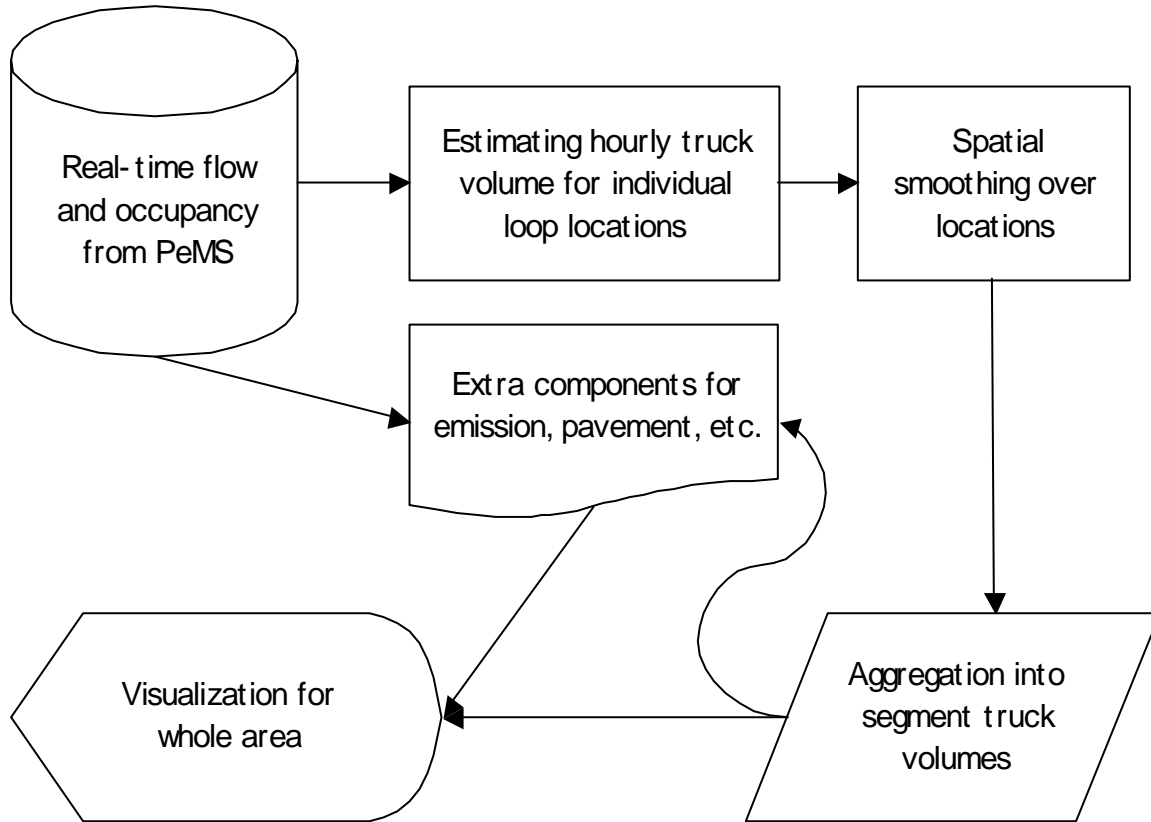


FIGURE 1 Data flow diagram of the proposed system for district-wide real-time truck volume estimation.

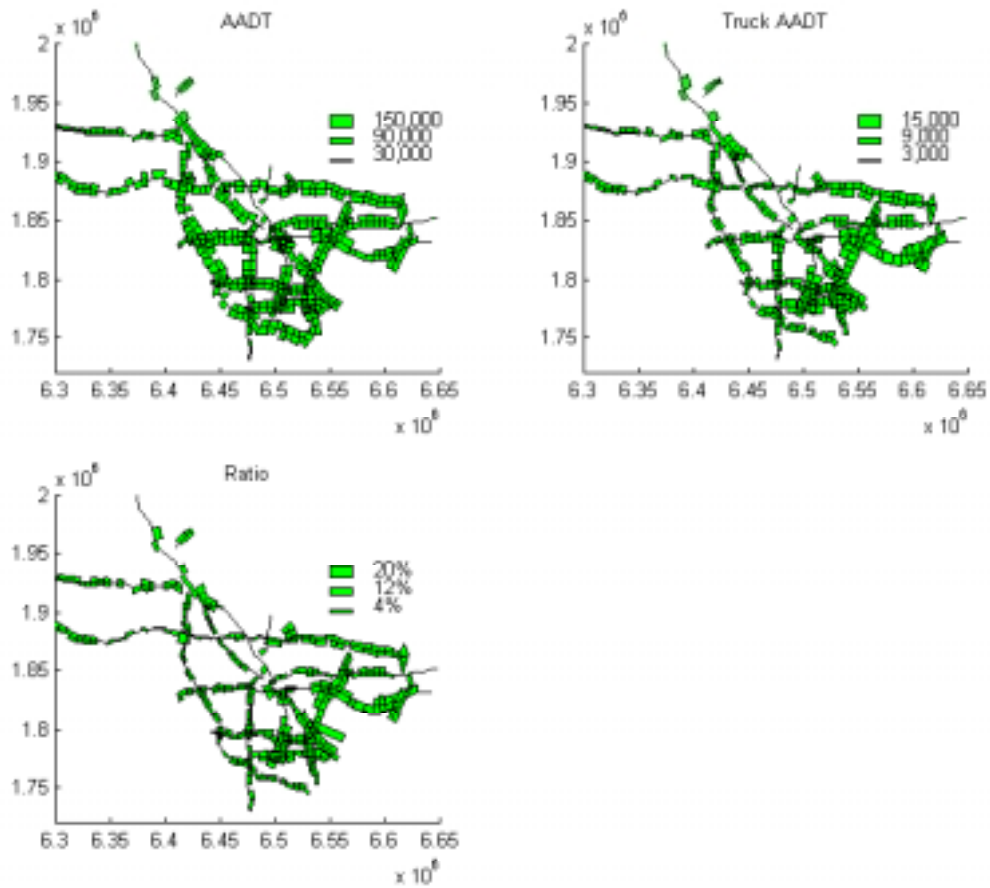


FIGURE 3 Total daily volume (top left), daily truck volume (top right), and the ratio of the two (bottom left) for Tuesday, May 20th, 2003.

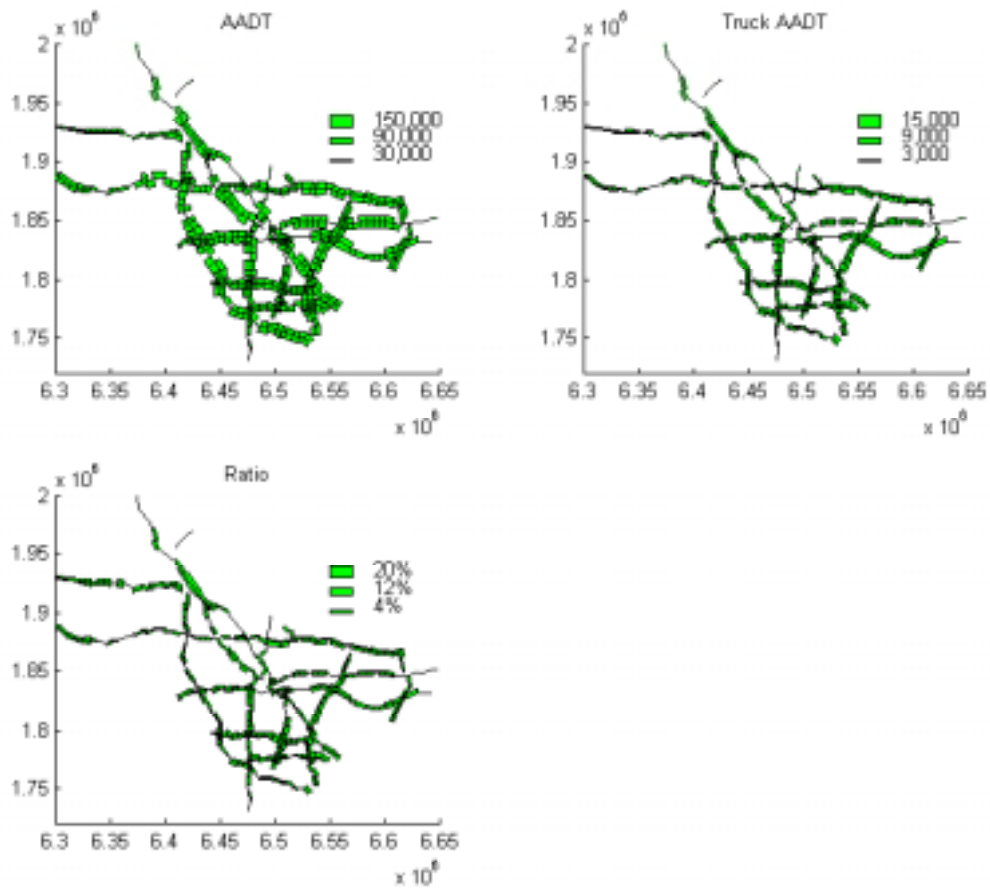


FIGURE 4 Total daily volume, daily truck volume, and the ratio of the two for Sunday, May 25th, 2003.

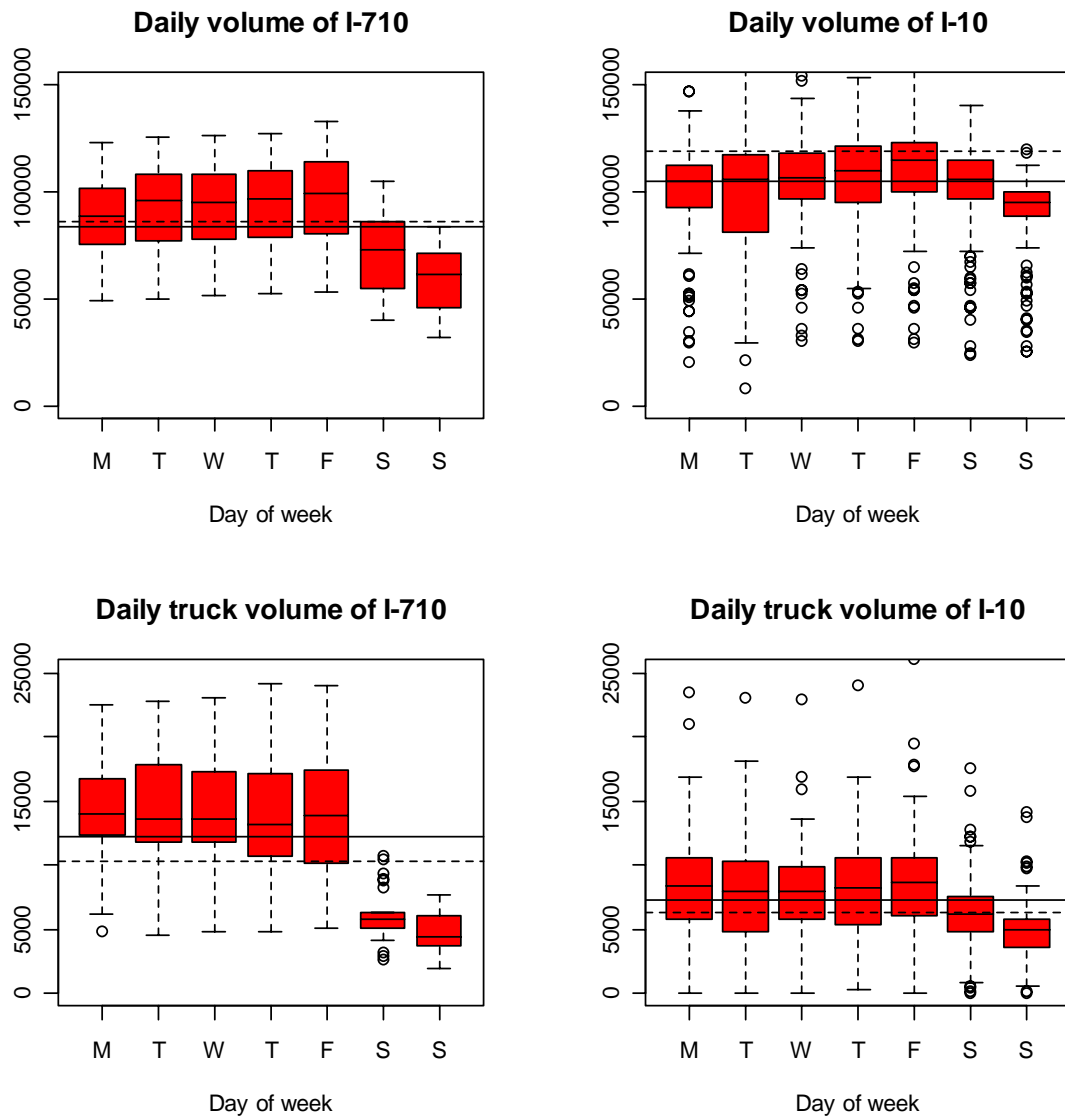


FIGURE 5 Day-of-week trends of daily volume (top) and daily truck volume (bottom) at detector locations in I-710 (left) and I-10 (right). Horizontal lines in each plot are AADT and TAADT of the whole freeway, estimated from Caltrans data (dotted line) or from our algorithm (solid line).

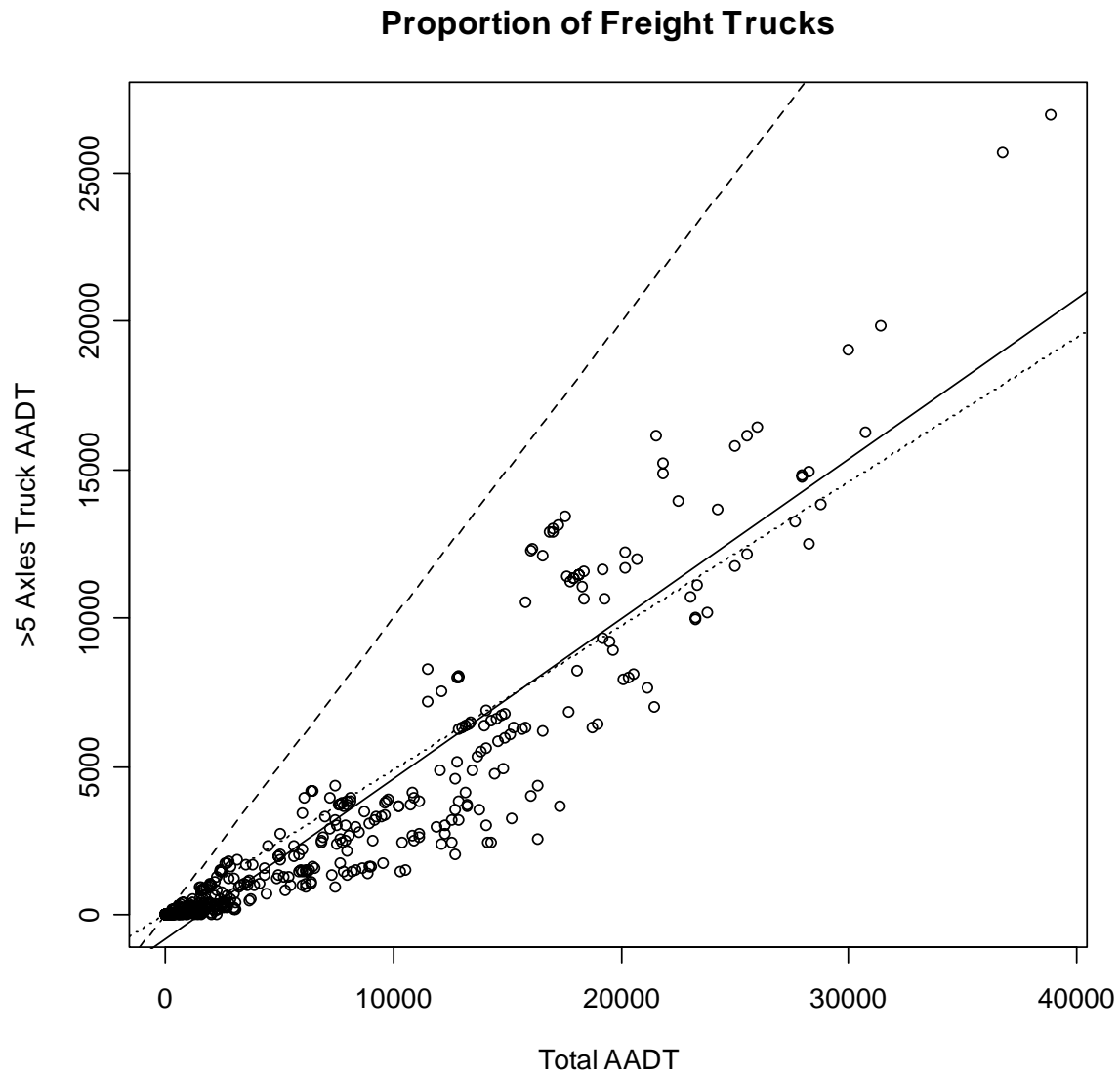


FIGURE 6 The relationship between total truck counts and >5 axles truck counts in Caltrans data (1). The dashed line is the baseline $y=x$ function, and the least squares regression line fitted with intercept (dotted line) and without intercept (solid line) are also drawn.

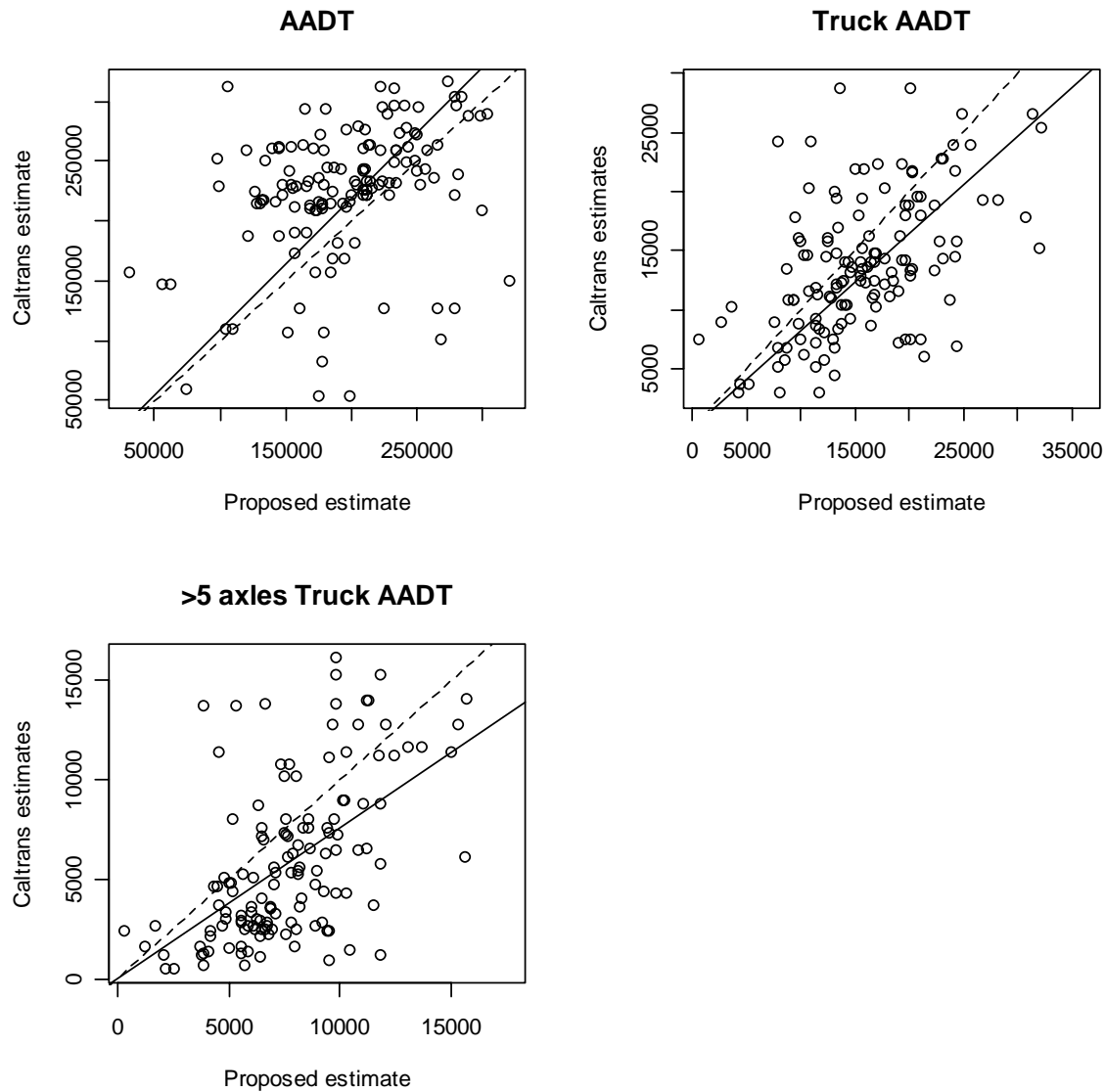


FIGURE 7 Comparison between the proposed estimates and Caltrans estimates. Comparisons for total AADT (top right), TAADT (bottom left) and >5 axles TAADT (bottom right) are shown. In each plot, dashed lines are baseline function $y=x$ and solid lines are the least squares regression line fitted without intercept.

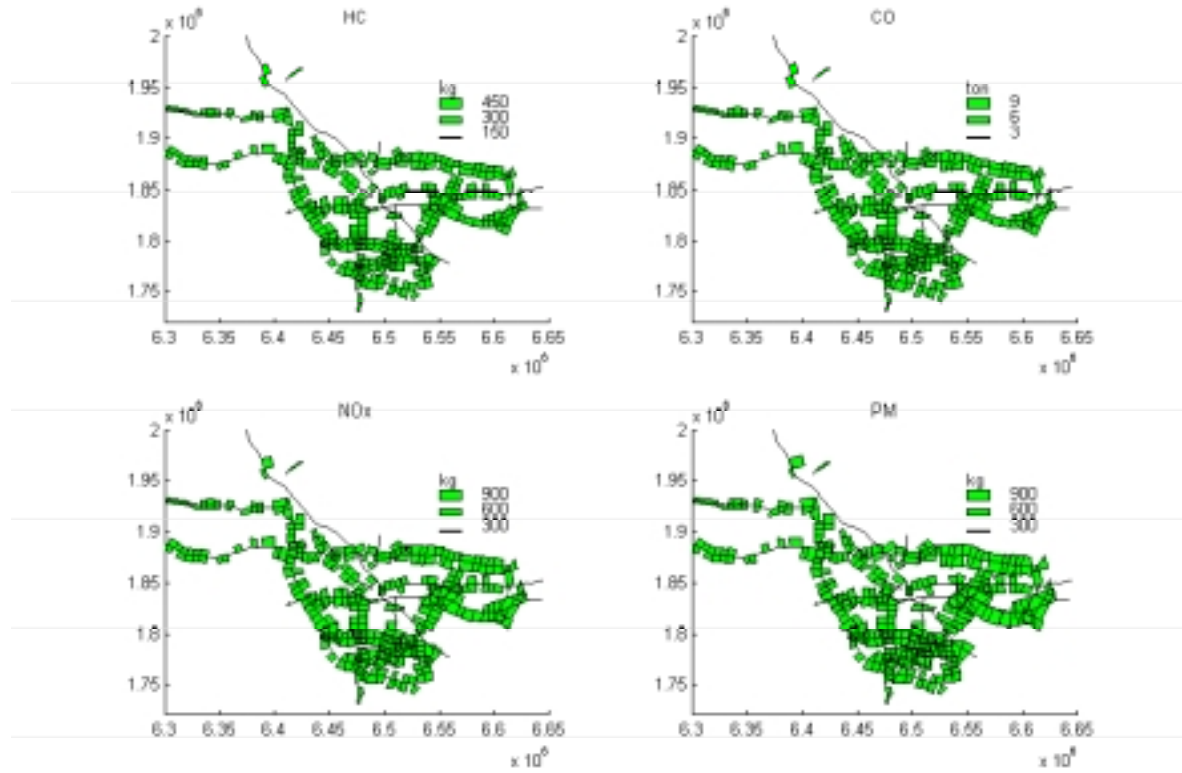


FIGURE 7 District wide distribution of highway mobile source emission for four pollutants for Tuesday, May 20th, 2003, estimated from the simplified emission factor model.

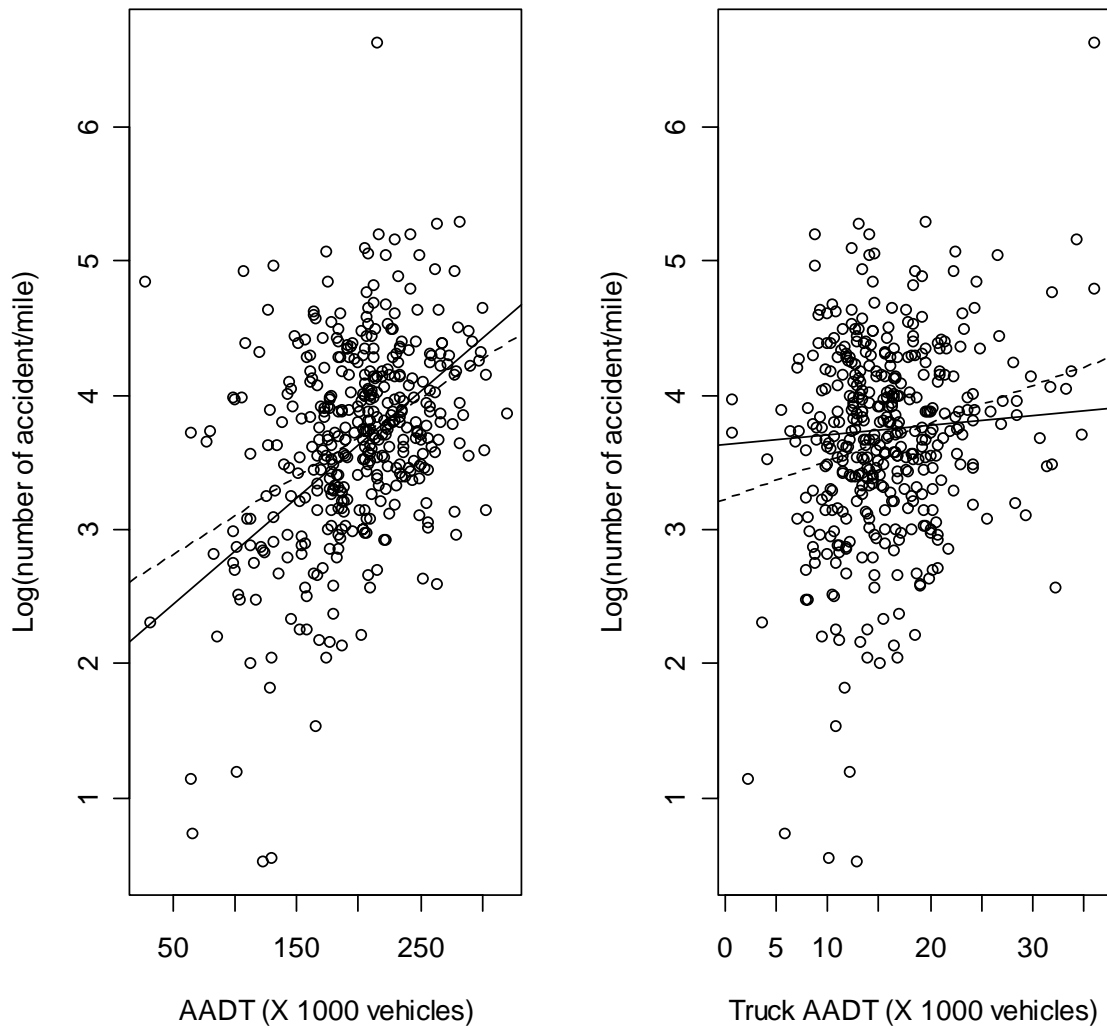


FIGURE 8 The relationship between the log crash rate and AADT (left) and TAADT (right). The least squares regression line (dashed lines) as well as the robust regression line of (9) (solid lines) is shown for each data.