Modeling Impact of Traffic Conditions on Variability of Midblock Roadside Fine Particulate Matter

Case Study of an Urban Arterial Corridor

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The objective of this study was to examine the concentration variation of midblock roadside particulate matter less than 2.5 µm ($PM_{2.5}$) as a function of very high resolution meteorological and traffic data. Morning peak period measurements were taken at a midblock roadside location on an urban arterial commuter roadway. For the impact of dynamic traffic conditions to be captured, data were analyzed at 10-s intervals, a substantially higher resolution than that used in typical roadside air quality study designs. Particular attention was paid to changes in traffic conditions, including fleet mix, queuing, and vehicle platooning over the course of the study period, and the effect of these changes on $PM_{2.5}$. Significant correlations were observed between vehicle platoons and increases in $PM_{2.5}$ concentrations. Traffic state analysis was employed to determine median $PM_{2.5}$ levels before and after the onset of congestion. A multivariate regression model was estimated to determine significant $PM_{2.5}$ predictors while controlling for autocorrelation. Significance was found not only in the simultaneous traffic variables but also in lagged traffic variables; in addition, the effects of vehicle types and wind direction were quantified. Modeling results indicated that traffic state (e.g., congestion) and vehicle type had a significant impact on roadside $PM_{2.5}$ concentrations. This study serves as a demonstration of the abilities of very-high-resolution data to identify the effects of relatively minute changes in traffic conditions on air pollutant concentrations.

Although the U.S. Environmental Protection Agency regulates concentrations of wide-scale maximum particulate matter less than 2.5 µm ($PM_{2.5}$) over 1 day and 1 year, peak exposures of 1 h or less could be more relevant from a health impact perspective (*1*). Commuters may receive a large portion of their daily particulate exposure in roadway microenvironments (small-scale environments comprising the roadway and its immediate surroundings), which are prone to high $PM_{2.5}$ concentrations and not regulated by ambient air quality standards (*2–5*). Elevated concentrations of air pollution in excess of ambient conditions along roadways indicate a direct relationship to motor vehicle emissions (*6*).

A review of existing literature showed that $PM_{2.5}$ exposure along roadway microenvironments has been thoroughly studied from the point of view of the traveler. This type of empirical study often focuses on in-vehicle exposure (*3, 7, 8*). Other studies have considered exposure for pedestrians, transit users, and bicyclists (*9–11*). These studies typically examine factors affecting exposure as the user moves throughout the network, facilitating an analysis of hot spots and in-vehicle exposure (as appropriate), while sacrificing certainty about the sources of $PM_{2.5}$ as the sampling location changes. Stationary roadside measurements allow for control over variables such as built environment and roadway type that are difficult or impossible to control in mobile studies. Several studies have used a stationary sampling approach to assess $PM_{2.5}$ exposure for pedestrians at intersections and transit users waiting at bus stops (*12–14*). Intersections have been widely shown to be hot spots of air pollution (*15*), though little or no stationary sampling has been conducted at midblock locations.

Most exposure studies use analyses of traffic data sources that are less than ideal. Often, high-resolution air pollutant samples are coupled with aggregate or modeled vehicle data; this approach limits the ability of the study to accurately determine sensitivity of a pollutant to changes in roadway conditions (*9, 16*). Similarly, because other studies that use high-resolution traffic data are often limited to air pollutant samples taken from a fixed monitoring site many miles away, conclusions about roadway pollutant sources are weakened (*5*).

This paper presents the results of an innovative midblock $PM_{2.5}$ sampling and modeling study in Portland, Oregon. The objective of this study was to determine the influence of arterial traffic conditions on concentrations of midblock roadside $PM_{2.5}$ by using a fine-grain statistical modeling approach. Particular attention was paid to changes in traffic conditions over the course of the study period, including fleet mix and bottleneck activation and vehicle platooning, and their effects on $PM_{2.5}$ concentrations. The data sampling and modeling approach also controlled for meteorological conditions with data of similar high resolution.

STUDY AREA

The study site is located on Southeast Powell Boulevard, at the intersection of Southeast 24th Avenue, roughly 3 mi east of the central business district. Powell Boulevard is a four-lane east-west urban arterial roadway that serves as one of the primary routes between the downtown district and the outlying suburbs. Annual average daily traffic is 31,500 vehicles at the study site. The corridor is typified by a variety of land uses, ranging from parkland and parking lots (as seen in Figure 1) to multistory businesses and schools.

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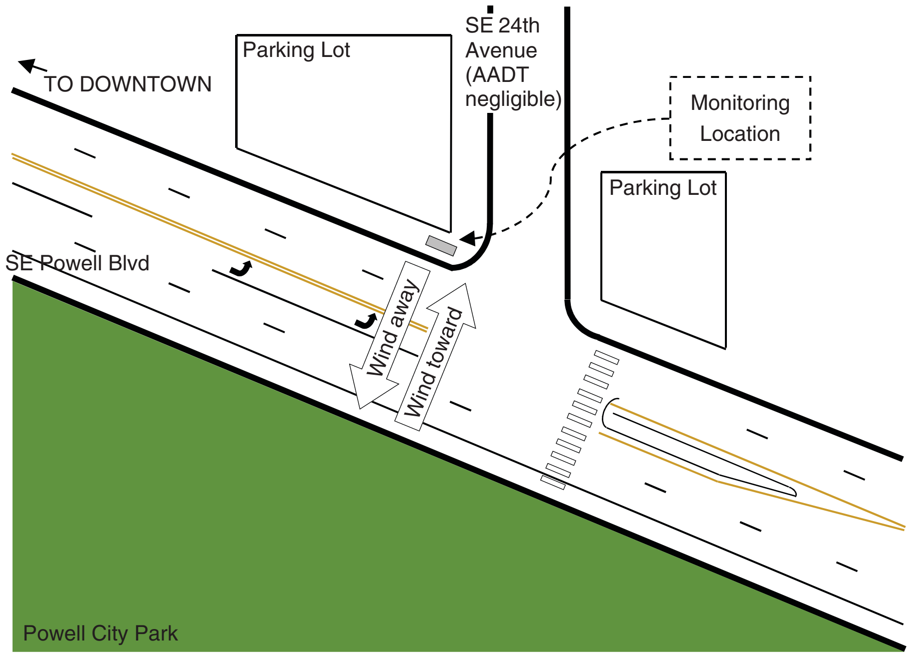

FIGURE 1 Built environment surrounding the study site on Powell Boulevard (SE = southeast; AADT = annual average daily traffic).

Southeast 24th Avenue is a small neighborhood street with negligible traffic. As such, the study site was considered an appropriate substitute for a midblock location. Signalized intersections are located two and three blocks away in the eastbound and westbound directions, respectively.

Westbound Powell Boulevard is often congested during morning peak hours. There are high volumes of private vehicles on this route, which also serves as a primary transit and freight route. Peak morning transit bus headways are 8 min in the downtown direction. The posted speed limit is 35 mph; however, during congested periods actual speeds can be substantially lower.

DATA COLLECTION

Field measurements were made on Wednesday, May 1, 2013, from 7:10 until 8:55 a.m. at the shaded corner site labeled "monitoring location" in Figure 1. There was no precipitation at the time of data collection. Data were gathered from a variety of sources. Portland State University supplied deployable instruments for particulate matter, temperature, relative humidity, and wind. The City of Portland Bureau of Transportation supplied traffic measurements.

$PM_{2.5}$ concentrations were measured with a DustTrak DRX Aerosol Monitor (TSI Model 8533), with a concentration range between 1 and 150,000 μg/m^3 and a resolution of 1% of the reading. The DustTrak monitor uses 90° light scattering at a sampling flow rate of 1.7 L/min. Although the monitor was factory-calibrated and working properly, it was calibrated to standard Arizona road dust; this calibration method has been shown to be inaccurate for measuring freshly emitted exhaust (*17–19*). Roadside particles have different sizes, shapes, compositions, and refractive index properties from those used for the Arizona Road Dust calibration standard; therefore, the DustTrak overestimates particulate matter mass concentrations in roadside environments (*20*). To compensate for the differences between roadside aerosols and the reference Arizona road dust aerosols (smaller and darker roadside particles), $PM_{2.5}$ readings were reduced by a factor of 2.3, on the basis of previous research (*17–19*).

Additionally, Huang and Tai (*21*) have shown that the light scattering used by the DustTrak is sensitive to high relative humidity because of an increase in light scattering efficiency as particles absorb ambient water. With the method outlined by Huang and Tai (*21*), the reduced $PM_{2.5}$ data were adjusted according to Equation 1:

$$PM_{2.5\text{corrected}} = PM_{2.5\text{reduced}} \times (-.0092 \times RH_i + 1.563) \qquad RH_i \geq 71.5\% \tag{1}$$

where

$PM_{2.5\text{corrected}}$ = finalized data,
$PM_{2.5\text{reduced}}$ = raw data reduced by a factor of 2.3, and
RH_i = instantaneous relative humidity (%).

Wind speed and direction were measured with an RM Young ultrasonic anemometer (Young Model 81000). The wind speed sensor has a range of 0 to 40 m/s and a resolution of 1% of the reading for wind speeds less than 30 m/s. The wind direction sensor has a resolution of ±2 degrees for wind speeds up to 30 m/s. Temperature and relative humidity were measured with an Onset HOBO U12-013 data logger. The temperature sensor has a resolution of ±0.35°C and the relative humidity sensor has a resolution of ±2.5%.

Data were collected at 1-Hz resolution. All devices were placed on a portable table approximately 2.5 m from the roadway; the aerosol monitor intake was mounted 1.5 m from the ground, following standard practice (*4, 8, 22*).

Traffic data were gathered from a permanently mounted Wavetronix SmartSensor HD radar detection device located at the same roadway cross section as the monitoring equipment. The radar device records vehicle counts, speed, occupancy (percentage of the time interval that the radar detection zone is occupied), and classification by vehicle length. Because heavy vehicles included any vehicle longer than 6 m, the results may have been biased (e.g., a pickup truck hauling a trailer would be classified as a heavy vehicle). The researchers used video data to validate the data, which were available at 10-sec intervals.

RESULTS

All data were aggregated to 10-sec intervals and combined into a single database. All analyses used this level of resolution unless otherwise noted. Data were cleaned and checked for outliers; one outlier data point was removed from the $PM_{2.5}$ data at the 7:13 a.m. mark, 3 min after the start of the data collection. The sample size was 631. Summary statistics are presented in Table 1. The average $PM_{2.5}$ concentration taken over the duration of the study period was 7.7 μg/m^3, lower than the typical near-road concentration range of ~15 to 160 μg/m^3 cited by Kaur et al. (*3*). A time series plot showing variation in $PM_{2.5}$ concentrations is presented in Figure 2. Spikes were observed throughout the study period, notably at 7:47 a.m., 8:10 a.m., and 8:48 a.m.; each of these spikes corresponded to westbound congestion and the passage of a westbound heavy vehicle.

For roughly two-thirds of the study period, the westbound direction of travel was heavily congested, characterized by a constant queuing of vehicles at the monitoring location. Westbound speeds deteriorated substantially at approximately 7:40 a.m. and had not recovered by the time the data collection ended at 8:55 a.m. In this paper, congestion refers to the general, long-term breakdown in traffic flow, and queuing refers to the dynamic, transient fluctuations in traffic flow. For visualization of the congestion and its context within the entire day's activity, a time series plot was constructed for both directions of travel with 1-min aggregations of the traffic data. Figure 3 shows total vehicle volumes, speeds, and occupancy rates. The dashed boxes indicate the study period, between 7:10 and 8:55 a.m.

Westbound volumes peaked just before the collapse in speeds; this peak suggests a maximum volume-to-capacity ratio had been reached. Eastbound travel experienced travel delays during the evening peak period, but not during the data collection period.

Average westbound speeds were approximately 30 mph at the start of the study period, but quickly dropped to below 10 mph. Westbound occupancy rates reflected the reduction in speed and are in line with field notes taken during the data collection: as volumes increased and speeds dropped, spacing between vehicles decreased, and thus the radar monitor detection zone was occupied for greater percentages of the time interval. Occupancy reached 100% twice in the study period

TABLE 1 Descriptive Statistics for $PM_{2.5}$ and Meteorological and Traffic Conditions

Variable	Mean	Median	Min.	Max.	SD
$PM_{2.5}$ (μg/m^3)	7.715	7.734	6.043	11.970	0.821
Temperature (°C)	8.333	5.493	4.558	16.060	4.219
Relative humidity (%)	63.970	74.560	37.550	78.940	15.341
Wind speed (m/s)	1.920	1.750	0.190	6.282	0.878
Passenger vehicles (per 10 s)					
Westbound	2.914	2.000	0.000	12.000	2.557
Eastbound	2.029	1.000	0.000	10.000	2.331
Heavy vehicles (per 10 s)					
Westbound	0.921	1.000	0.000	6.000	1.016
Eastbound	0.298	0.000	0.000	3.000	0.583

NOTE: Min. = minimum; max. = maximum; SD = standard deviation.

CONGESTION IDENTIFICATION

The availability of very-high-resolution traffic data opens up the possibility of analysis of pollutant concentration by traffic state. Traffic volume data provide an indication of the number of vehicles present near the monitoring site, but these numbers do not necessarily indicate the state of the traffic, that is, whether a roadway is congested or uncongested. For identifying traffic states empirically, a method derived from Bertini (*23*) was employed with two traffic states specified (congested and uncongested). Figure 4 illustrates the process. Cumulative speeds, $N(t)$, were plotted against time for the duration of the study period (top row in Figure 4). The curve's slope at time t is the speed at that time. A rescaled cumulative (oblique) speed curve was then created to amplify changes in speed (bottom row in Figure 4). The oblique speed curve was created by reducing $N(t)$ from v_0t, shown in Equations 2 and 3:

$$v_0 = \frac{N(t_N) - N(t_0)}{t_N - t_0} \tag{2}$$

$$t = t' - t_0 \tag{3}$$

where v_0 is an oblique scaling rate and t is the elapsed time from the beginning of the study period.

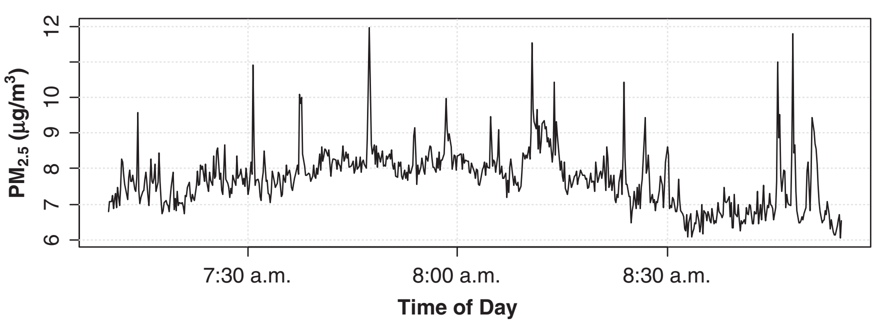

FIGURE 2 Time series for $PM_{2.5}$ concentration for the duration of the study period.

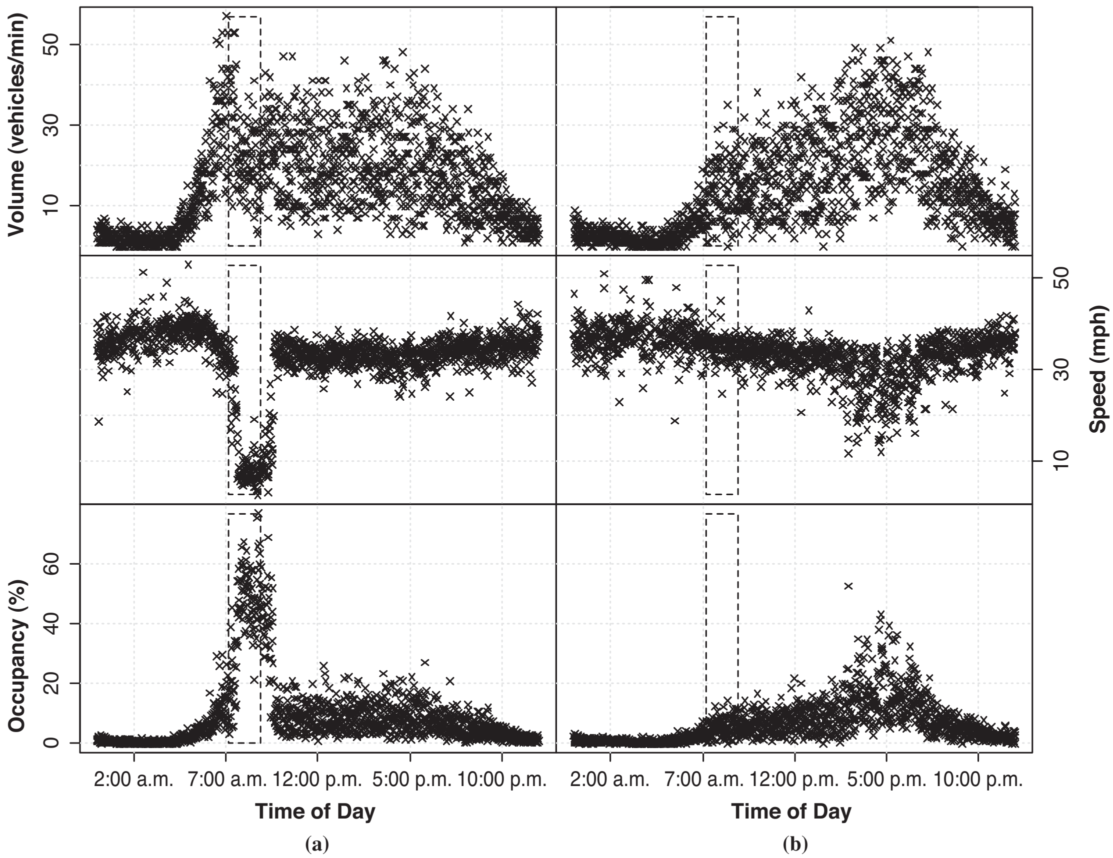

FIGURE 3 Directional traffic volumes, speeds, and occupancy rates for the entire study day (May 1, 2013) for (*a*) westbound and (*b*) eastbound traffic (dashed boxes indicate study period).

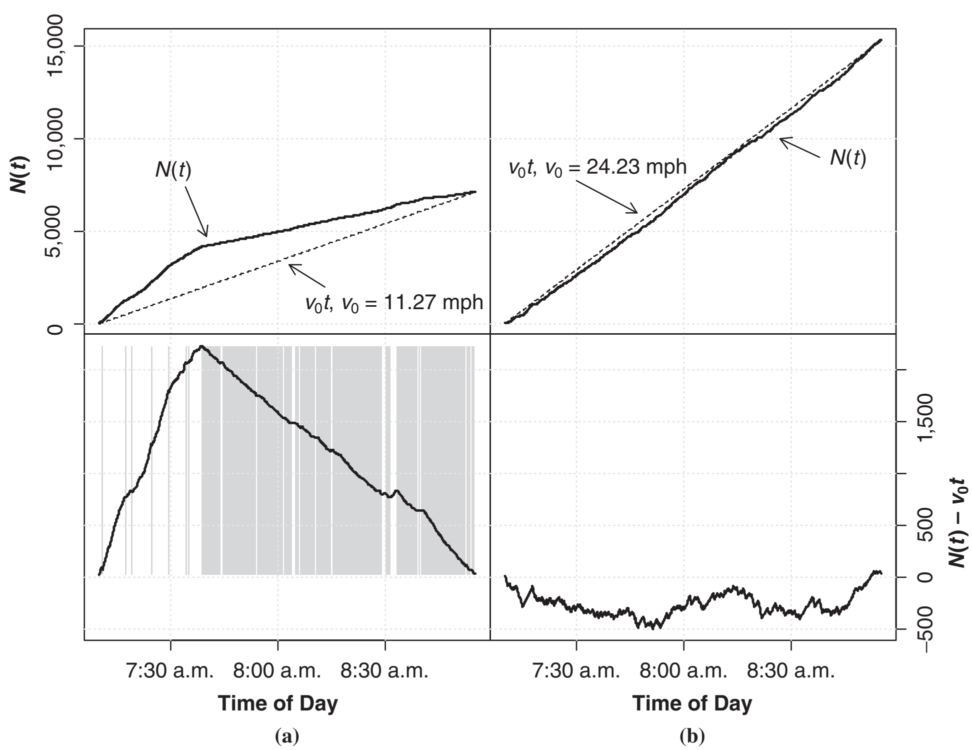

FIGURE 4 Cumulative speeds (*top*) and rescaled cumulative (oblique) speed curve, constructed with cumulative speeds $N(t)$ and oblique cumulative speeds $N(t) - v_0t$ (*bottom*): (*a*) westbound and (*b*) eastbound (shaded areas in oblique curve indicate active queue).

A local maximum on an oblique speed curve indicates a time at which a speed reduction occurred, and a local minimum indicates a time at which a speed increase occurred. These two conditions are referred to as queuing activation and deactivation points, respectively. The shaded portion of the oblique speed curve in Figure 4 indicates an active queue.

The onset of consistently congested conditions is clearly displayed in the westbound direction, beginning at 7:38 a.m. From that point, the queue was primarily active. No congested conditions occurred in the eastbound direction.

The cyclic nature of vehicle presence in the study area is evident when viewed in an autocorrelation function (ACF) plot and a partial autocorrelation function (PACF) plot of traffic volumes. ACF and PACF plots illustrate the similarities between observations as a function of the time lags between the observations. Given lag h, the ACF does not account for linear dependence between time t and time $t+h$; the PACF, which removes the linear dependence for observations at time $t+1$ through time $t+h-1$, indicates the unique autocorrelation for lag h. Both of these functions are commonly used to determine patterns. Cyclical arrival times were facilitated by upstream signals in either direction. The westbound upstream signal had a median cycle length of 123 s during the morning period, and the eastbound upstream signal had a median cycle length of 125 s. These cycles are evident in the vehicle volume ACFs and PACFs in Figure 5, *a* and *b*,

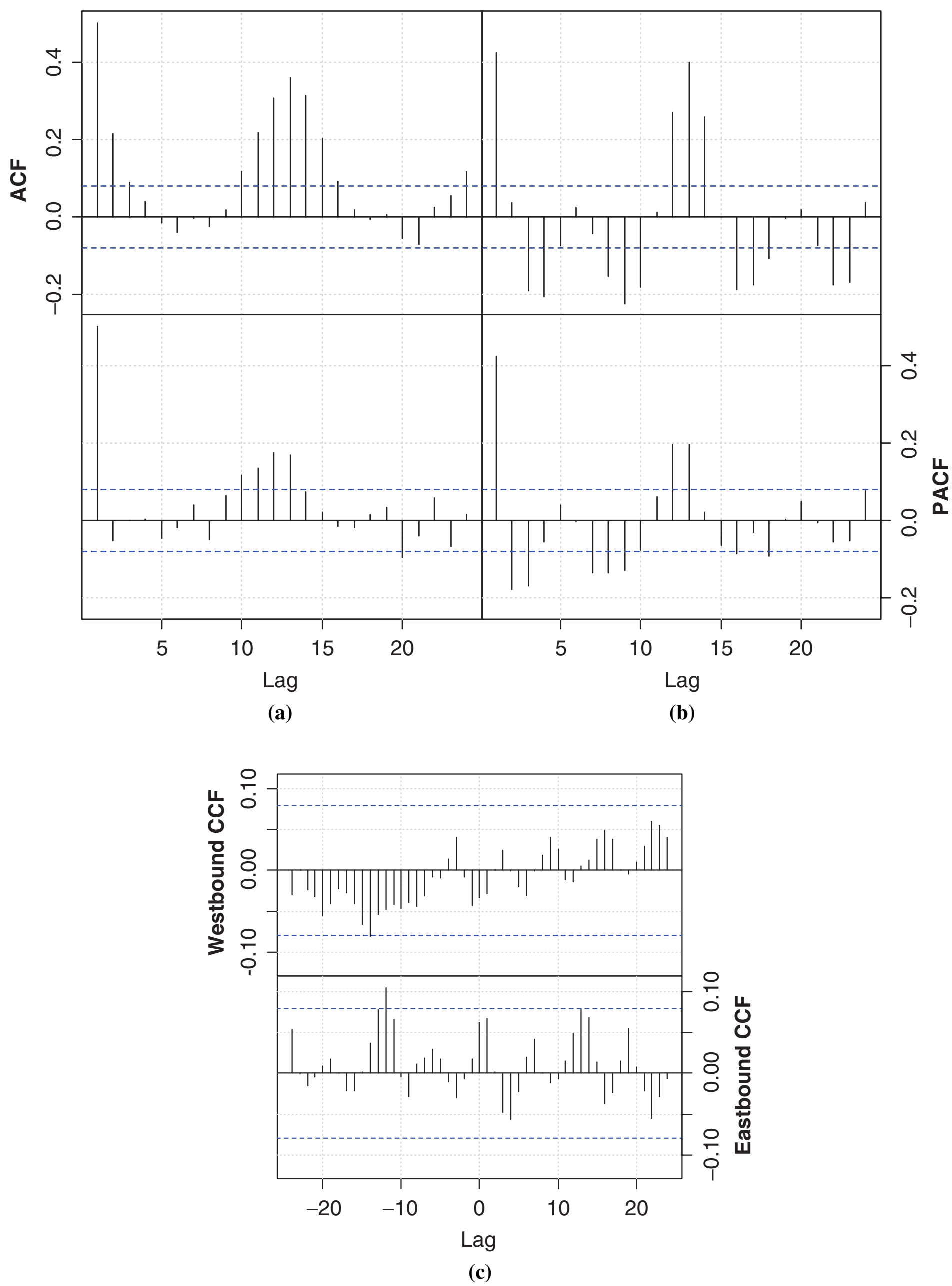

FIGURE 5 Autocorrelation of vehicle volumes showing platooning with upstream signal cycles (*a*) westbound and (*b*) eastbound and (*c*) cross-correlation of vehicle volumes with $PM_{2.5}$ concentrations (1 lag = 10 s; CCF = cross-correlation function).

in which one lag equals 10 s. Directional differences in the ACFs and PACFs are evident. The eastbound response has a clear spike at 13 lags, or 130 s, because of traffic platooning. The westbound direction had a slightly more dampened response, likely because of congestion, which mitigated any upstream cycle effect attributable to the constant vehicle presence at the sensor location.

The cyclical arrival times are referred to as vehicle platooning, or the grouping of vehicles after departing from an upstream signal. For the investigation of the effect of vehicle platoons on $PM_{2.5}$ concentrations, a cross-correlation function was made for each direction.

The cross-correlation function in Figure 5*c* illustrates sample correlations between $PM_{2.5}$ concentrations at time t and traffic volumes at time $t + h$ for $h = 0, \pm1, \pm2, \pm3$, and so forth. Negative values for h indicate a correlation between volumes at a time h units before t and $PM_{2.5}$ concentrations at time t. The dashed lines in Figure 5*c* indicate the statistical significance level, calculated with

$$\frac{z_{1-\alpha/2}}{\sqrt{N}}$$

where z is the z-value at a given level of significance α and N is the sample size. At 95% confidence, the significance threshold is 0.078. No westbound correlations were significant; this result indicates that westbound vehicle platooning did not have a significant effect on $PM_{2.5}$ concentrations. In the eastbound direction of travel, $PM_{2.5}$ concentrations were significantly positively correlated (+10.4%) with vehicles passing at 12 lags, or 120 s. This lag time roughly matched the upstream cycle length as well as the eastbound vehicle ACF and PACF. Eastbound vehicle platooning, then, significantly positively correlated with $PM_{2.5}$ concentrations. Platooning correlations were likely easier to identify in the eastbound direction because of the uncongested conditions and clear vehicle arrival times for the duration of the study period.

STATISTICAL MODELING

Assessment of the joint traffic and meteorological effects on $PM_{2.5}$ concentrations required an advanced statistical approach. Ordinary least squares regression is typically the starting point, but consideration had to be made for the highly autocorrelated nature of the $PM_{2.5}$ measurements. Ordinary least squares requires independence of the residuals to ensure efficient estimates. To address the autocorrelation, a lagged dependent variable was added to the regressors. To mitigate positive skew, a natural logarithmic transformation was applied to both the dependent variable ($PM_{2.5}$) and lagged dependent variable.

Independent variables considered for the model are listed in Table 2. Traffic variables included total volume (passenger and heavy vehicles), occupancy rate (as an indicator of congestion), and queuing status (on the basis of the analysis in Figure 4). Wind speed, wind direction, and relative humidity were included as indicators of meteorological conditions. Wind direction was simplified into directions toward and away from the monitoring location, as illustrated in Figure 1. This simplification was performed by taking the sine of the angle of wind direction with respect to the roadway. Wind perfectly perpendicular to the roadway, blowing toward the monitoring location, was coded as a 1. Wind perfectly parallel to the roadway was coded as a 0. Wind directions between perpendicular and parallel were interpolated between 1 and 0 with the sine function. This same technique was applied for wind blowing away from the monitoring station.

For the possible role of wind direction in the dispersion of vehicle emissions to be emphasized, the wind direction variable was interacted with traffic volumes in the model. That is, a vehicle passing while the wind was blowing across the roadway, toward the monitoring station, received a nonzero value (the product of traffic volume and the sine of the wind direction). A vehicle passing while the wind was blowing parallel to the roadway received a zero value. This method approximates vehicle plume characteristics without the effects of vehicle-induced turbulence.

Lagged terms were considered for traffic and wind speed variables after the cross-correlation function in Figure 5*b* indicated lagged volume variables were useful predictors of $PM_{2.5}$ concentrations.

The final log-linear model, with $p = .05$ as the significance threshold, exhibited negligible correlation between the residuals and was determined to satisfy the OLS requirement for independent error terms. The final model is presented in Table 3.

Model results indicated higher traffic volumes were associated with increased $PM_{2.5}$ concentrations when the wind was blowing toward the monitoring station. Lower traffic-related concentrations when the wind was blowing away from the station were likely the result of lower background $PM_{2.5}$ levels in the neighborhoods north of Powell Boulevard. $PM_{2.5}$ concentrations were affected by traffic volumes several periods in the past, up to 20 lags, or 200 s. Several eastbound traffic variables were significant, but only one westbound traffic variable was significant; this finding was probably the result of the relatively low variation in westbound traffic conditions after

TABLE 2 Definitions of Regression Variables

Variable	Description	Type	Unit
Dependent: ln ($PM_{2.5}$)	Natural log of concentration at time t	Continuous	$\mu g/m^3$
Independent			
Lagged dependent variable: ln ($PM_{2.5}$)	Natural log of concentration at time $(t - 1)$	Continuous	$\mu g/m^3$
Traffic conditions			
Passenger volume	Number of passenger vehicles passing (vehicle length < 6 m)	Continuous	Vehicles per 10 s
Heavy-vehicle volume	Number of heavy vehicles passing (vehicle length > 6 m)	Continuous	Vehicles per 10 s
Occupancy	Percentage of time interval that vehicle detection zone was occupied	Continuous	%
Queuing	Queuing status	Dichotomous	0 = inactive, 1 = active
Meteorological conditions			
Wind speed	Wind speed	Continuous	m/s
Wind direction	Sine of the angle of wind direction perpendicular to traffic direction	Continuous	Unitless
Relative humidity	Relative humidity	Continuous	%
Lagged terms: traffic and wind speed	Traffic volumes and wind variables lagged up to time $(t - 24)$	Continuous	Various

TABLE 3 Multivariate Ordinary Least Squares with Lagged Dependent Variable Model

Variable	Lag	Coefficient	SE	*p*	Unit Increase Effects on Dependent Variable (semielasticity)
Intercept	0	.63261	.05693	<.001	na
ln ($PM_{2.5}$)	1	.63829	.03013	<.001	na
Traffic conditions: westbound occupancy	0	.00046	.00013	<.001	Increase by .05% per percentage point occupancy increase
Meteorological conditions					
Relative humidity	0	.00138	.00020	<.001	Increase by .14% per percentage point relative humidity increase
Wind speed	1	−.01274	.00368	.001	Decrease by 1.27% per 1 m/s increase
	2	.00917	.00368	.013	Increase by .92% per 1 m/s increase
Vehicle volume × wind					
Wind toward monitoring station: eastbound passenger vehicle	8	.00488	.00214	.023	Increase by .49% per additional vehicle
	11	.00455	.00215	.035	Increase by .46% per additional vehicle
	20	.00448	.00214	.037	Increase by .45% per additional vehicle
Eastbound heavy vehicle	0	.02418	.01075	.025	Increase by 2.45% per additional vehicle
Wind away from monitoring station: westbound passenger vehicle	0	−.00400	.00144	.006	Decrease by .40% per additional vehicle

NOTE: Dependent variable = ln ($PM_{2.5}$); R^2 ($R^2_{adjusted}$) = .6589 (.6533); residual standard error (SE) = .06138 on 600 degrees of freedom; Akaike information criterion = −1,663.29; na = not applicable.

the onset of congestion. The lack of variability in westbound traffic conditions limited the ability of the model to separate westbound vehicle effects (occupancy from traffic volume). The continually congested westbound conditions might have contributed to the serial correlation in $PM_{2.5}$ concentrations and were captured by the correlation coefficient.

The occupancy variable served as an indicator of congestion conditions; in Figure 3 higher occupancy rates were shown to correspond with congestion. The model confirmed that westbound congestion was significantly associated with increases in $PM_{2.5}$ concentrations.

Semielasticities (($e^{\beta} - 1) \times 100$) were calculated from the log-linear model coefficients. Eastbound heavy vehicles had a larger semielasticity (2.45% per additional vehicle) than any eastbound passenger vehicle (maximum .49% per vehicle) when the wind was blowing toward the monitoring station. This finding was to be expected as diesel engines emit more particulate matter than gasoline engines (*24, 25*).

EFFECTS OF TRAFFIC STATE

As a further investigation of effects of traffic state on $PM_{2.5}$ concentrations, median concentrations during queuing states were compared before and after the onset of congestion at 7:38 a.m. (see Figure 4 for westbound queuing conditions). Box plots of the concentrations are presented in Figure 6. Lower median concentrations were observed for active queuing periods before congestion than for inactive periods. In contrast, higher median concentrations were observed for active queuing periods after the onset of congestion at 7:38 a.m. than for inactive periods.

After the onset of congestion, active queuing periods were characterized by vehicles queuing closely and accelerating from low speeds. These two factors may account for the increase in $PM_{2.5}$ concentrations (active versus inactive). Before the onset of congestion, active queuing periods were characterized by brief decreases in speed, though for time durations that were too short to bring traffic to congested conditions (thus avoiding extended queues or acceleration from low speeds). Short queuing periods outside of congestion, then, likely lead to traffic conditions with lower accelerations, which may have resulted in lower emissions rates and lower $PM_{2.5}$ concentrations. The active and inactive $PM_{2.5}$ concentrations shown in Figure 6 were statistically significantly different at $p = .05$, for both precongested and congested periods.

Finally, a method was devised for estimating the amount of $PM_{2.5}$ per vehicle. Figure 7 shows the amount of $PM_{2.5}$ measured per number of vehicles detected (in both directions) over the duration of the study period, in micrograms per cubic meter per vehicle. After the onset of congestion, the two cumulative curves began to diverge, and the ratio of $PM_{2.5}$ per vehicle began to increase slightly. At the congestion mark at 7:38 a.m., the ratio was 1.07. At the end of the study period at 8:55 a.m., the ratio was 1.25. Thus, as the congestion

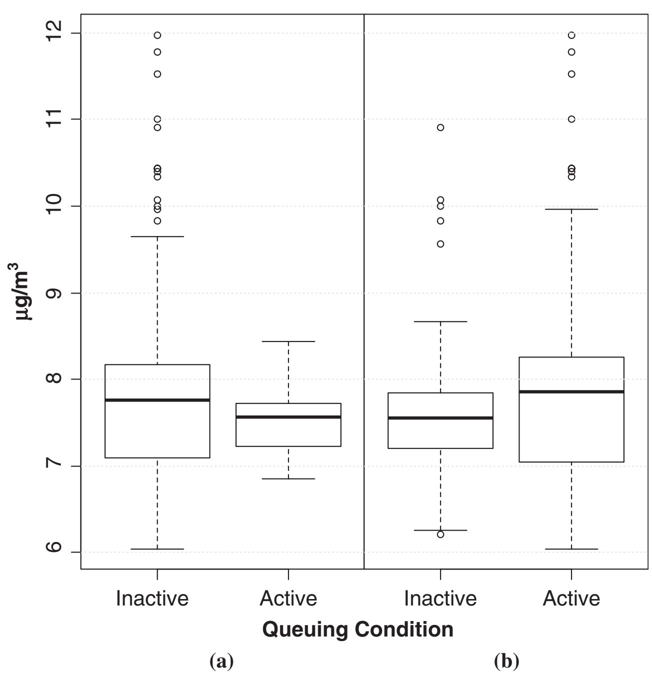

FIGURE 6 $PM_{2.5}$ **concentrations during inactive and active queuing conditions in (*a*) precongestion and (*b*) congestion conditions.**

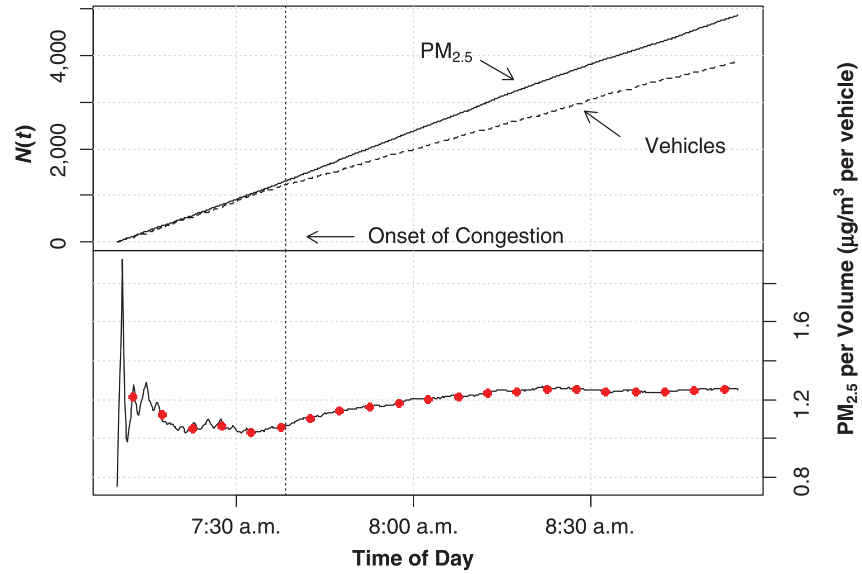

FIGURE 7 Cumulative $PM_{2.5}$ and vehicle curves (*top*) and $PM_{2.5}$ per vehicle (*bottom*) (dots indicate 5-min averages of the ratio curve).

continued, the $PM_{2.5}$ per vehicle increased; this finding indicates a possible air quality effect of long periods of congestion.

CONCLUSION

This paper demonstrates the ability of high-resolution traffic data to aid in understanding variation in $PM_{2.5}$ concentrations in an urban roadway microenvironment. To the best of the authors' knowledge, this is the first study to combine very-high-resolution $PM_{2.5}$ meteorological and traffic data in a roadside midblock stationary sampling study design.

Although mobile measurements are able to provide useful information relating to hot spots and traveler exposure, they are unable to reliably describe sources and behavior of $PM_{2.5}$ on roadsides, which are complicated environments and require controlling for many different factors simultaneously to understand pollutant variations. It was demonstrated that 10-sec traffic data can be used to show platooning and that the platooning is significantly correlated with $PM_{2.5}$ concentrations. Because this type of analysis would be impossible with data resolutions greater than the upstream signal cycle length (approximately 2 min in this case), the need for high-resolution data analysis to detect platooning is demonstrated. Similarly, congested periods and dynamic traffic states were identified to examine related changes in $PM_{2.5}$ concentrations and the ratio of $PM_{2.5}$ per vehicle. These results indicate possible connections between queuing in and out of congested periods and roadside air quality.

A multivariate regression model was used to determine significant predictors of $PM_{2.5}$ concentrations while controlling for autocorrelation. Significance was found not only in main effect traffic variables but also in past readings of traffic variables, and it was possible to single out effects of vehicle classification type and wind direction. Heavy vehicles were shown to have five times the impact on $PM_{2.5}$ concentrations as passenger vehicles. Although more research is needed in this area, it is likely these results are generally representative of conditions in other midblock arterial locations, although some local calibration will always be required.

Accurate representation of roadside environments is crucial to understanding exposure to $PM_{2.5}$ for all roadway users. Data availability plays an important role in this representation, as do appropriate statistical models to uncover $PM_{2.5}$ predictors in complicated microenvironments. This study makes use of a small sampling period (2 h) to demonstrate both the potential of rich data sources and the need for further long-term study in stationary sampling roadside exposure research. Future work will analyze high-resolution traffic and air quality data over longer time periods and examine the expected benefits of collecting high-resolution air quality data (such as those used in this paper) for project-specific analysis. Another area for examination is the potential application of high-resolution traffic and roadside air quality data for calibrating and validating high-resolution simulation models of traffic air quality, such as in the model developed by Kim et al. (*26*).

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