

Spatiotemporal Aspects of Real-Time PM_{2.5}: Low- and Middle-Income Neighborhoods in Bangalore, India

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S Supporting Information

ABSTRACT: We measured outdoor fine particulate matter (PM_{2.5}) concentrations in a low- and a nearby middle-income neighborhood in Bangalore, India. Each neighborhood included sampling locations near and not near a major road. One-minute average concentrations were recorded for 168 days during September 2008 to May 2009 using a gravimetric-corrected nephelometer. We also measured wind speed and direction, and PM_{2.5} concentration as a function of distance from road. Average concentrations are 21–46% higher in the low- than in the middle-income neighborhood, and exhibit differing spatiotemporal patterns. For example, in the middle-income neighborhood, median concentrations are higher near-road than not near-road (56 versus 50 $\mu\text{g m}^{-3}$); in the low-income neighborhood, the reverse holds (68 $\mu\text{g m}^{-3}$ near-road, 74 $\mu\text{g m}^{-3}$ not near-road), likely because of within-neighborhood residential emissions (e.g., cooking; trash combustion). A moving-average subtraction method used to infer local- versus urban-scale emissions confirms that local emissions are greater in the low-income neighborhood than in the middle-income neighborhood; however, relative contributions from local sources vary by time-of-day. Real-time relative humidity correction factors are important for accurately interpreting real-time nephelometer data.



INTRODUCTION

Outdoor fine particulate matter (PM_{2.5}) is associated with an increased risk of chronic cough, allergic disorders, decreased lung function, cardiopulmonary disease, and death.^{1–4} Health effects of PM may occur for a range of exposure durations, from one hour or less^{5–8} to more than a decade.^{1,3} Annual and 24-h averages at central monitoring sites often provide little information about spatiotemporal variability of air pollution.^{9–11} Much of the research on PM_{2.5} has been conducted in developed countries, yet the poorest ambient air quality is generally found in developing-country cities.^{12–16}

This study explores spatiotemporal variability in outdoor PM_{2.5} in Bangalore, India (population 8 million; area 710 km²). Bangalore is experiencing rapid urban growth and rising automobility: population has more than quadrupled in 40 years, to 7.2 million in 2010; motor vehicle registration increased nearly 20-fold since 1980, to more than 3 million vehicles in 2008.^{15,17} With the Government of Karnataka's regulation of vehicle emissions and fuel quality, some areas of Bangalore have shown a decrease of SO₂ and PM₁₀ concentrations.^{18,19} However, annual average PM₁₀ concentrations at 5 of 6 government

monitoring sites did not decrease from 1999 to 2009; 5 of 6 sites exceed national standards (120 $\mu\text{g m}^{-3}$ in industrial areas; 60 $\mu\text{g m}^{-3}$ elsewhere).²⁰ For 2008–2009, monitored annual average PM₁₀ concentrations ranged from 63 $\mu\text{g m}^{-3}$ in a designated sensitive area to 183 $\mu\text{g m}^{-3}$ in a designated industrial area.²⁰

We measured real-time, outdoor PM_{2.5} in two Bangalore neighborhoods (low-income, middle-income). We selected PM_{2.5} because real-time instruments are readily available, because concentrations are known to be especially high in Indian cities, and because the health effects of PM are well studied. For example, the World Health Organization estimates that in low- and middle-income countries, outdoor urban PM causes ~1.9% of deaths (~20% of deaths from environmental risk factors).²¹ PM_{2.5} includes primary and secondary components, and generally is not considered to be a tracer for vehicle emissions in most urban areas.

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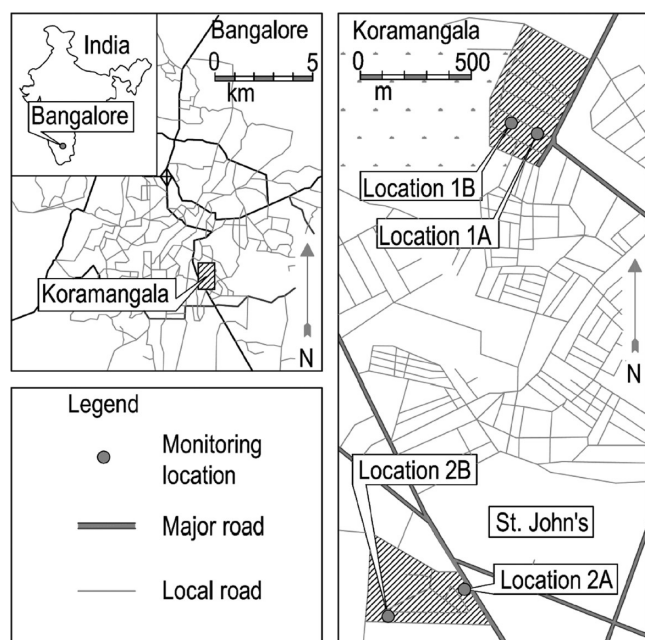


Figure 1. Study locations: (1A) low-income near-road, (1B) low-income not near-road, (2A) middle-income near-road, (2B) middle-income not near-road.

One aim of this article is to infer spatial patterns in emissions based on concentrations' temporal variability. A second aim is to test the following hypothesis in Bangalore. Based on spatial patterns in developed countries, we hypothesized that $PM_{2.5}$ concentrations would decrease at increasing distance from a road and that near-road concentrations would be greater when the wind is blowing from the road (i.e., measurements are downwind of the road) than the reverse (measurements are upwind). The main contributions of this paper include developing and applying a set of analyses for real-time concentrations, and reporting how air pollution concentrations differ between low- and middle-income communities in a developing country.

MATERIALS AND METHODS

Field Study Setup. Equipment consisted of two optical aerosol detectors and a weather station. The direct-reading optical aerosol detector, a DustTrak nephelometer (model 8520, TSI Inc., Shoreview, MN), estimates $PM_{2.5}$ mass concentrations based on light-scattering. The DustTrak provides an inexpensive real-time estimate of $PM_{2.5}$ mass, but measurements must be corrected for humidity and local aerosol properties (see below). The weather station (model PWS 1000 TB, Zephyr Instruments, East Granby, CT) included an anemometer, weather vane, and sensors for temperature and relative humidity.

Measurements were carried out in two neighborhoods in the Koramangala district of Bangalore, India. The low-income neighborhood (Rajendra Nagar; population ~ 6500 ; area $\sim 0.15 \text{ km}^2$) is one of the largest slums in Bangalore.²² The site consists of dense 1- to 5-story housing and little or no vegetation. A major road runs to the southeast. The middle-income neighborhood (faculty housing for St. John's National Academy of Health Sciences; population ~ 300 ; area $\sim 0.15 \text{ km}^2$) is characterized by low-density 2- to 3-story housing with trees (5–10 m tall) and

other vegetation. The neighborhood is bordered by a 3-m privacy wall and a major road to the east.

In each neighborhood, two monitoring sites were established: near a major road ($<50 \text{ m}$) and not near a major road ($>250 \text{ m}$) (Figure 1). Instruments were placed on rooftops, at 7–10 m height. This elevation, which was necessary to ensure the security of the instruments, is consistent with U.S. EPA guidance.²³ Concentrations may differ aloft versus at ground level. During each ~ 2 -week monitoring period, both monitors were placed in one neighborhood (one near-road, one not near-road). We also conducted regular transect samples (78 in total, or roughly 2–3 per week) to measure $PM_{2.5}$ as a function of distance from the road. Data were collected September 2008 through May 2009. Figure S1 and Table S1 display data coverage.

Analysis. We collected 2404 h of data in which all three real-time instruments (weather station; two nephelometers) were operating. When the relative humidity (RH) exceeded 95%, nephelometer data become nonsystematically distorted²⁴ and were excluded ($<0.1\%$ of the data). When RH is above 60%, light-scattering devices may overestimate $PM_{2.5}$ mass concentrations; Laulainen^{25,26} developed a correction curve, which was empirically fit by Chakrabarti²⁷ to yield the correction factor (CF) applied here:

$$CF = 1 + 0.25(RH^2)/(1 - RH) \quad (1)$$

This correction has been shown to be a good fit in several locations, including Los Angeles, Minneapolis, southern Italy, and Great Smokey Mountain National Park (USA), despite potential differences in the composition of particles measured at these sites.^{27–30}

Light-scattering measurements have been shown to correlate well with gravimetric sampling if a correction factor is applied to adjust for bias.^{30–33} Few instrument comparisons have been done in outdoor urban environments in India. Because calibrations were unavailable for Bangalore, we employ here the following gravimetric calibration, derived recently for another large city in India:

$$G^* = 3.91D^{0.706} \quad (2)$$

Here, G^* is the gravimetric-corrected $PM_{2.5}$ concentration ($\mu\text{g m}^{-3}$) and D is the RH-corrected nephelometer $PM_{2.5}$ reading ($\mu\text{g m}^{-3}$). Equation 2 ($R^2: 0.79$) was obtained by comparing 32 paired RH-corrected nephelometer and gravimetric daily average concentrations in Delhi, India.³⁴ Gravimetric calibration relationships vary based on PM composition. Our approach implicitly assumes that, while PM composition would vary between Delhi and Bangalore, sources and composition are similar enough that Delhi's calibration provided a reasonable proxy for calibration in Bangalore. Future work could usefully test that hypothesis. For a linear correction factor, relative results presented below (e.g., concentration comparisons between neighborhoods; proportion of measured concentrations that is attributable to local sources) would not depend on the actual correction factor employed.

To analyze the effect of wind on $PM_{2.5}$ concentration, data were separated into five conditions: (1) *toward*: wind blowing from the road toward the monitors (within a 45° range); (2) *away*: wind blowing from the monitors toward the road (45° range); (3) *perpendicular*: wind direction parallel to road (neither toward nor away from the monitors; 270° range); (4) *variable*: wind direction is not consistent; and (5) *calm*: wind speed less than 0.3 m s^{-1} . For example, for the low-income sites, the road

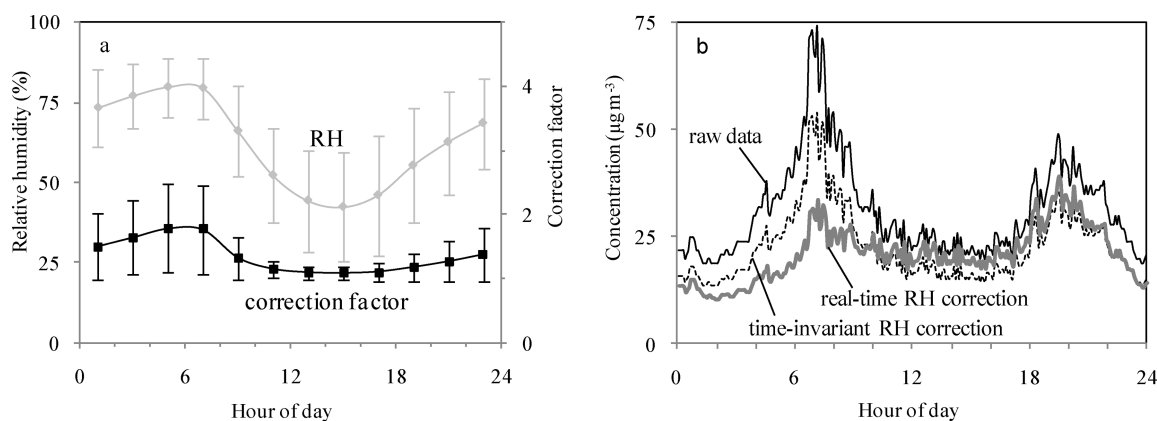


Figure 2. (a) Mean relative humidity (RH) and nephelometer correction factor by time of day. Error bars indicate 1 standard deviation over the 168 days of measurement. (b) Sample comparison of RH correction techniques for real-time $PM_{2.5}$ concentration. Data are for Sept. 18, 2008, middle-income, near-road location. The solid black line is nephelometer output (uncorrected). The gray line uses real-time RH correction and reflects our best estimate for the true concentration. The dashed line reflects a single RH correction factor based on that day's average RH. Results from the time-invariant correction overestimated morning peak concentrations by 68%.

was east–southeast of the monitors (bearing: $\sim 112.5^\circ$ [north = 0°]; Figure 1), so “toward” conditions were winds from the east–southeast (bearing: 90° – 135°). Figure S2 displays wind speed and direction by season. Figure S3 shows wind conditions by time-of-day.

To discern a spatial signature from the temporal $PM_{2.5}$ mass concentrations, a moving average subtraction method developed by Watson and Chow³⁵ was applied to paired data in each neighborhood. In this approach, short-duration concentration pulses are hypothesized as attributable to local sources (<0.5 km). Concentrations after removing the short-term spikes at the not near-road site are interpreted as the regional contribution (>5 km). The concentration difference between the baseline at the near-road site and the baseline at the not near-road site is interpreted as attributable to neighborhood sources (~ 0.5 –5 km). Raw data and calculated baselines for a sample day are given in Figure S4.

The moving average subtraction method requires specifying the “underwriting” function that mathematically identifies and removes short-term concentration peaks. The term “underwriting” is used because the resulting time series (concentrations with peaks removed) are less than the original time series (true concentrations, including peaks). In our base case, we employed the underwriting function identified by Watson and Chow: concentrations are smoothed at multiple time scales, always selecting the lower concentration (original measurement versus “smoothed” time series). We separately implemented an alternative underwriting function that is the moving 1.5 percentile of the surrounding 60 min (see SI). This second approach serves as a sensitivity analysis. Because the main approach likely underestimates the proportion of concentrations attributable to local emissions (see below), the second approach was designed to yield larger estimates for that parameter.

RESULTS AND DISCUSSION

Relative Humidity Correction. The RH correction factor varied by time of day, averaging 1.78 during 4:00–8:00 a.m. and 1.09 during noon–6:00 pm (Figure 2a); the overall average is 1.35. The potential importance of using real-time RH to correct real-time nephelometer data is illustrated in Figure 2b.

At times-of-day when RH was approximately equal to the daily average RH (e.g., 10:00 in Figure 2b), the real-time approach and the time-invariant (i.e., 24-h average) approach yielded similar results. At other times, however, the two approaches diverged. For example, at 8:00 in Figure 2b, concentration estimates were 68% higher using the time-invariant RH-correction than for the real-time approach; here, use of time-invariant (24-h average) corrections would have dramatically overestimated the size of morning concentration peaks.

$PM_{2.5}$ Measurements. Figure 3 displays the typical daily patterns of $PM_{2.5}$ at each monitoring location. Concentrations were $\sim 33\%$ higher in the low-income than in the middle-income neighborhood. In the middle-income neighborhood, concentrations were $\sim 11\%$ higher near-road than not near-road. Concentrations were $\sim 36\%$ and $\sim 43\%$ higher during the morning (7:00–9:00) and evening (18:00–21:00) peaks, respectively, than during other times. The two neighborhoods are similar in land area, but because of the $\sim 20\times$ difference in population density, many more people breathe the more-polluted air (low-income neighborhood) than the comparatively “cleaner” air (middle-income neighborhood).

Two aspects of Figure 3 merit highlighting. First, the degree of spatial variability changes strongly by time of day. During afternoons (12:00–16:00), concentrations were similar among the four locations (spatial coefficient of variability [CV]: 12%); during morning peaks (7:00–9:00), the four locations were most variable (CV: 51%). At night (midnight–6:00 a.m.), concentrations differed by $\sim 60\%$ between neighborhoods, but exhibited near-zero within-neighborhood difference (CV: $\sim 5\%$). This finding is consistent with a recent report from Southern California that spatial impacts of road PM vary by time-of-day.³⁶ A second noteworthy feature is that for the low-income neighborhood, morning concentrations were generally greater not near-road than near-road, a finding that differs from nearly all published results.^{37,38} This result is likely because of within-neighborhood sources (e.g., cooking; trash combustion), a hypothesis supported by diurnal trends mentioned above and by the spatial contributions analysis below. The effect of local emission sources on ambient $PM_{2.5}$ was similarly seen in low-income neighborhoods in Accra, Ghana, where biomass fuels are also extensively used.³⁹ In general, trends in Figure 3 reflect

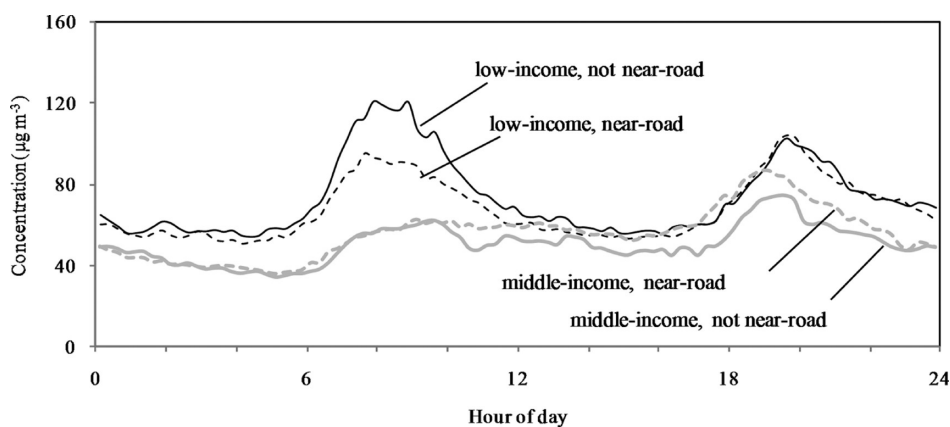


Figure 3. Median $PM_{2.5}$ concentration by time of day for the four locations, based on all data (2404 h). For the middle-income neighborhood, concentrations are higher near-road than not near-road; for the low-income neighborhood, the reverse pattern holds.

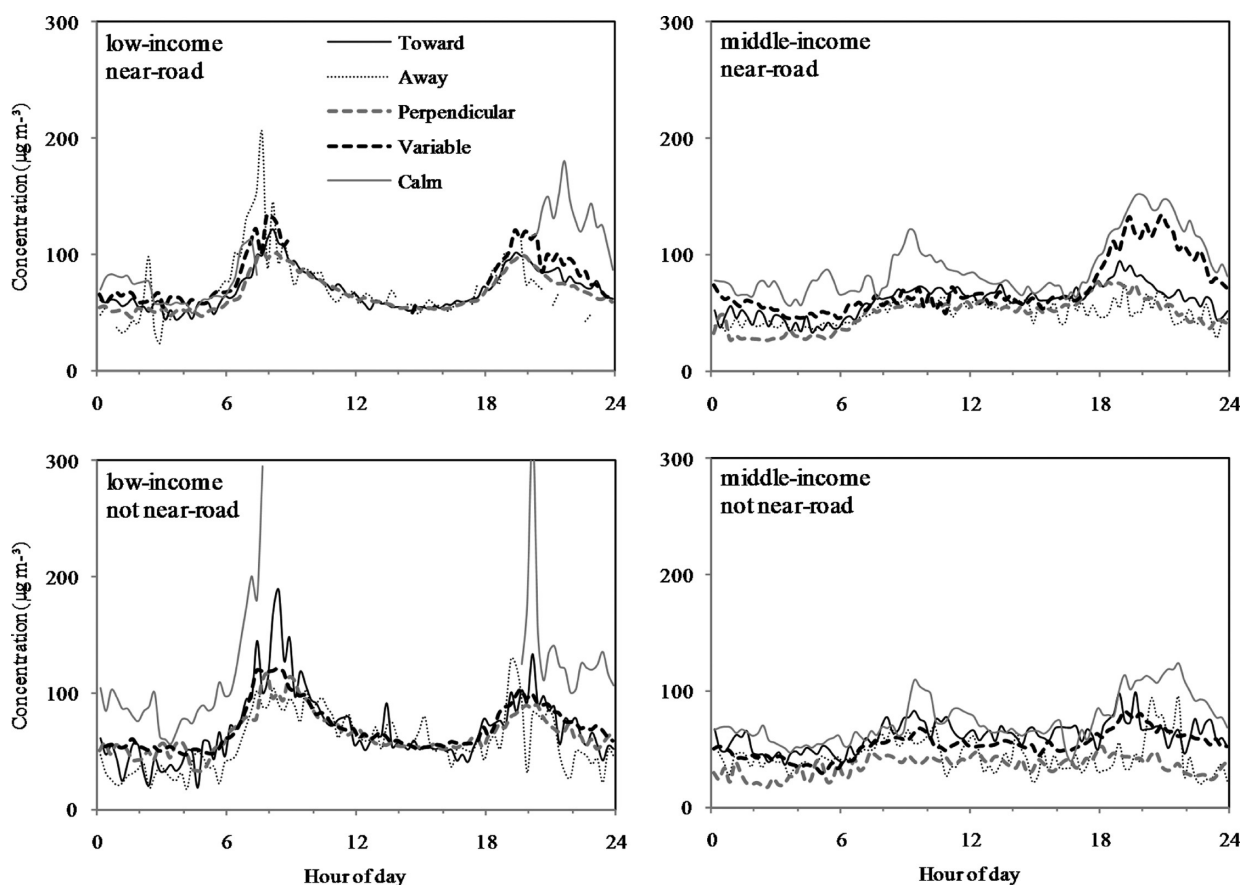


Figure 4. Median $PM_{2.5}$ concentrations by location, time-of-day, and wind condition.

temporal patterns in emissions (e.g., morning and evening cooking) and meteorology (see below).

Paired and unpaired t tests (see SI) indicated modest weekend/weekday differences. In the middle-income neighborhood, mean concentrations were 6–8% lower on weekends ($p < 0.05$). In the low-income near-road site, concentrations were 10% higher on weekends ($p < 0.01$). In the low-income not near-road site, weekend and weekday concentrations were nearly identical (<1% difference). Weekend–weekday comparisons vary by hour-of-day (see SI); during mornings (2:00–10:00)

and evenings (19:00–24:00), weekend–weekday differences were statistically significant at three or more of the four locations.

Wind Effects. Calm conditions resulted in high $PM_{2.5}$ concentrations in all locations (Figure 4). In the low-income neighborhood, results suggested significant sources within-neighborhood: during the morning peak at the near-road location, the highest concentrations occurred when the wind was blowing away or variably, indicating a significant $PM_{2.5}$ source located within the neighborhood; at the not near-road location, the highest concentrations occurred when the wind was blowing

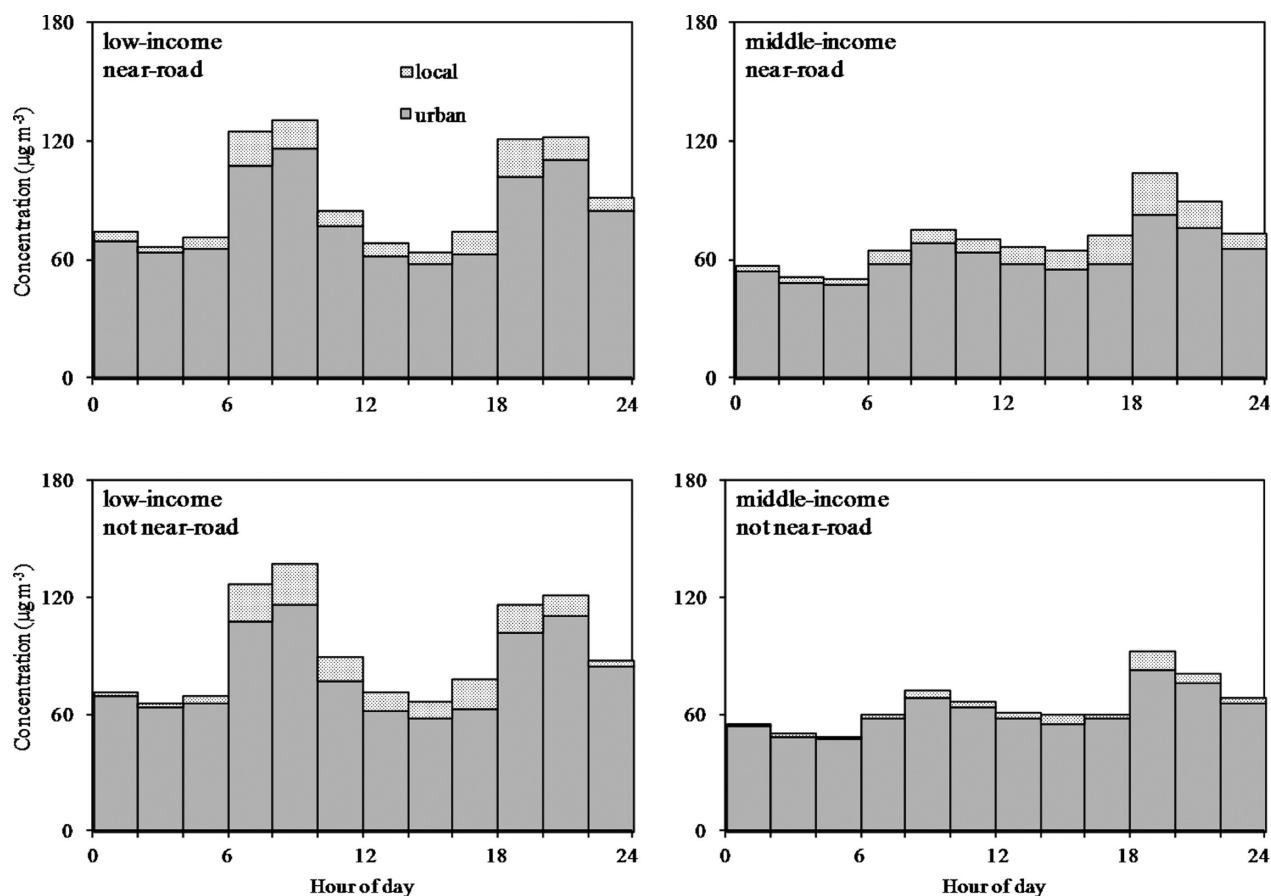


Figure 5. Median $PM_{2.5}$ concentration by local- and urban-scale contributions, by time of day and location using the moving-average subtraction method.

toward or variably, further emphasizing a significant $PM_{2.5}$ source located between the two monitoring sites. Differences in concentration based on wind condition primarily happened during the diurnal peaks, when a higher amount of $PM_{2.5}$ sources were local (see below). Not during the peaks, when $PM_{2.5}$ concentrations were likely near urban background levels (see below), the concentrations were similar near- and not near-road. Overall, these findings provide strong evidence that in the low-income area, within-neighborhood emissions have a greater impact than traffic emissions. Methodologically, the findings support the idea that temporal patterns in real-time measurements can yield insights into the spatial patterns of emissions.

In contrast to the low-income neighborhood, the middle-income neighborhood exhibited highest concentrations during calm and “toward” conditions and lowest when the wind was blowing away or perpendicular, all of which suggests the road as the main local source of emissions.

Local- and Urban-Scale Contributions. Figure 5 presents findings from the moving-average subtraction method.³⁵ Average contributions from local sources were 5–13% among the four locations. Average absolute contributions from local sources were $1.7\times$ higher in the low-income than in the high-income neighborhood (9.7 versus $5.8 \mu\text{g m}^{-3}$). In the low-income neighborhood, local source contributions occurred throughout the day, but were $\sim 1.7\times$ higher during morning and evening peaks than during other times of day. In the middle-income neighborhood, local source contributions occurred primarily during

the evening peak: local source contributions were $\sim 1.8\times$ higher during evening peaks than during other times of day. The 2-h period with the overall highest contribution from local sources ($\sim 19\%$) occurred during 16:00–18:00 at the not near-road low-income location, which is consistent with a strong local nonroad source such as cooking or trash burning.

Comparison between Figures 3 and 5 suggests that, as applied here, the moving average subtraction method may be a lower-bound estimate of contributions from local sources. Specifically, a portion of the baseline concentrations (concentrations after removing peaks; see Figure S4) likely were attributable to local emissions. If correct, local contributions were underestimated while urban contributions were overestimated, and results from the moving average subtraction are more applicable as a relative metric (e.g., comparisons among locations or times) than as an absolute metric.

As expected, in our sensitivity analysis, results from the alternative underwriting function indicate larger values for local contribution. For example, for the low-income not near-road location, the average local contribution increased from 11% (main approach) to 25% (sensitivity analysis). However, several core conclusions remain unchanged in the sensitivity analysis. For example, local sources remained predominant during peak commuting hours; and, in the low-income neighborhood (but not in the middle-income neighborhood), the concentration attributable to local sources is higher not near-road than near-road. Further details are in the SI.

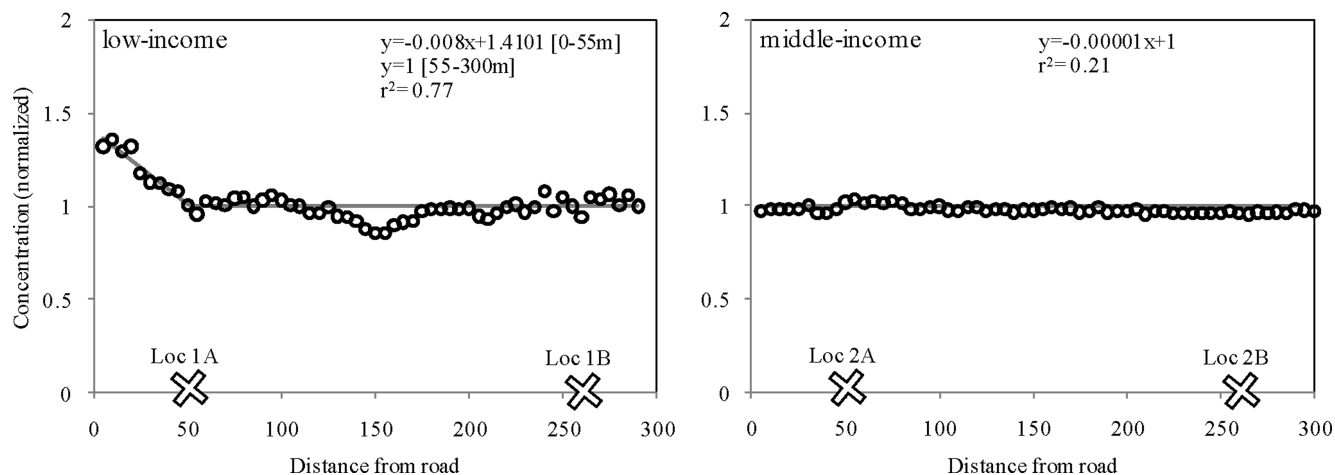


Figure 6. Median mid-day $\text{PM}_{2.5}$ concentration normalized per transect. Transect path was approximately a straight line from road past both monitoring locations.

Mid-Day Transects. Transect measurements, which recorded concentration versus distance from road, were combined into 5-m bins and normalized to the median value for that transect. The overall median values for all 78 transects are in Figure 6. In both neighborhoods, little signature from the road was seen. In the low-income neighborhood, normalized concentrations increased to 1.4 on-road, with an impact distance of ~ 50 m. In the middle-income neighborhood, concentrations were at or near the normalized concentration of 1 for all distances, indicating near-zero spatial variability in these transects. The factor of 1.4 reported for a low-income Bangalore neighborhood (on-road versus in-neighborhood; Figure 6) is similar to the factor of ~ 1.5 reported for New Delhi, India, by Apte et al. for $\text{PM}_{2.5}$ concentration differences between inside an unenclosed vehicle versus on a residential rooftop.³⁴ Transects typically occurred between 11:00 and 18:00. As seen in Figure 3, concentrations were relatively spatially homogeneous during that time; thus, concentrations in Figure 6 likely were dominated by regional $\text{PM}_{2.5}$. The impact of being near-road (Figure 6) was likely greater at other times-of-day; for further exploration see Hu et al.'s recent findings from Los Angeles.³⁶

The midday trough (Figure 3) and the comparatively low degree of spatial variability midday (Figure 6) were associated with increases in atmospheric mixing height in the late morning.^{40,41} Available data from the Modern Era Retrospective-analysis for Research Application (MERRA) provided by NASA's Global Modeling and Assimilation Office (GMAO) indicate that the surface boundary layer in Bangalore is, on average, $\sim 6\times$ greater in the afternoon (1120 m during 14:00–16:00 for 2005–2007) than in the morning (180 m during 5:00–9:00).

For developing countries, almost no information currently exists about spatiotemporal variability in air pollution concentrations, or about differences between high- and low-income neighborhoods.^{39,42} We found that concentrations were ~ 21 –46% higher in the low- than in the middle-income neighborhood, a value within the range seen in Accra, Ghana.³⁹ Approaches developed here, which employed time-resolved measurements to discern spatial patterns in emissions, could usefully be applied elsewhere, especially if colocated real-time RH measurements are available. We observed that “rules of thumb” from developed country contexts may or may not apply

in Bangalore. For example, we observed at least one pattern that differs significantly from published results for developed countries: in the low-income neighborhood, average concentrations were lower near-road than in-neighborhood (Figure 3). The likely cause for that trend was within-neighborhood emissions (e.g., residential cooking using solid fuels, combustion of household waste) in the low-income area.

■ ASSOCIATED CONTENT

S Supporting Information. Data coverage timeline (Figure S1) and table with hours of data per neighborhood (Table S1); wind-rose plots by seasons (Figure S2) and graphs showing wind classification by time of day (Figure S3); a sample of raw data with baselines (Figure S4); results from the alternative underwriting function analysis (Figure S5); and, weekend/weekday effect at each monitoring location with statistical analysis (Figure S6; Table S2). This material is available free of charge via the Internet at <http://pubs.acs.org>.

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■ REFERENCES

(1) Dockery, D. W.; Pope, C. A.; Xu, X.; Spengler, J. D.; Ware, J. H.; Fay, M. E.; Ferris, B. G.; Speizer, F. E. An association between air

- pollution and mortality in six US cities. *N. Engl. J. Med.* **1993**, *329*, 1753–1759.
- (2) Samet, J. M.; Dominici, F.; Currier, I.; Coursac, I.; Zeger, S. L. Fine particulate air pollution and mortality in 20 US cities, 1987–1994. *N. Engl. J. Med.* **2000**, *343*, 1742–1749.
- (3) Zemp, E.; Elsasser, S.; Schindler, C.; Kunzli, N.; Perruchoud, A. P.; Domenighetti, G.; Medici, T.; Ackermann-Lieblich, U.; Leuenberger, P.; Monn, C.; Bolognini, G.; Bongard, J. P.; Brandli, O.; Karrer, W.; Keller, R.; Schoni, M. H.; Tschopp, J. M.; Villiger, B.; Zellweger, J. P. Long-term ambient air pollution and respiratory symptoms in adults (SAPALDIA study). *Am. J. Respir. Crit. Care Med.* **1999**, *159*, 1257–1266.
- (4) Padhi, B. K.; Padhy, P. K. Assessment of intra-urban variability in outdoor air quality and its health risks. *Inhalat. Toxicol.* **2008**, *20*, 973–979.
- (5) Delfino, R. J.; Zeiger, R. S.; Seltzer, J. M.; Street, D. H. Symptoms in pediatric asthmatics and air pollution: differences in effects by symptom severity, anti-inflammatory medication use and particulate averaging time. *Environ. Health Perspect.* **1998**, *106*, 751–761.
- (6) Delfino, R. J.; Zeiger, R. S.; Seltzer, J. M.; Street, D. H.; McLaren, C. E. Association of asthma symptoms with peak particulate air pollution and effect modification by anti-inflammatory medication use. *Environ. Health Perspect.* **2002**, *110*, A607–A617.
- (7) Michaels, R. A.; Kleinman, M. T. Incidence and apparent health significance of brief airborne particle excursions. *Aerosol Sci. Technol.* **2000**, *32*, 93–105.
- (8) Salvi, S.; Blomberg, A.; Rudell, B.; Kelly, F.; Sandstrom, T.; Holgate, S. T.; Frew, A. Acute inflammatory responses in the airways and peripheral blood after short-term exposure to diesel exhaust in healthy human volunteers. *Am. J. Respir. Crit. Care Med.* **1999**, *159*, 702–709.
- (9) Ghose, M. K.; Paul, R.; Banerjee, R. K. Impact of roadway traffic and transport on human health. *Environ. Monit. Assess.* **2005**, *108*, 151–167.
- (10) Kaushik, C. P.; Ravindra, K.; Yadav, K.; Mehta, S.; Haritash, A. K. Assessment of ambient air quality in urban centres of Haryana (India) in relation to different anthropogenic activities and health risks. *Environ. Monit. Assess.* **2006**, *122*, 27–40.
- (11) Van Atten, C.; Brauer, M.; Funk, T.; Gilbert, N. L.; Graham, L.; Kaden, D.; Miller, P. J.; Bracho, L. R.; Wheeler, A.; White, R. H. Assessing population exposures to motor vehicle exhaust. *Rev. Environ. Health* **2005**, *20*, 195–214.
- (12) Han, X.; Naeher, L. P. A review of traffic-related air pollution exposure assessment studies in the developing world. *Environ. Int.* **2006**, *32*, 106–120.
- (13) Donkelaar, A. van; Martin, R. V.; Brauer, M.; Kahn, R.; Levy, R.; Verduzco, C.; Villeneuve, P. J. Global Estimates of Ambient Fine Particulate Matter Concentrations from Satellite-based Aerosol Optical Depth: Development and Application. *Environ. Health Perspect.* **2010**, doi: 10.1289/ehp.0901623.
- (14) Smith, K. R.; Apte, M. G.; Yuqing, M.; Wongsekiattirat, W.; Kulkarni, A. Air pollution and the energy ladder in Asian cities. *Energy* **1994**, *19*, 587–600.
- (15) United Nations Department of Economic and Social Affairs (Population Division). *World Urbanization Prospects: The 2006 Revision*; Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat: New York, 2007.
- (16) Gupta, I.; Kumar, R. Trends of particulate matter in four cities in India. *Atmos. Environ.* **2006**, *40*, 2552–2566.
- (17) Government of Karnataka Transportation Department. *Vehicle Statistics*; 2008.
- (18) Nagendra, S. M. S.; Venugopal, K.; Jones, S. L. Assessment of air quality near traffic intersections in Bangalore city using air quality indices. *Transp. Res. Part D: Transp. Environ.* **2007**, *12*, 167–176.
- (19) Sabapathy, A. Air quality outcomes of fuel quality and vehicular technology improvements in Bangalore city, India. *Transp. Res. Part D: Transp. Environ.* **2008**, *13*, 449–454.
- (20) Karnataka State Pollution Control Board. *Annual Average of Ambient Air Quality for the Period 1999–2000 to 2008–2009 in Bangalore City*; 2009.
- (21) Lopez, A. D.; Mathers, C. D.; Ezzati, M.; Jamison, D. T.; Murray, C. J. L. Global and regional burden of disease and risk factors, 2001: systematic analysis of population health data. *Lancet* **2006**, *367*, 1747–1757.
- (22) Bageshree, S. Title deeds for Koramangala slum dwellers after a long wait. *The Hindu* **2008**, July 17th.
- (23) Watson, J.; Chow, J. C.; DuBois, D.; Green, M.; Frank, N.; Pitchford, M. *Guidance For Network Design and Optimum Site Exposure For PM2.5 And PM10*; Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency: Washington, DC, 1997.
- (24) Fischer, S. L.; Koshland, C. P. Field performance of a nephelometer in rural kitchens: effects of high humidity excursions and correlations to gravimetric analyses. *J. Exposure Sci. Environ. Epidemiol.* **2006**, *17*, 141–150.
- (25) McMurtry, P. H.; Zhang, X.; Lee, C.-T. A review of atmospheric aerosol measurements. *J. Geophys. Res.* **1996**, *101*, 19189–19197.
- (26) Laulainen, N. S. Summary of conclusions and recommendations from a visibility science workshop; technical basis and issues for a national assessment for visibility impairment; PNL-8606; U.S. Department of Energy, Pacific Northwest Laboratory, 1993.
- (27) Chakrabarti, B.; Fine, P. M.; Delfino, R.; Sioutas, C. Performance evaluation of the active-flow personal DataRAM PM2.5 mass monitor (Thermo Anderson pDR-1200) designed for continuous personal exposure measurements. *Atmos. Environ.* **2004**, *38*, 3329–3340.
- (28) Day, D. E.; Malm, W. C.; Kreidenweis, S. M. Aerosol light scattering measurements as a function of relative humidity. *J. Air Waste Manage. Assoc.* **2000**, *50*, 710–716.
- (29) Donato, A.; Contini, D.; Belosi, F. Real time measurements of PM2.5 concentrations and vertical turbulent fluxes using an optical detector. *Atmos. Environ.* **2006**, *40*, 1346–1360.
- (30) Ramachandran, G.; Adgate, J. L.; Pratt, G. C.; Sexton, K. Characterizing indoor and outdoor 15 minute average PM2.5 concentrations in urban neighborhoods. *Aerosol Sci. Technol.* **2003**, *37*, 33–45.
- (31) Yanosky, J. D.; Williams, P. L.; MacIntosh, D. L. A comparison of two direct-reading aerosol monitors with the federal reference method for PM2.5 in indoor air. *Atmos. Environ.* **2002**, *36*, 107–113.
- (32) Wallace, L. A.; Wheeler, A. J.; Kearney, J.; Van Ryswyk, K.; You, H.; Kulka, R. H.; Rasmussen, P. E.; Brook, J. R.; Xu, X. Validation of continuous particle monitors for personal, indoor, and outdoor exposures. *J. Exposure Sci. Environ. Epidemiol.* **2011**, *21*, 49–64.
- (33) Chung, A.; Chang, D. P. Y.; Kleeman, M. J.; Perry, K. D.; Cahill, T. A.; Dutcher, D.; McDougall, E. M.; Stroud, K. Comparison of real-time instruments used to monitor airborne particulate matter. *J. Air Waste Manage. Assoc.* **2001**, *51*, 109–120.
- (34) Apte, J. S.; Kirchstetter, T. W.; Reich, A. H.; Deshpande, S. J.; Kaushik, G.; Chel, A.; Marshall, J. D.; Nazaroff, W. W. Exposure concentrations of fine, ultrafine, and black carbon particles in auto-rickshaws in New Delhi, India. *Atmos. Environ.* **2011**, in press.
- (35) Watson, J. G.; Chow, J. C. Estimating middle-, neighborhood-, and urban-scale contributions to elemental carbon in Mexico City with a rapid response aethalometer. *J. Air Waste Manage. Assoc.* **2001**, *51*, 1522–1528.
- (36) Hu, S.; Fruin, S.; Kozawa, K.; Mara, S.; Paulson, S. E.; Winer, A. M. A wide area of air pollutant impact downwind of a freeway during pre-sunrise hours. *Atmos. Environ.* **2009**, *43*, 2541–2549.
- (37) Karner, A. A.; Eisinger, D. S.; Niemeier, D. A. Near-roadway air quality: synthesizing the findings from real-world data. *Environ. Sci. Technol.* **2010**, *44*, 5334–5344.
- (38) Zhou, Y.; Levy, J. I. Factors influencing the spatial extent of mobile source air pollution impacts: a meta-analysis. *BMC Public Health* **2007**, *7*, 89.
- (39) Dionisio, K. L.; Arku, R. E.; Hughes, A. F.; Vallarino, J.; Carmichael, H.; Spengler, J. D.; Agyei-Mensah, S.; Ezzati, M. Air Pollution in Accra Neighborhoods: Spatial, Socioeconomic, and Temporal Patterns. *Environ. Sci. Technol.* **2010**, *44*, 2270–2276.
- (40) Freiman, M. T.; Hirshel, N.; Broday, D. M. Urban-scale variability of ambient particulate matter attributes. *Atmos. Environ.* **2006**, *40*, 5670–5684.
- (41) Janhall, S.; Olofson, K. F. G.; Andersson, P. U.; Pettersson, J. B. C.; Hallquist, M. Evolution of the urban aerosol during winter temperature inversion episodes. *Atmos. Environ.* **2006**, *40*, 5355–5366.

(42) Hedley, A. J.; McGhee, S. M.; Barron, B.; Chau, P.; Chau, J.; Thach, T. Q.; Wong, T. W.; Loh, C.; Wong, C. M. Air pollution: costs and paths to a solution in Hong Kong--understanding the connections among visibility, air pollution, and health costs in pursuit of accountability, environmental justice, and health protection. *J. Toxicol. Environ. Health* **2008**, *71*, 544–554.

Supporting Information

This file contains supporting information for

Spatio-temporal aspects of real-time PM_{2.5}: low- and middle-income neighborhoods in Bangalore, India
Adam F. Both, Arun Balakrishnan, Bobby Joseph, Julian D. Marshall

The following information is below: Data coverage timeline (Figure S1) and table with hours of data per neighborhood (Table S1); wind-rose plots by seasons (Figure S2) and graphs showing wind classification by time of day (Figure S3); a sample of raw data with baselines (Figure S4); results from the alternative underwriting function analysis (Figure S5); and, weekend/weekday effect at each monitoring location with statistical analysis (Figure S6; Table S2).

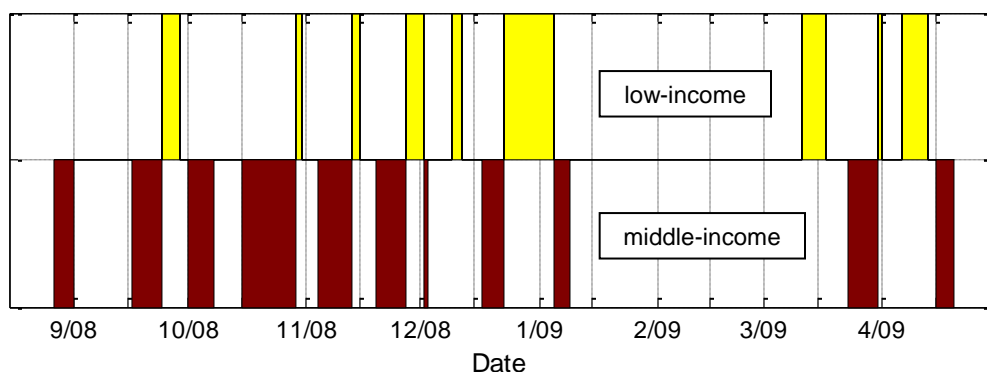


FIGURE S1. Days for which data was collected. Times without coverage are the result of equipment downtime or power outages.

Table S1. Hours of data in which all three instruments were operating

low-income neighborhood	883
middle-income neighborhood	1521
total	2404

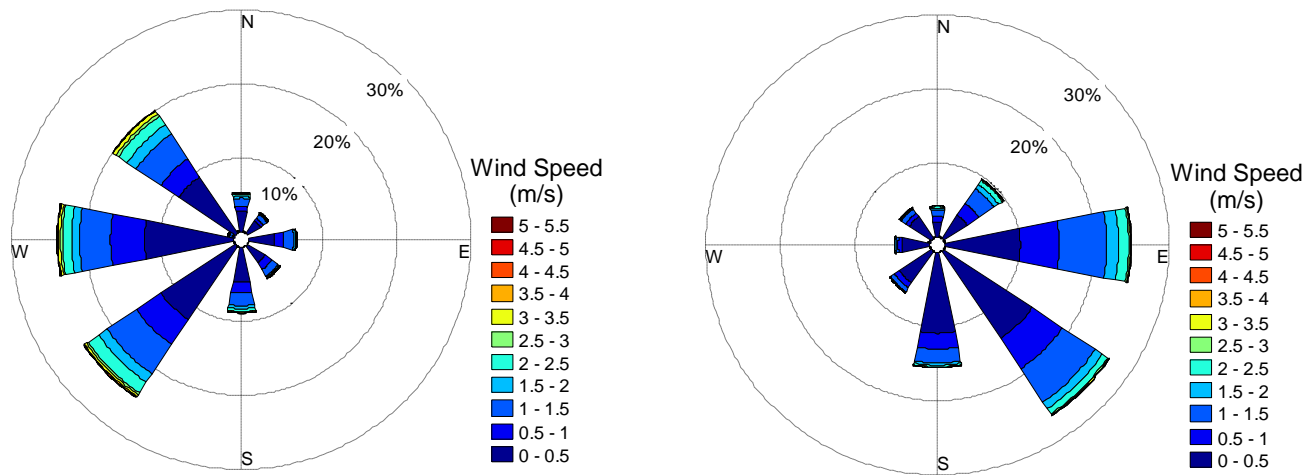


FIGURE S2. Wind roses showing wind speed and direction for the monsoon season (July-September) (left panel) and post-monsoon (October-April) (right panel).

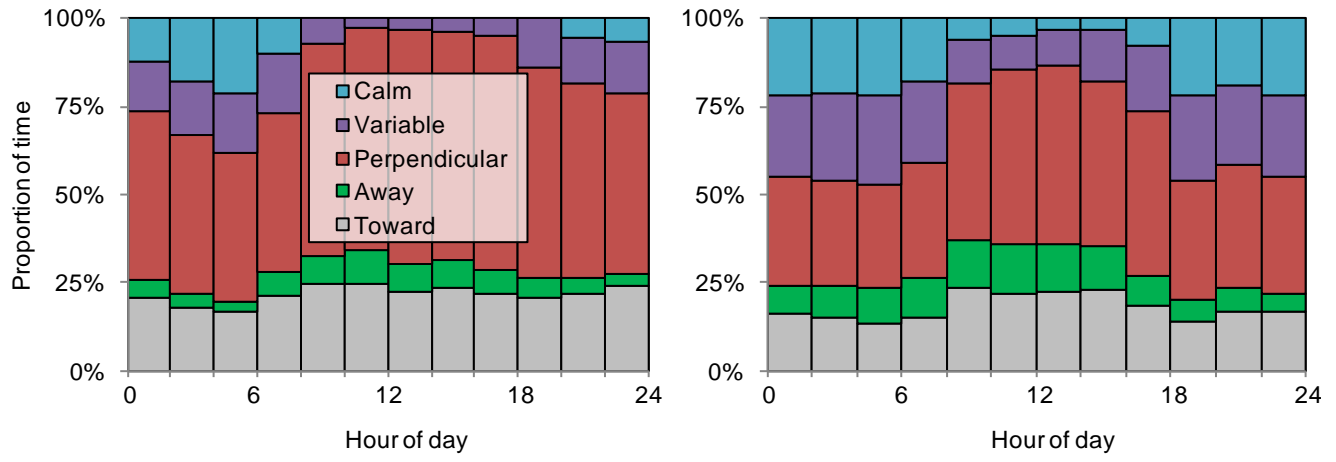


FIGURE S3. Wind classification by time of day for low-income (left panel) and middle-income (right panel) neighborhood.

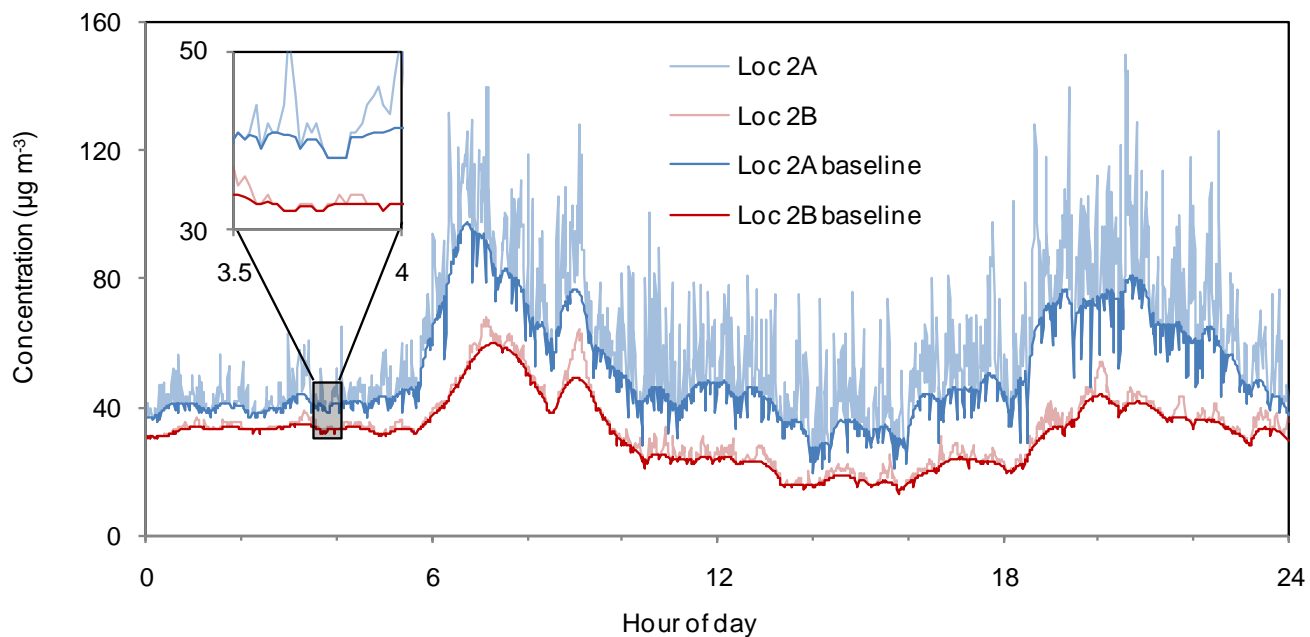


FIGURE S4a. Sample of raw data, plus moving-average-subtraction-method baselines, for one 24-h period (October 16, 2008) at the middle-income neighborhood. Inset box provides example zoom-in.

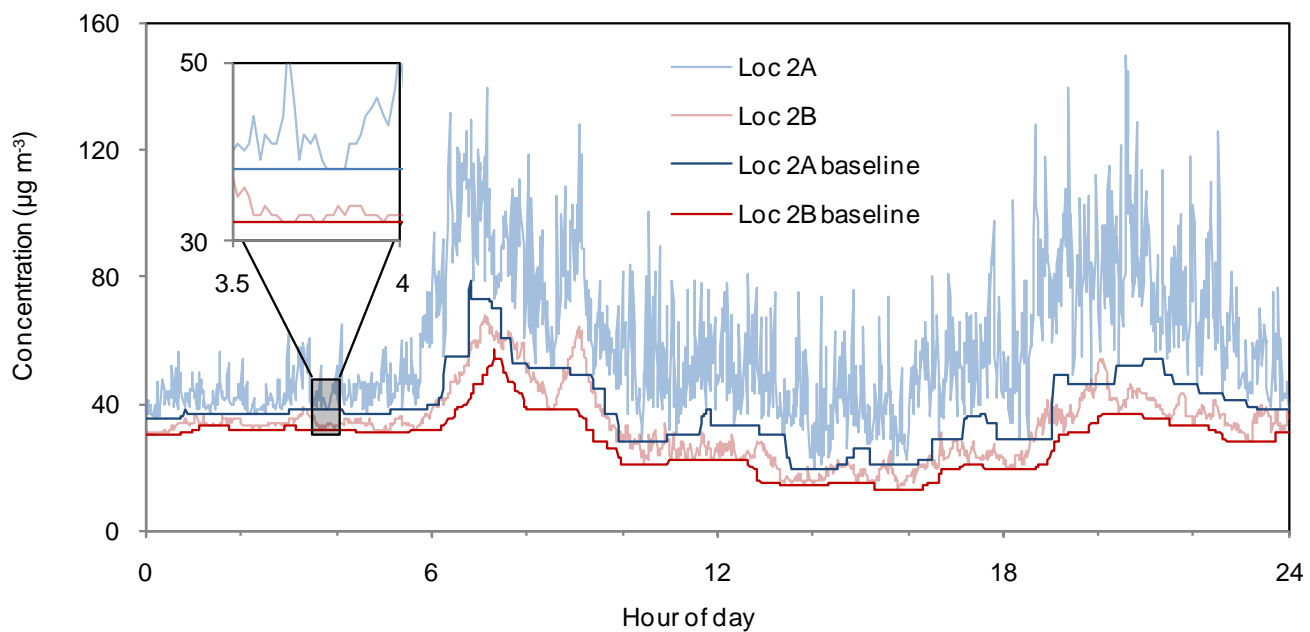


FIGURE S4b. Sample of raw data, plus moving 1.5 percentile method baselines, for one 24-h period (October 16, 2008) at the middle-income neighborhood. Inset box provides example zoom-in.

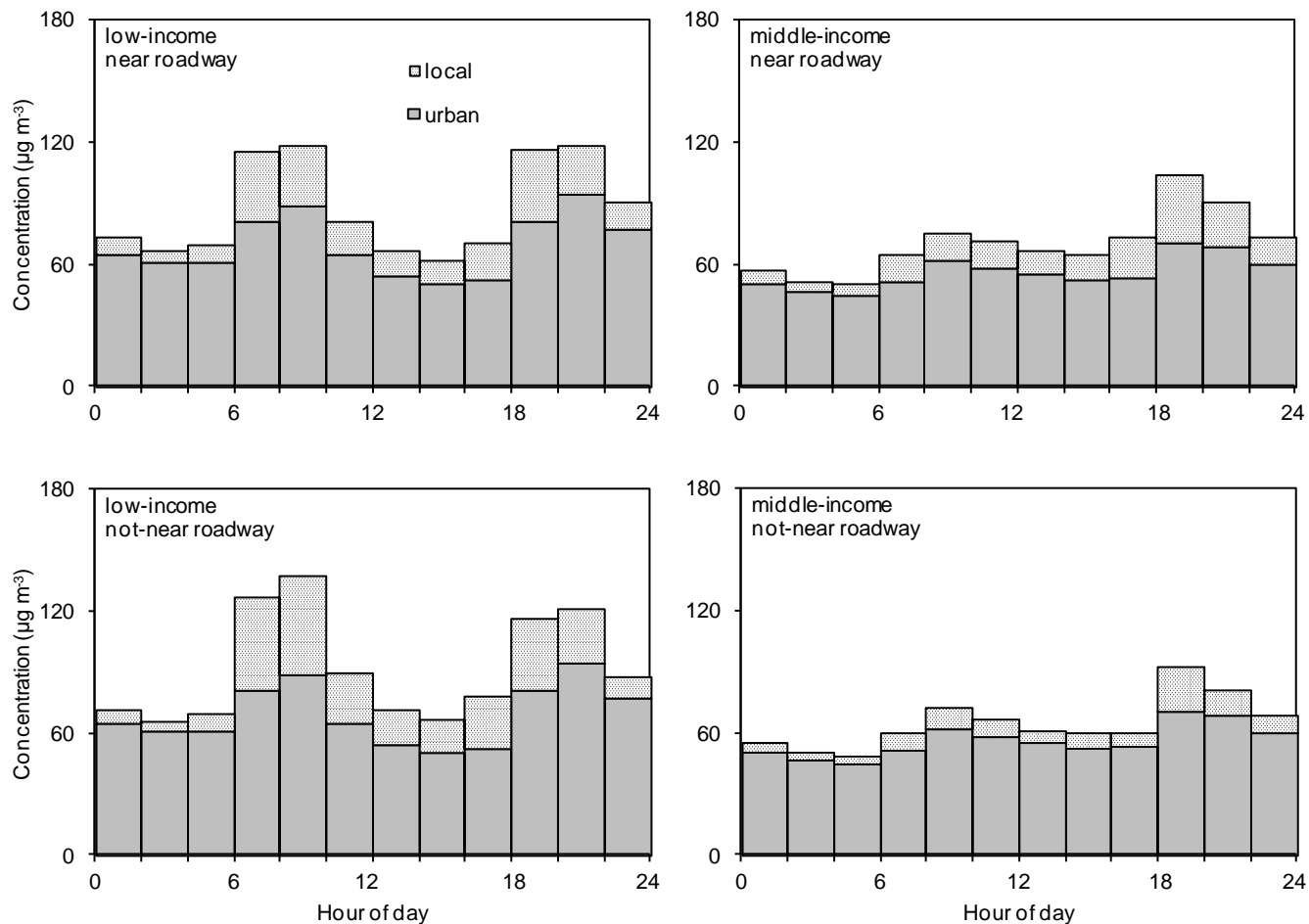


FIGURE S1a. Median PM_{2.5} concentration by local- and urban-scale contributions, by time of day and location using the alternative underwriting function (see Figure S4b).

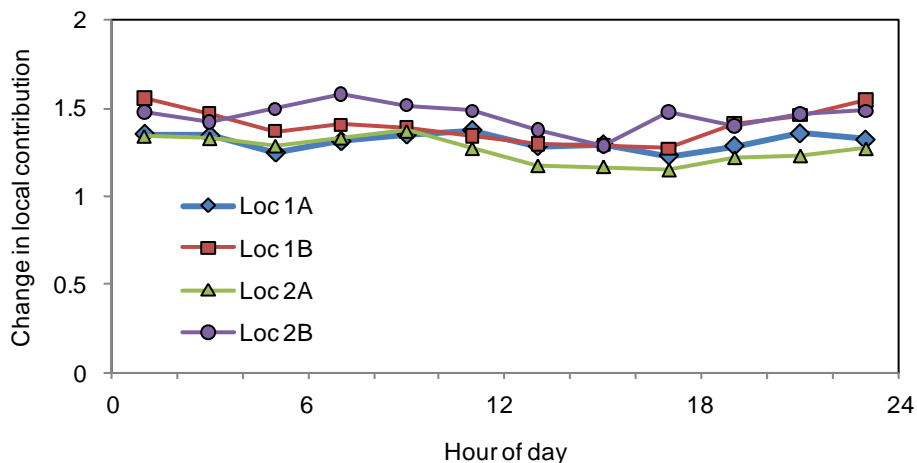


FIGURE S2b. Change in local contribution ($[\text{alternate \% local}]/[\text{mean of alternate \% local and original \% local}]$), for the sensitivity analysis versus the base case underwriting function. Variations by time-of-day and location are modest.

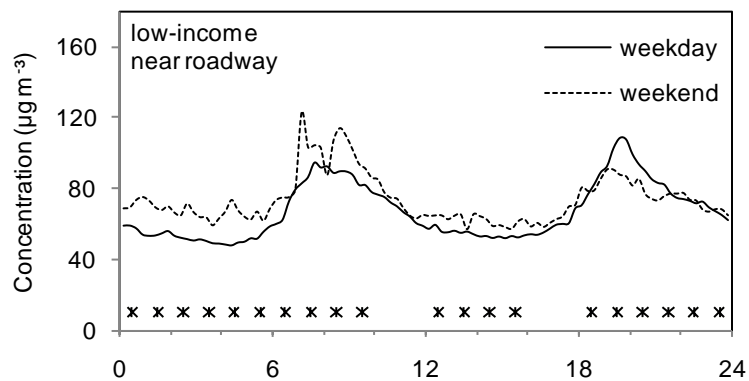


Table S2a. Loc 1A weekend effect

	Weekday	Weekend
Mean	66.89	73.56
Standard Dev.	15.92	13.77

paired t-test p(2-tail) = 2.0E-9
unpaired t-test p(2-tail) = 0.0022

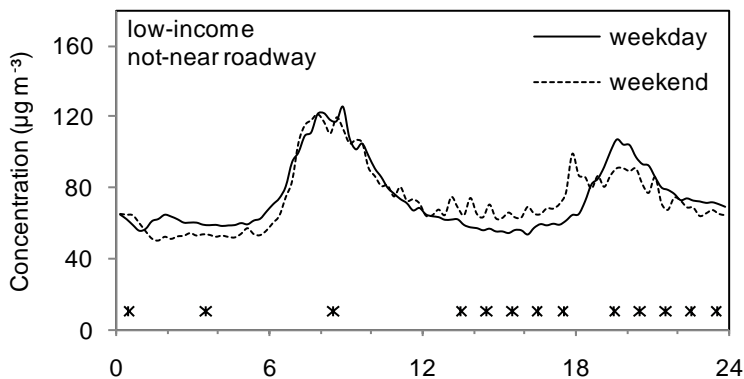


Table S2b. Loc 1B weekend effect

	Weekday	Weekend
Mean	74.00	73.90
Standard Dev.	19.17	18.11

paired t-test p(2-tail) = 0.92
unpaired t-test p(2-tail) = 0.97

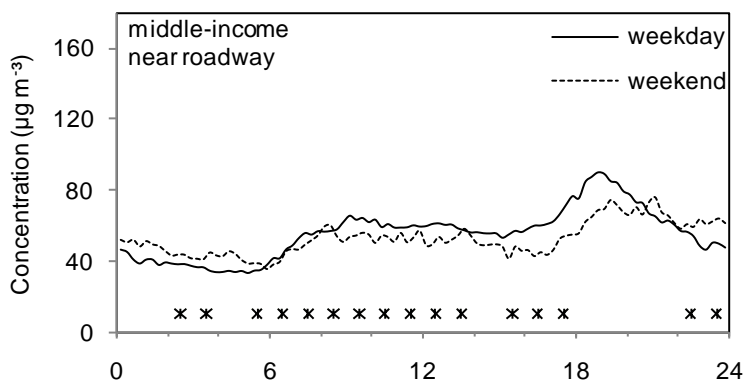


Table S2c. Loc 2A weekend effect

	Weekday	Weekend
Mean	55.94	52.61
Standard Dev.	13.99	9.08

paired t-test p(2-tail) = 0.0011
unpaired t-test p(2-tail) = 0.052

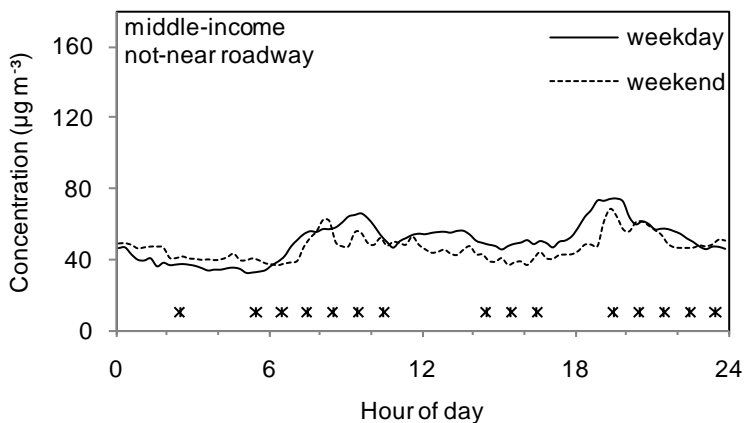


Table S2d. Loc 2B weekend effect

	Weekday	Weekend
Mean	50.42	46.53
Standard Dev.	10.68	6.98

paired t-test p(2-tail) = 3.6E-6
unpaired t-test p(2-tail) = 0.0032

FIGURE S6. Weekend/weekday effect (panels from top to bottom: locations 1A, 1B, 2A and 2B; see Figure 1 in the main text). Asterisks (*) identify hours with a statistically significant difference using matched-hour, unpaired t-tests ($p < 0.05$).