



Supplement of

Assessing vehicle fuel efficiency using a dense network of CO_2 observations

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Introduction

In S1, we describe the time series of the number of BEACO₂N nodes reporting CO₂ during the from January through June for the years 2018-2020. In S2, we show the locations in the PeMS measurement network in the region of the SF Bay Area shown on the map, as well as an estimate of LDV and HDV VMT for a typical week in this domain. In S3, we describe the hourly BEACO₂N-STILT prior for the typical weekday for CO₂ emissions in the 1km pixels that encompass the highway stretch that is the focus of our analysis. The figure also shows vkm traveled for each hour on this stretch of highway. In S4, error analysis for PeMS values for speed, LDV and HDV volume is described. In S5, we list EMFAC2017 vehicle classes and indicate whether we have classified them as LDV or HDV based on estimated vehicle length. In S6, we show both LDV and HDV emissions rates as a function of speed. We also compare a piece-wise linear to a spline fit of these two curves. In S7, we show the diel cycle for contribution to total emissions by congestion and vehicle type as estimated using PeMS-EMFAC. In S8, we describe the calculation of uncertainty in emissions rates derived using the BEACO₂N-STILT system. In S9, we derive emission rates from the BEACO₂N-STILT prior and discuss improvements of the posterior over the prior. In S10, we explore how non-constant speed may impact emissions rates for a given hourly average speed.

Section S1.

Throughout the period examined in this study, the number of BEACO₂N sensors reporting data varied from due to power or instrument failure.



Figure S1. Number of BEACO₂N sites reporting CO₂ data used in BEACO₂N-STILT inversion for January-June in 2018 (top) 2019 (middle) and 2020 (bottom)

Section S2.

The Caltrans Performance Measurement System Network consists of thousands of magnetic loop monitors imbedded in highways across the state of California (http://pems.dot.ca.gov). Each station consists of loop sensors in each lane that report hourly values for total vehicle flow, HDV percentage, and average speed. Using station locations, vehicle flow, and HDV percentage, hourly vkm can be calculated as outlined in the main text.



Figure S2: Left: Locations of Caltrans PeMS monitoring stations (black and red). The solid blue line marks the 40% contour of the BEACO₂N cumulative influence function during January – June 2020. Right: LDV vkm, HDV vkm estimated based on PeMS data.

Section S3.

We focus our analysis on the hours 4am – 10pm. During this period, emissions from traffic are much larger than all other sources in the pixels used in this analysis. From 11pm – 3am, total vkm and therefore emissions from traffic are low.



Figure S3: (top) Diel variation of total vkm (from PEMS observations) for the stretch of roadway indicated in Figure 2 for a typical weekday. (bottom) Prior estimates of emissions from biogenic sources (orange), vehicle emissions (blue), point sources and area sources (yellow).

Section S4.

We apply linear fits (for speed and LDV) and hourly ratios (for HDV) to nearest neighbors, second nearest neighbors, and third nearest neighbors to create modeled values for all times for which we have observations. Using these modeled values we estimate mean error and spread for all PeMS sites over the time period studied, finding that speed accurate to about 5km hr⁻¹, LDV/hr to ~300 vehicles and HDV to ~55 vehicles for the east and west directions of flow on I-80. Precision is much higher than these values as shown on the right.



Figure S4: Mean average error (left) and distribution of error (right) for modeled speed (top), LDV flow (middle), and HDV flow (bottom).

Section S5.

While EMFAC2017 provided speed-dependent emission rate estimates for 41 vehicle classes, PeMS characterizes vehicles in two categories based on length. In order to use EMFAC2017 emission rates in combination with PeMS traffic counts to estimate total emissions, we classify EMFAC2017 categories as LDV or HDV based on length.

EMFAC Vehicle Class	Grouping for this work
All Other Buses	0
LDA	1
LDT1	1
LDT2	1
LHD1	1
LHD2	1
МСҮ	1
MDV	1
МН	0
Motor Coach	0
OBUS	0
РТО	0
SBUS	0
T6 Ag	0
T6 CAIRP heavy	0
T6 CAIRP small	1
T6 OOS heavy	0
T6 OOS small	1
T6 Public	0
T6 instate	0
T6 instate	1
construction small	
T6 instate heavy	0
T6 instate small	1
T6 utility	0
T6TS	0
T7 Ag	0
T7 CAIRP	0
T7 CAIRP construction	0
T7 NNOOS	0
T7 NOOS	0
Τ7 ΡΟΑΚ	0

T7 Public	0
T7 SWCV	0
T7 Single	0
T7 other port	0
T7 single construction	0
T7 tractor	0
T7 tractor construction	0
T7 utility	0
T7IS	0
UBUS	0

Table S1. Breakdown of EMFAC vehicle classes we characterize as LDV or HDV based on length. "1" denotes LDV and "0" denotes HDV.

Section S6.

As described in the main text, emission rates for LDV and HDV on each road segment between individual PeMS monitoring stations are computed hourly as a function hourly average speed. Here we show emission rates as a function of speed.

We also compare piece-wise linear fits to the spline fits used in this study. With the exception of emissions rates for LDV at speeds lower than 20 km h⁻¹, there is little difference between these fits. High uncertainty in emission rates at low hourly average speeds because of travel at non-constant speeds is likely to outweigh any difference between these fits (see Fig S7).



Figure S5: We show emission rates (g CO_2 / km) of different vehicle classes as a function of speed. (top and middle) Red lines indicate emission rates for individual vehicle classes as reported by EMFAC2017. Black lines indicate extrapolation using Oakridge National Lab data. Heavy blue lines indicate emission rates for LDV and HDV groups calculated by taking the vkm-weighted mean of emission rates for all vehicles within a group at a particular speed. (bottom) We compare piecewise-linear fits of this data to spline fits. Black lines indicate spline fit. Blue lines indicate piecewise-linear fits.

Section S7.

Figure S5 shows the hourly variation in the relative contributions of LDV speed, HDV percentage, and HDV speed to the deviation in CO_2 / vkm from the reference value of 265 g CO_2 / vkm. The solid line is the mean, and the shaded envelope represents the day-to-day variance. In the morning and mid-day, HDV percentage and LDV speed have opposite impacts on CO_2 / vkm, leading to smaller variations in CO_2 / vkm than the variations in the separate effects of speed and HDV %. During evening rush hour, low vehicle speeds result in higher emission rates, leading to large positive deviations. High day-to-day variance in vehicle speed contributes to high day-to-day variance in emission rates, shown as the envelope surrounding the solid line. At times near midnight, large, positive deviations are observed, mostly as a consequence of high HDV percentage, but also because traffic flows at rates higher than 104.6 kph, leading to higher emission rates. Night-to-night variance in HDV percentage is low, thus variance in nighttime predicted CO_2 / vkm is small. HDV speed has little impact on CO_2 / vkm.



Figure S6: (Top) PeMS-EMFAC-derived emissions rate deviations from baseline of 6% of all vehicles HDV, and vehicle speed constant at 105 kph resulting from car speed, truck percentage, and truck speed for the average day on the week shown in Figure 3. (Bottom) Total deviation in emissions rate by hour of day. % Deviation (right axis) shows percent deviation for all curves from emissions rate of 6% HDV at 105 kph. For all plots, solid line represents median values and shaded area represents variance.

Section S7.

Determination of Uncertainty in Emissions Rate Estimates

For the set of BEACO₂N emissions corresponding in time to the data in each 7.8 g CO₂ / vkm bin of PeMS-derived emissions rates, we find a BEACO₂N-derived emissions rate estimate. To do this, we take all BEACO2N traffic emissions occurring simultaneously with the PeMS-derived emissions rates and further bin these points based on vkm, as shown in Figure 3. For each vkm bin, we then find the median emissions value and the variance of emissions values, σ^2 . We assume the error in our estimate of the median emissions for each vkm bin to be $\delta ems = \frac{\sigma}{\sqrt{n}}$. We then fit median emissions values to the line

$$ems = \frac{gCO_2}{vkm}vkm$$
,

to find $\frac{gCO_2}{vkm}$, using δems as weights in the MATLAB fitlm function, and take the reported SE in slope to be the error in our calculated $\frac{gCO_2}{vkm}$.

Section S9.

The prior inventory was constructed to reflect vehicle type (LDV v. HDV) dependence on emissions, but not speed-dependence in emissions. In order to illustrate improvement of the posterior (Figure 3) over the prior, we repeat the analysis described in the main text to show emission rates calculated for the prior. Calculated emissions rates for the prior are nearly constant over a wide range (237.5 – 262.5 g CO₂ / vkm) of PeMS-EMFAC emission rates. Where they do vary, they are substantially different than those estimated in the posterior.



Figure S7:

Emission rate estimates calculated for the BEACO₂N-STILT prior in the same manner in which they were calculated for the posterior vs. PeMS-EMFAC emissions estimates with uncertainty estimate. Black line shows fit of to posterior (Fig 3) weighted by variance: y = 0.97(.01)x. Grey envelope is 5% deviation from fit. Red line represents 1:1 line.

Section S10.

While PeMS reports hourly averaged speeds for each sensing station, non-constant speeds due to congestion can result in range of possible emissions rates that can occur for a particular hourly averaged speed.



