Published in final edited form as:
Epidemiology. 2014 January ; 25(1): 58–67. doi:10.1097/EDE.0000000000000027.

$PM_{2.5}$ exposure and birth outcomes: Use of satellite- and monitor-based data

Ayaz Hyder,
Yale University, School of Public Health, New Haven, Connecticut, USA

Hyung Joo Lee,
Harvard University, Department of Environmental Health, Harvard School of Public Health, Boston, Massachusetts, USA

Keita Ebisu,
Yale University, School of Forestry and Environmental Studies, New Haven, Connecticut, USA

Petros Koutrakis,
Harvard University, Department of Environmental Health, Harvard School of Public Health, Boston, Massachusetts, USA

Kathleen Belanger, and
Yale University, School of Public Health, New Haven, Connecticut, USA

Michelle Lee Bell
Yale University, School of Forestry and Environmental Studies, New Haven, Connecticut, USA

Abstract

Background—Air pollution may be related to adverse birth outcomes. Exposure information from land-based monitoring stations often suffers from limited spatial coverage. Satellite data offer an alternative data source for exposure assessment.

Methods—We used birth certificate data for births in Connecticut and Massachusetts, U.S. (2000-2006). Gestational exposure to $PM_{2.5}$ was estimated from US Environmental Protection Agency monitoring data and from satellite data. Satellite data were processed and modeled using 2 methods – denoted satellite (1) and satellite (2) – before exposure assessment. Regression models related $PM_{2.5}$ exposure to birth outcomes while controlling for several confounders. Birth outcomes were mean birth weight at term birth, low birth weight at term (LBW <2500g), small for gestational age (SGA, <10th percentile for gestational age and sex), and preterm birth (<37 weeks).

Results—Overall, the exposure assessment method modified the magnitude of the effect estimates of $PM_{2.5}$ on birth outcomes. Change in birth weight per inter-quartile range (2.41 μg/m3)-increase in $PM_{2.5}$ was -6g (95% confidence interval = -8 to -5), -16g (-21 to -11) and -19g (-23 to -15), using the monitor, satellite (1) and satellite (2) methods, respectively. Adjusted odds

Corresponding author's contact information: Ayaz Hyder Dalla Lana School of Public Health, University of Toronto 155 College Street, 5th floor Toronto, Ontario, Canada, M5T 3M7 Phone: 1-416-978-2201 Fax: 1-416-978-8299 ayaz.hyder@utoronto.ca.

Conflicts of Interest The authors reported no other financial interests related to this research.

ratios, based on the same 3 exposure methods, for term LBW were 1.01 (0.98 to 1.04), 1.06 (0.97 to 1.16), and 1.08 (1.01 to 1.16); for SGA, 1.03 (1.01 to 1.04), 1.06 (1.03 to 1.10) and 1.08 (1.04 to 1.11); and for preterm birth, 1.00 (0.99 to 1.02), 0.98 (0.94 to 1.03) and 0.99 (0.95 to 1.03).

Conclusions—Under exposure assessment methods, we found associations between $PM_{2.5}$ exposure and adverse birth outcomes particularly for birth weight among term births and for SGA. These results add to the growing concerns that air pollution adversely affects infant health and suggest that analysis of health consequences based on satellite-based exposure assessment can provide additional useful information.

Air pollution adversely affects human health.[1-3] Specifically, particulate matter is associated with respiratory and cardiovascular disease.[4,5] Maternal exposure to particulate matter, $PM_{2.5}$ (particles with aerodynamic diameter ≤2.5μm) is associated with several birth outcomes, although findings are not completely consistent across studies.[6-9] Birth outcomes that have been assessed include birth weight, term low birth weight (LBW; birth weight <2,500g for term births [gestational age ≥37 weeks]), and small for gestational age (SGA; birth weight <10th percentile for gestational age and sex).

Air pollution and birth outcomes are an important topic of research. The economic burden in the United States associated with preterm birth, which include social and healthcare costs, was $26.2 billion in 2005.[10] Cost of hospitalization for low birth weight/preterm birth in the US was $5.8 billion in 2001.[11] Studies have also shown that particulate matter may be associated with inflammation in pregnant women[12,13] and affect fetal growth[14]—both of which may be detrimental to a normal course of pregnancy and fetal development. Also, consequences of adverse birth outcomes beyond the perinatal period may include delayed development and decreased academic achievement[15] and short stature[16] in childhood, as well as medical/social disabilities[17] and respiratory disease[18] in adulthood. Given this social, economic and health burden of adverse birth outcomes and the ubiquity of air pollution exposure, there is a need to better understand the health risks posed by airborne particulate matter and other environmental toxins/hazards.[6,7,19,20]

International collaborative efforts[21] and several U.S. studies have found associations between $PM_{2.5}$ and birth outcomes (LBW[9], term LBW,[22,23] birth weight,[9,24-26] and SGA[24,27]). However, other studies have found no or null associations between $PM_{2.5}$ and birth outcomes (term LBW,[28,29] birth weight,[25,30] SGA,[25] and preterm birth[7,31]). In almost all of these studies, data for exposure assessment were obtained from central monitoring sites operated and maintained by state and national agencies, such as the US Environmental Protection Agency (EPA), primarily for regulatory purposes.

Use of data from regulatory monitors is a reasonable and cost-effective method to estimate exposure for air pollution studies; however, major challenges of this approach include limited spatial and temporal coverage. In the US, monitors are located primarily in densely populated urban centers. Since monitors record air pollution levels at a specific time and location, exposure estimates for persons located far from monitors may not be possible or, if estimated, may be less reliable. Many studies limit subjects to those within a certain distance from the monitor. The choice of distance depends on the pollutant's spatial heterogeneity, temporal correlation in pollutant levels nearby monitors, and other regional-scale

characteristics (e.g., industry type, population density, traffic patterns). Temporal coverage is another limitation of data from existing monitoring systems. For example, in the EPA's Air Quality System (AQS), frequency of data collection can vary by site, pollutant, time of year and start date of measurement. Particles are often measured every three or six days. Therefore, it is not uncommon for data from central monitoring systems to be missing or unreliable. Given these considerations, alternative methods for exposure assessment are needed.

Air quality modeling, land-use regression models, and satellite-based predictions are some of the methodologies being developed to predict air-pollution levels in epidemiology studies.[32] For birth outcomes studies, the first two methodologies are more common[22,23,33-36] (although see the paper by Kloog and colleagues[26] for a satellite-based approach). Our group[37,38] recently produced estimates of $PM_{2.5}$ levels that have higher predictability than current land-use regression models and satellite methods. Specifically, novel methods were developed for calibrating satellite-based measurements of aerosol optical depth (a measure of light extinction due to aerosols in the atmospheric column[38]), and statistical modeling was used to address missing data (due to cloud cover) in these calibrated data.[37] From these studies, we had access to $PM_{2.5}$ estimates that were highly predictive of PM measurements (R^2=0.88 for cross-validated model, as reported by Lee et al.[37]). Low predictability between modeled and monitor-based values likely introduces greater uncertainty in health effect estimates.

We investigated $PM_{2.5}$ and birth outcomes using a traditional exposure approach (existing monitoring data) and an emerging method (modeled estimates based on satellite data). We consider how these relationships are affected by including observations with satellite-based exposures but no monitor-based exposure estimates to assess the potential added value of satellite-based estimates for exposure.

METHODS

Data and outcome assessment

We obtained detailed birth certificate data for all births in Connecticut and Massachusetts for 2000-2006 (n=834,332). We excluded births that were conceived before the year 2000 because $PM_{2.5}$ exposure data from satellite methods was not yet available. The birth certificate data included maternal characteristics (residential address, age, education, parity, tobacco use, marital status, race/ethnicity), birth characteristics (date of last menstrual period, prenatal care and type of birth) and baby's characteristics (date of birth, birth weight, type of birth and gestational age).

We excluded births that were missing residential address (2%), non-singleton deliveries (5%), birth weight <1,000g or >5,500g (1%), and births with implausible gestational age-birth weight combinations (0.02%). These criteria have been applied in similar research.[39] Births with gestational age <20 weeks or >46 weeks were excluded (0.3%). Clinical gestational age was used in all analyses; when missing, we used the calculated gestational age when available.

For analysis of mean birth weight and term LBW, only term births (gestational age ≥37 weeks) were included. Preterm births were those with gestation <37 weeks. We classified births as small for gestational age if birth weight was <10th percentile value for gestational age and sex according to U.S. data-based cut-off values (restricted to gestational ages 22 to 44 weeks).[40] Therefore, we limited the SGA analysis to births with gestational age in this range. The final number of observations included in each model differed based on the health outcome and exposure assessment method.

We used date of birth and gestational age to establish start and end dates of gestational exposure and to estimate exposure during the entire pregnancy and each trimester. Trimesters were defined as 1-13 weeks, 14-26 weeks, and 27 weeks until birth. Trimester-specific apparent temperature was estimated using data from the National Climatic Data Center.[41]

Exposure assessment

Two methods were used for $PM_{2.5}$ exposure assessment: monitor data and modeled estimates based on satellite data. Monitor data were obtained from the EPA's Air Quality System system for 2000-2006 (Fig.). We omitted monitor data with qualifier codes indicating uncommon, natural or anthropogenic events, and data with quality assurance issues, based on EPA flag codes. We used the closest monitor to mothers' residence with a cut-off distance of 50km, based on our previous work (K Ebisu, unpublished data). The average distance between monitor and mothers' location was 14km (standard deviation = 11km; 25% quartile = 5km; and 75% quartile = 21km). $PM_{2.5}$ values were calculated for each of these monitors and for each week of pregnancy. This process avoids biasing exposure estimates because some monitors did not provide concentration data for the entire study period. Analysis excluded births with exposure data for fewer than 75% of weeks in each trimester. The closest monitor to the mother's residence that met these criteria was used to estimate overall and trimester-specific exposure by averaging weekly values.

Satellite-based $PM_{2.5}$ predictions were modeled under two related yet slightly different methods, which we denote Satellite (1) and Satellite (2) (described below), using measurements from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument onboard Terra and Aqua satellites. Both modeling approaches produced daily $PM_{2.5}$ concentrations for each 10x10km grid cell over our study area (Fig.). These data were available only for 2000 to 2006. Satellite data consisting of aerosol optical depth measurements were obtained from National Aeronautics and Space Administration. Other researchers[42,43] have used AOD measurements directly to estimate $PM_{2.5}$, (via a functional relationship between AOD and $PM_{2.5}$). We elected not to do so because of lack of high predictability and because of missing data due to cloud cover.

To address these two limitations, we used a calibration and modeling approach, which has been described earlier.[37,38] Briefly, we start by using a mixed-effects model to generate relationships between each day of observed $PM_{2.5}$ levels in Northeast US and AOD values corresponding to monitors' locations. In the mixed effects model, fixed effects explained the average intercept and the slope of the $PM_{2.5}$-AOD slope for the entire study period, and random effects accounted for daily variability of $PM_{2.5}$-AOD relationships. This daily AOD

calibration approach substantially enhanced the $PM_{2.5}$ predictive power of AOD, rendering it a robust predictor of $PM_{2.5}$. Next, we performed a cluster analysis using the K-means method, which breaks up data into K clusters (K=9 for the Satellite (1) method and K=8 for the Satellite (2) method), such that the data point in each cluster is closest to the mean of the cluster.[44] This method of classification allowed us to identify the set of days with a similar spatial pattern of $PM_{2.5}$. The cluster analysis under the Satellite (1) method was based on $PM_{2.5}$ concentration differences between observed $PM_{2.5}$ values and regional $PM_{2.5}$ values (i.e., daily averages of all available $PM_{2.5}$ measurements over the study region on a given day), whereas under the Satellite (2) method we used actual observed $PM_{2.5}$ values.

Another difference between the two satellite methods was in how we predicted $PM_{2.5}$ values for days with missing AOD data. In the Satellite (1) method, we formulated a general additive model (GAM) for each cluster, in which predicted $PM_{2.5}$ concentrations from the mixed effects model were regressed on regional $PM_{2.5}$ levels and a spatial smooth function of latitude and longitude. Here, regional $PM_{2.5}$ accounted for daily variability in $PM_{2.5}$ levels. In this way, we generated a single spatial surface of $PM_{2.5}$ concentrations for each cluster and predicted $PM_{2.5}$ concentrations for days with missing data. In contrast, in the Satellite (2) method, we assumed that relationships between predicted (from mixed effects model) and regional $PM_{2.5}$ concentrations in each grid cell were constant for each cluster. Thus, we derived cluster- and grid-specific relationships using regression models and estimated all the missing $PM_{2.5}$ concentrations. Both approaches produced $PM_{2.5}$ estimates that were highly predictive, and, therefore better suited to health effects studies. In summary, the main differences between the two satellite methods were in how observed data were clustered to identify spatiotemporal patterns, and how each cluster of data was used to predict $PM_{2.5}$. The Satellite (2) approach provided greater spatial heterogeneity in predicted $PM_{2.5}$ values.

A recent birth outcomes study in Eastern Massachusetts used a different method to estimate $PM_{2.5}$ from satellite data.[26].The main differences relate to calibration and modeling of raw satellite data in terms of the modeling approach, and the use of different variables in the calibration and modeling steps.

As with exposures based on monitor data, weekly exposures were used to calculate trimester-specific and overall exposure during gestation for each birth based on mother's residence. Satellite data were unavailable for grid cells containing mostly water (0.5% and 3% of births in Connecticut and Massachusetts, respectively). For these observations, we used satellite data from the closest grid cell (based on grid centroid-to-residence ≤10km). We excluded subjects with a residential address on islands because satellite estimates were unavailable for such geographic areas.

Statistical analysis

We formulated several models based on the combination of data used for exposure assessment (Monitor, Satellite [1], or Satellite [2]; and the included observations (subset of births with exposure estimates under both land-based monitors and satellite methods [Joint], or all subjects with exposure estimates for that exposure method [All]).

For example, a model labeled “Satellite (2), All” includes all subjects with estimated $PM_{2.5}$ exposure based on the second method of modeling satellite data. Note that all “Joint” models have the same sample size, whereas “All” models have different sample sizes. “Satellite (1)” and “Satellite (2)” models had identical timeframe/spatial resolution (i.e., same subjects). Each model was applied to the four birth outcomes separately. This approach allows evaluation of the association between exposure method and the health effects for the same study population. Also, we can evaluate how inclusion of subjects with exposure estimates for one exposure method but not another modifies effect estimates.

We used logistic regression for binary outcomes (term LBW, SGA, preterm birth) and linear regression for the continuous outcome birth weight. We controlled for the following variables: mother's age (<20, 20-24, 25-29, 30-34, 35-40, ≥ 40years); marital status (married, not married); mother's education (<12, 12, 13-15, ≥16 years); mother's race/ethnicity (white/non-Hispanic, black/non-Hispanic, Asian/non-Hispanic, Hispanic/other-Hispanic, other/non-Hispanic or unknown ethnicity); prenatal care (Adequacy of Prenatal Care Utilization Index[64]: unknown/missing, inadequate, intermediate, adequate [basic or intensive]); smoking (none, 1-9, 10-20, >20 cigarettes/day); type of birth (vaginal/vaginal after cesarean birth vs. cesarean); parity (0, 1, 2, ≥3 previous live births); season of conception (winter, spring, summer, fall); medical risk factors (0 or ≥1 factors, e.g. anemia); medical risk due to previous preterm birth or SGA (yes, no); baby's sex (boy, girl); and gestational age (continuous). All models controlled for year of conception, trimester-specific apparent temperature, and state of residence (Connecticut or Massachusetts). We also did a sensitivity analysis using mean instead of apparent temperature. For each outcome, we evaluated the effects of overall gestational exposure and of first-, second-, and third-trimester exposure. For trimester models, we included residuals from regressing exposure estimates from the trimester of interest against other trimesters to control for correlation in exposures among trimesters, similar to methods used previously.[9]

RESULTS

Low birth weight was observed in 2% of all term births (n=628,131), with overall mean birth weight of 3,449g (standard deviation 472g). Ten percent (n=662,921) of infants were SGA and 6% (n=656,769) were preterm (Table 1). The sample size for preterm births reflected our exclusion of all births occurring 37 weeks before 31 December 2006 (end of study period). This exclusion rule was necessary to ensure that all births in 2006 had an equal chance of being counted as a preterm birth. For SGA, we included only births with gestation 22-44 weeks, which resulted in different sample sizes for SGA and LBW. Descriptive statistics on other covariates were based on all eligible births (n=662,921) (Table 1). Mothers were mainly white with non-Hispanic ethnicity (68%), educated (41% with >16 years education), and married (70%). For a majority of births, prenatal care was deemed adequate (82%) and the method of delivery was vaginal or vaginal after cesarean (73%).

Satellite $PM_{2.5}$ exposures were estimated for 367 10x10km grid cells, whereas there were 98 EPA-Air Quality System monitors providing point measurements. Monitoring sites were located within Connecticut or Massachusetts or within 50km of their borders. Mean $PM_{2.5}$

exposure during the entire pregnancy based on each method of exposure assessment (Monitor, Satellite [1] and Satellite [2], were similar – 11.9 ,11.2 , and 11.4 $\mu g/m^3$, respectively, but differed in other statistical properties (Table 2). Satellite-based exposure estimates tended to have smaller standard deviations, narrower ranges and smaller inter-quartile ranges (IQR). These differences were also apparent in trimester-level estimates, where confidence intervals for the third trimester were wider than for other trimesters (Table 2). These wider intervals may be due to variable lengths of exposure in births that reached the third trimester. For all models, we reported results using an increment of 2.41$\mu g/m^3$ (IQR of exposure during gestation using monitor-based data), in order to make effect estimates comparable across analyses.

Gestational $PM_{2.5}$ exposure was associated somewhat differently with the various birth outcomes (Table 3). Term LBW and SGA were generally associated with $PM_{2.5}$ across all exposure methods, although more strongly with Satellite data, and especially Satellite (2) data. $PM_{2.5}$ exposures were linked with increased risk of term LBW only in the first trimester, while SGA was linked with exposures in all trimesters (although more weakly) (Table 4). A consistent gradient in risk by exposure method was observed in the models across most trimesters (Table 3). Risk of term LBW per IQR increase in $PM_{2.5}$ was 1% (95%CI= -0.02 to 4), 6% (-0.03 to 16) and 8% (1 to 16), using Monitor, Satellite (1), and Satellite (2) methods, respectively. The change in birth weight was negatively associated with $PM_{2.5}$ exposure, regardless of window of exposure. The change in birth weight per IQR increase in $PM_{2.5}$ was -6g (95%CI= -8 to -5) using the Monitor method and about three times that using either satellite method. The risk of SGA, when using satellite methods was 6% (3 to 10) for Satellite (1) and 8% (4 to 11) for Satellite (2). These risk values are about twice that using the Monitor method (3%, [1 to 4]). For preterm birth, risks were marginally higher risk for some exposure methods, but with no clear excess either overall or by trimester. Our results were not sensitive to using mean instead of apparent temperature (results not shown). Models with satellite-based exposure estimates tended to have much wider confidence intervals (Table 3).

DISCUSSION

Air pollution has previously been associated with birth outcomes using various exposure methods.[6,8] We assessed whether associations between $PM_{2.5}$ and birth outcomes were affected by use of monitor or satellite exposure methods. As satellite data become more readily available, their application for exposure assessment will likely become more common, and studies li are needed to evaluate this alternative exposure method.

We are aware of three health studies that have used modeled satellite-based $PM_{2.5}$ estimates.[26,45,46] One of these studies, which looked at acute myocardial infarctions,[45] used the same exposure model was ours.[47] In the birth outcomes study,[25] the authors used land-use and traffic density data and satellite data to model $PM_{2.5}$ in Western Massachusetts. They used birth certificate data (2000-2008) and estimated risk of preterm birth and change in birth weight using inclusion criteria similar to ours: their results for change in birth weight are comparable to ours. In addition, we looked at a different and wider geographic region, compared satellite-and monitor-based exposures in our model, and looked at a wider range

of birth outcomes (including small for gestational age and low birth weight). Unlike that earlier study, we did not find an association between $PM_{2.5}$ and preterm birth. However, our results are not directly comparable to that study due to differences in location, time period, modeling of satellite-based exposure estimates and model covariates. The previous study also did not compare results for risk estimates using monitors; that was done in another study,[46] although not for birth outcomes. Our estimates of risk (for term LBW and SGA) and change in birth weight are comparable to previous studies using monitor-based exposures.[9,22,24,27,48]

The magnitude of the association between $PM_{2.5}$ and birth outcomes tended to be higher using the Satellite (2) exposure method (Table 3). This could relate to greater variability in $PM_{2.5}$ measurements based on monitors rather than satellite methods. Greater variability may attenuate associations towards the null due to exposure misclassification. In other words, areas with very high or low $PM_{2.5}$ estimates could influence the fitting of the model to the data and thus affect risk estimates, more than if $PM_{2.5}$ estimates were less spatially varied. Therefore, future research is needed on appropriate characterization of spatial heterogeneity for $PM_{2.5}$. This is especially true for differentiation of risk estimates based on various exposure methods (e.g., satellite, land-use regression models).

Satellite data can overcome some disadvantages of using monitor data for exposure assessment in health studies. Analysis of monitor data may lead to exposure misclassification and selection bias because sites are typically located for regulatory rather than research purposes. Monitors may not provide full coverage or represent population-based exposure.[49] Also, U.S. populations at varying distances from monitors differ in other ways.[50,51] For example, populations living in census tracts with a monitor tended to be characterized by having more non-Hispanic blacks, lower education, lower income, greater unemployment and higher poverty.[51] Another limitation of monitor data is that monitors may be discontinued or temporarily out of operation (e.g., under maintenance). For many pollutants (e.g., $PM_{2.5}$, ozone), measures are not taken daily, which limits temporal coverage.

In contrast, satellite data provide near-complete spatial coverage of daily pollutant levels. Even so, uncertainty exists in the unprocessed satellite data and its calibration to observed data. Also, uncertainty may be introduced by the statistical procedure used to estimate pollutant levels for days when satellite data are missing due to cloud cover. Satellite data provide near-complete spatial coverage because exposure estimates are not possible to calculate for grid cells containing a substantial fraction of water (e.g., lakes and coastal regions).[52] Also, coastal populations may have different demographic compositions (e.g., socioeconomic status) than populations living inland. A potential solution would be to use satellite data with finer spatial resolution. Another important issue for studies of air pollution and birth outcomes is the relevant gestational window of exposure. Although time-series analyses controlling for season of conception have been used to identify the relevant exposure window, the daily time scale of the satellite data is especially suited for such analyses.

Satellite methods provide a novel way to estimate health risks associated with air pollution in rural areas with few monitors. Also, it may be possible to investigate rural-urban differences in risk estimates. Rural populations differ from urban populations in terms of health and demographic and socioeconomic characteristics. U.S. studies have suggested that premature mortality, obesity, and cardiovascular disease were higher in rural areas than in urban or semi-urban areas, and that these disparities were related to urban-rural differences in socioeconomic and demographic characteristics.[53,54] The air pollutant mixture in rural areas may differ from urban areas (e.g., due to industry type, traffic patterns). Therefore, it is important to include rural populations in health effects studies. Traditional methods of assessing exposure focus more heavily on urban populations, excluding these rural populations. The use of satellite methods may allow study of broader scientific questions (i.e., whether effect estimates differ by rural vs. urban populations), in addition to increasing sample size through higher temporal and spatial coverage.

Several biologic mechanisms may be responsible for the association between air pollution exposure and adverse birth outcomes. Preterm birth may occur due to environmental disruptors of the endocrine systems that control parturition,[55] activation of molecular and cellular pathways involved in uterine contraction and quiescence through toxicant-induced inflammation response,[12] and interaction of external compounds with biochemical pathways responsible for the breakdown of the cervical matrix.[55] Birth weight-related outcomes (birth weight and term LBW and SGA) associated with $PM_{2.5}$ exposure may be due to mechanisms similar to those previously found for the effects of maternal smoking on fetal growth and development. Such mechanisms may include oxidative stress, vascular resistance in the placenta, and fetal exposure to toxic chemicals.[56,57] Even though exposure to maternal smoking may be associated with a greater decrease in birth weight than $PM_{2.5}$ exposure (150 to 300g[57] vs. 19g in our study under the Satellite (2) method), the following should be kept in mind. First, the population for maternal smoking exposure is much smaller than for $PM_{2.5}$ exposure. Second, it is much more difficult for individuals to avoid $PM_{2.5}$ exposure than maternal smoking. Other potential mechanisms involving particulate matter exposure may include, (1) mitochondrial dysfunction (in the placenta) in response to PM_{10} exposure, which may affect nutrient transfer and growth of the placenta and, in turn, fetal growth and development,[58] and (2) the production of reactive oxygen species as a detoxification response to maternal smoking or exposure to air pollution further increasing the probability of DNA damage during fetal development and growth. Ongoing animal and human studies, including epigenetic studies looking at gene-environment interactions, continue to improve our limited understanding of these and other biologic mechanisms for adverse birth outcomes.[59-61]

There were several limitations of our study. First, smoking habits, alcohol consumption, prenatal care and maternal risk data on birth certificates are less reliable than from other data sources such as questionnaires and cohort data.[62] Despite these data reliability issues, birth certificate data are frequently used in health effects studies of air pollution and birth outcomes because they provided reliable estimates of birth weight and date of birth, both of which are essential for evaluating several birth outcomes.[8,9,22,26,63] Second, our data were limited in their spatial resolution. We excluded mothers living more than 50km from monitors, which may have introduced exposure misclassification due to spatial

heterogeneity of pollutants (i.e., the 10x10km resolution is a necessary limitation of satellite data rather than being selected as an appropriate scale at which to predict $PM_{2.5}$ levels). Related to this, even though satellite data were calibrated to monitor data, grid cells where these monitors were located may be better predictors of $PM_{2.5}$ levels than grid cells without monitors (e.g., rural areas, suburbs). Lastly, neither method of exposure assessment – monitor- or satellite-based – captures individual-level exposures or identifies sources of air pollution. This drawback is common to most air pollution and health studies; possible solutions include using personal monitors for exposure assessment and simulation models (e.g., regional air quality modeling) or source apportionment.

In summary, our study compares associations between $PM_{2.5}$ exposure and birth outcomes, using a traditional data source for exposure assessment (land-based monitoring stations) and a new and emerging exposure method (satellite data that have been calibrated and modeled specifically for use in health effects studies). As satellite data continue to improve in their calibration, modeling and spatial resolution, they will become increasingly useful in health effects studies. Future studies should consider the spatial resolution of satellite data in the context of the specific pollutant under investigation (e.g., satellite data for some pollutants are available but at very large spatial resolution [100km or more]), and should compare associations based on multiple sources of data for exposure assessment so that our results are robust and more useful for policy makers in environmental risk assessments, as each exposure method has its own strengths and challenges.

Acknowledgments

We thank Gavin Pereira for guidance on the statistical analyses and clarifying some concepts related to gestational exposure. We thank the State of Connecticut and State of Massachusetts for providing the birth certificate data. This study was approved by the Connecticut DPH HIC and the Massachusetts DPH HIC.

Source of Funding:

This work was supported by funding from the National Institute of Environmental Health Sciences (R01ES016317 and R01ES019587).

REFERENCES

1. Dockery DW, Pope CA 3rd, Xu X, Spengler JD, Ware JH, Fay ME, Ferris BG Jr. Speizer FE. An association between air pollution and mortality in six U.S. cities. N Engl J Med. 1993; 329(24): 1753–9. [PubMed: 8179653]
2. Pope CA 3rd, Burnett RT, Thun MJ, Calle EE, Krewski D, Ito K, Thurston GD. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. JAMA. 2002; 287(9):1132–41. [PubMed: 11879110]
3. Samet JM, Dominici F, Curriero FC, Coursac I, Zeger SL. Fine particulate air pollution and mortality in 20 U.S. cities, 1987-1994. N Engl J Med. 2000; 343(24):1742–9. [PubMed: 11114312]
4. Pelucchi C, Negri E, Gallus S, Boffetta P, Tramacere I, La Vecchia C. Long-term particulate matter exposure and mortality: a review of European epidemiological studies. BMC Public Health. 2009; 9:453. [PubMed: 19995424]
5. Chen H, Goldberg MS, Villeneuve PJ. A systematic review of the relation between long-term exposure to ambient air pollution and chronic diseases. Rev Environ Health. 2008; 23(4):243–97. [PubMed: 19235364]
6. Shah PS, Balkhair T. Knowledge Synthesis Group on Determinants of Preterm LBWb. Air pollution and birth outcomes: a systematic review. Environ Int. 2011; 37(2):498–516. [PubMed: 21112090]

7. Stieb DM, Chen L, Eshoul M, Judek S. Ambient air pollution, birth weight and preterm birth: a systematic review and meta-analysis. Environ Res. 2012; 117:100–11. [PubMed: 22726801]
8. Maisonet M, Correa A, Misra D, Jaakkola JJ. A review of the literature on the effects of ambient air pollution on fetal growth. Environ Res. 2004; 95(1):106–15. [PubMed: 15068936]
9. Bell ML, Ebisu K, Belanger K. Ambient air pollution and low birth weight in Connecticut and Massachusetts. Environ Health Perspect. 2007; 115(7):1118–24. [PubMed: 17637932]
10. Preterm Birth: Causes, Consequences, and Prevention. The National Academies Press; 2007.
11. Russell RB, Green NS, Steiner CA, Meikle S, Howse JL, Poschman K, Dias T, Potetz L, Davidoff MJ, Damus K, Petrini JR. Cost of Hospitalization for Preterm and Low Birth Weight Infants in the United States. Pediatrics. 2007; 120(1):e1–e9. [PubMed: 17606536]
12. van den Hooven EH, de Kluizenaar Y, Pierik FH, Hofman A, van Ratingen SW, Zandveld PY, Lindemans J, Russcher H, Steegers EA, Miedema HM, Jaddoe VW. Chronic air pollution exposure during pregnancy and maternal and fetal C-reactive protein levels: the Generation R Study. Environ Health Perspect. 2012; 120(5):746–51. [PubMed: 22306530]
13. Lee PC, Talbott EO, Roberts JM, Catov JM, Sharma RK, Ritz B. Particulate air pollution exposure and C-reactive protein during early pregnancy. Epidemiology. 2011; 22(4):524–31. [PubMed: 21516040]
14. Hansen CA, Barnett AG, Pritchard G. The effect of ambient air pollution during early pregnancy on fetal ultrasonic measurements during mid-pregnancy. Environ Health Perspect. 2008; 116(3): 362–9. [PubMed: 18335104]
15. McGowan JE, Alderdice FA, Holmes VA, Johnston L. Early Childhood Development of Late-Preterm Infants: A Systematic Review. Pediatrics. 2011; 127(6):1111–1124. [PubMed: 21624885]
16. Pallotto EK, Kilbride HW. Perinatal outcome and later implications of intrauterine growth restriction. Clin Obstet Gynecol. 2006; 49(2):257–69. [PubMed: 16721105]
17. Moster D, Lie RT, Markestad T. Long-Term Medical and Social Consequences of Preterm Birth. New England Journal of Medicine. 2008; 359(3):262–273. [PubMed: 18635431]
18. Walter EC, Ehlenbach WJ, Hotchkin DL, Chien JW, Koepsell TD. Low birth weight and respiratory disease in adulthood: a population-based case-control study. Am J Respir Crit Care Med. 2009; 180(2):176–80. [PubMed: 19372251]
19. Schwartz J. Air pollution and children's health. Pediatrics. 2004; 113(4 Suppl):1037–43. [PubMed: 15060197]
20. Nieuwenhuijsen MJ, Dadvand P, Grellier J, Martinez D, Vrijheid M. Environmental risk factors of pregnancy outcomes: a summary of recent meta-analyses of epidemiological studies. Environ Health. 2013; 12:6. [PubMed: 23320899]
21. Dadvand P, Parker J, Bell ML, Bonzini M, Gehring U, Glinianaia SV, Gouveia N, Ha E, Jalaludin B, Rich DQ, Slama R, Nieuwenhuijsen M, Woodruff T, group obotI. O-107: Maternal Exposure to Particulate Air Pollution and Fetal Growth; A Multi- Country Evaluation of Effect and Heterogeneity. Epidemiology. 2012; 23(5S) 10.1097/01.ede.0000416765.64481.0d.
22. Ghosh JK, Wilhelm M, Su J, Goldberg D, Cockburn M, Jerrett M, Ritz B. Assessing the influence of traffic-related air pollution on risk of term low birth weight on the basis of land-use-based regression models and measures of air toxics. Am J Epidemiol. 2012; 175(12):1262–74. [PubMed: 22586068]
23. Wilhelm M, Ghosh JK, Su J, Cockburn M, Jerrett M, Ritz B. Traffic-related air toxics and term low birth weight in Los Angeles County, California. Environ Health Perspect. 2012; 120(1):132–8. [PubMed: 21835727]
24. Bell ML, Belanger K, Ebisu K, Gent JF, Lee HJ, Koutrakis P, Leaderer BP. Prenatal exposure to fine particulate matter and birth weight: variations by particulate constituents and sources. Epidemiology. 2010; 21(6):884–91. [PubMed: 20811286]
25. Parker JD, Woodruff TJ, Basu R, Schoendorf KC. Air pollution and birth weight among term infants in California. Pediatrics. 2005; 115(1):121–8. [PubMed: 15629991]
26. Kloog I, Melly SJ, Ridgway WL, Coull BA, Schwartz J. Using new satellite based exposure methods to study the association between pregnancy pm2.5 exposure, premature birth and birth weight in Massachusetts. Environ Health. 2012; 11:40. [PubMed: 22709681]

27. Rich DQ, Demissie K, Lu SE, Kamat L, Wartenberg D, Rhoads GG. Ambient air pollutant concentrations during pregnancy and the risk of fetal growth restriction. J Epidemiol Community Health. 2009; 63(6):488–96. [PubMed: 19359274]
28. Madsen C, Gehring U, Walker SE, Brunekreef B, Stigum H, Naess O, Nafstad P. Ambient air pollution exposure, residential mobility and term birth weight in Oslo, Norway. Environ Res. 2010; 110(4):363–71. [PubMed: 20227069]
29. Morello-Frosch R, Jesdale BM, Sadd JL, Pastor M. Ambient air pollution exposure and full-term birth weight in California. Environ Health. 2010; 9:44. [PubMed: 20667084]
30. Basu R, Woodruff TJ, Parker JD, Saulnier L, Schoendorf KC. Comparing exposure metrics in the relationship between PM2.5 and birth weight in California. J Expo Anal Environ Epidemiol. 2004; 14(5):391–6. [PubMed: 15361898]
31. Gehring U, Wijga AH, Fischer P, de Jongste JC, Kerkhof M, Koppelman GH, Smit HA, Brunekreef B. Traffic-related air pollution, preterm birth and term birth weight in the PIAMA birth cohort study. Environ Res. 2011; 111(1):125–35. [PubMed: 21067713]
32. Zou B, Wilson JG, Zhan FB, Zeng Y. Air pollution exposure assessment methods utilized in epidemiological studies. J Environ Monit. 2009; 11(3):475–90. [PubMed: 19280026]
33. Gehring U, van Eijsden M, Dijkema MB, van der Wal MF, Fischer P, Brunekreef B. Traffic-related air pollution and pregnancy outcomes in the Dutch ABCD birth cohort study. Occup Environ Med. 2011; 68(1):36–43. [PubMed: 20798012]
34. Nethery E, Teschke K, Brauer M. Predicting personal exposure of pregnant women to traffic-related air pollutants. Sci Total Environ. 2008; 395(1):11–22. [PubMed: 18334266]
35. Wilhelm M, Ghosh JK, Su J, Cockburn M, Jerrett M, Ritz B. Traffic-related air toxics and preterm birth: a population-based case-control study in Los Angeles County, California. Environ Health. 2011; 10:89. [PubMed: 21981989]
36. Chang HH, Reich BJ, Miranda ML. Time-to-event analysis of fine particle air pollution and preterm birth: results from North Carolina, 2001-2005. Am J Epidemiol. 2012; 175(2):91–8. [PubMed: 22167746]
37. Lee HJ, Coull BA, Bell ML, Koutrakis P. Use of satellite-based aerosol optical depth and spatial clustering to predict ambient PM2.5 concentrations. Environ Res. 2012; 118(0):8–15. [PubMed: 22841416]
38. Lee HJ, Liu Y, Coull BA, Schwartz J, Koutrakis P. A novel calibration approach of MODIS AOD data to predict PM2.5 concentrations. Atmos. Chem. Phys. 2011; 11(15):7991–8002.
39. Alexander GR, Himes JH, Kaufman RB, Mor J, Kogan M. A United States national reference for fetal growth. Obstet Gynecol. 1996; 87(2):163–8. [PubMed: 8559516]
40. Oken E, Kleinman KP, Rich-Edwards J, Gillman MW. A nearly continuous measure of birth weight for gestational age using a United States national reference. BMC Pediatr. 2003; 3:6. [PubMed: 12848901]
41. National Climatic Data Center. Land-based Data: Global Summary of Day. 2012
42. Alston EJ, Sokolik IN, Doddridge BG. Investigation into the use of satellite data in aiding characterization of particulate air quality in the Atlanta, Georgia metropolitan area. J Air Waste Manag Assoc. 2011; 61(2):211–25. [PubMed: 21387938]
43. Zhang H, Hoff RM, Engel-Cox JA. The relation between Moderate Resolution Imaging Spectroradiometer (MODIS) aerosol optical depth and PM2.5 over the United States: a geographical comparison by U.S. Environmental Protection Agency regions. J Air Waste Manag Assoc. 2009; 59(11):1358–69. [PubMed: 19947117]
44. Wu, J. Advances in K-means Clustering. Springer Theses Springer; Berlin Heidelberg: 2012. Cluster Analysis and K-means Clustering: An Introduction.; p. 1-16.
45. Madrigano J, Kloog I, Goldberg R, Coull BA, Mittleman MA, Schwartz J. Long-term exposure to PM2.5 and incidence of acute myocardial infarction. Environ Health Perspect. 2013; 121(2):192–6. [PubMed: 23204289]
46. Wang ZX, Liu Y, Hu M, Pan XC, Shi J, Chen F, He KB, Koutrakis P, Christiani DC. Acute health impacts of airborne particles estimated from satellite remote sensing. Environ Int. 2013; 51:150–159. [PubMed: 23220016]

47. Kloog I, Koutrakis P, Coull BA, Lee HJ, Schwartz J. Assessing temporally and spatially resolved PM2.5 exposures for epidemiological studies using satellite aerosol optical depth measurements. Atmos Environ. 2011; 45(35):6267–6275.
48. Ritz B, Wilhelm M, Hoggatt KJ, Ghosh JKC. Ambient Air Pollution and Preterm Birth in the Environment and Pregnancy Outcomes Study at the University of California, Los Angeles. Am J Epidemiol. 2007; 166(9):1045–1052. [PubMed: 17675655]
49. Goswami E, Larson T, Lumley T, Liu LJS. Spatial Characteristics of Fine Particulate Matter: Identifying Representative Monitoring Locations in Seattle, Washington. Journal of the Air & Waste Management Association. 2002; 52(3):324–333. [PubMed: 11926195]
50. Bravo MA, Bell ML. Spatial heterogeneity of PM10 and O3 in Sao Paulo, Brazil, and implications for human health studies. J Air Waste Manag Assoc. 2011; 61(1):69–77. [PubMed: 21305890]
51. Bell ML, Ebisu K. Environmental Inequality in Exposures to Airborne Particulate Matter Components in the United States. Environ Health Perspect. 2012
52. Levy RC, Remer LA, Tanre D, Mattoo S, Kaufman YJ. Algorithm for remote sensing of troposhperic aerosol over dark targets from MODIS: Collections 005 and 051: Revision 2. Feb. 2009 2009.
53. Eberhardt MS, Pamuk ER. The Importance of Place of Residence: Examining Health in Rural and Nonrural Areas. American Journal of Public Health. 2004; 94(10):1682–1686. [PubMed: 15451731]
54. National Center for Health Statistics (U.S.). Health, United States, 2001 : with Urban and rural health chartbook. U.S. Dept. of Health and Human Services, Centers for Disease Control and Prevention For sale by the Supt. of Docs., U.S. G.P.O.; Hyattsville, MD Washington, D.C.: 2001. DHHS publication
55. The Role of Environmental Hazards in Premature Birth: Workshop Summary. The National Academies Press; 2003.
56. Martin TR, Bracken MB. ASSOCIATION OF LOW BIRTH WEIGHT WITH PASSIVE SMOKE EXPOSURE IN PREGNANCY. Am J Epidemiol. 1986; 124(4):633–642. [PubMed: 3752056]
57. DiFranza JR, Aligne CA, Weitzman M. Prenatal and Postnatal Environmental Tobacco Smoke Exposure and Children's Health. Pediatrics. 2004; 113(Supplement 3):1007–1015. [PubMed: 15060193]
58. Janssen BG, Munters E, Pieters N, Smeets K, Cox B, Cuypers A, Fierens F, Penders J, Vangronsveld J, Gyselaers W, Nawrot TS. Placental mitochondrial DNA content and particulate air pollution during in utero life. Environ Health Perspect. 2012; 120(9):1346–52. [PubMed: 22626541]
59. Janssen BG, Godderis L, Pieters N, Poels K, Kici Ski M, Cuypers A, Fierens F, Penders J, Plusquin M, Gyselaers W, Nawrot TS. Placental DNA hypomethylation in association with particulate air pollution in early life. Part Fibre Toxicol. 2013; 10(1):22. [PubMed: 23742113]
60. Joubert BR, Haberg SE, Nilsen RM, Wang X, Vollset SE, Murphy SK, Huang Z, Hoyo C, Midttun O, Cupul-Uicab LA, Ueland PM, Wu MC, Nystad W, Bell DA, Peddada SD, London SJ. 450K epigenome-wide scan identifies differential DNA methylation in newborns related to maternal smoking during pregnancy. Environ Health Perspect. 2012; 120(10):1425–31. [PubMed: 22851337]
61. Wilhelm-Benartzi CS, Houseman EA, Maccani MA, Poage GM, Koestler DC, Langevin SM, Gagne LA, Banister CE, Padbury JF, Marsit CJ. In utero exposures, infant growth, and DNA methylation of repetitive elements and developmentally related genes in human placenta. Environ Health Perspect. 2012; 120(2):296–302. [PubMed: 22005006]
62. Dietz PM, Adams MM, Kendrick JS, Mathis MP. Completeness of ascertainment of prenatal smoking using birth certificates and confidential questionnaires: variations by maternal attributes and infant birth weight. PRAMS Working Group. Pregnancy Risk Assessment Monitoring System. Am J Epidemiol. 1998; 148(11):1048–54. [PubMed: 9850126]
63. Ritz B, Wilhelm M, Zhao Y. Air pollution and infant death in southern California, 1989-2000. Pediatrics. 2006; 118(2):493–502. [PubMed: 16882800]

64. Kotelchuck M. The Adequacy of Prenatal Care Utilization Index: its US distribution and association with low birth weight. Am J Public Health. 1994; 84(9):1486–1489. [PubMed: 8092377]

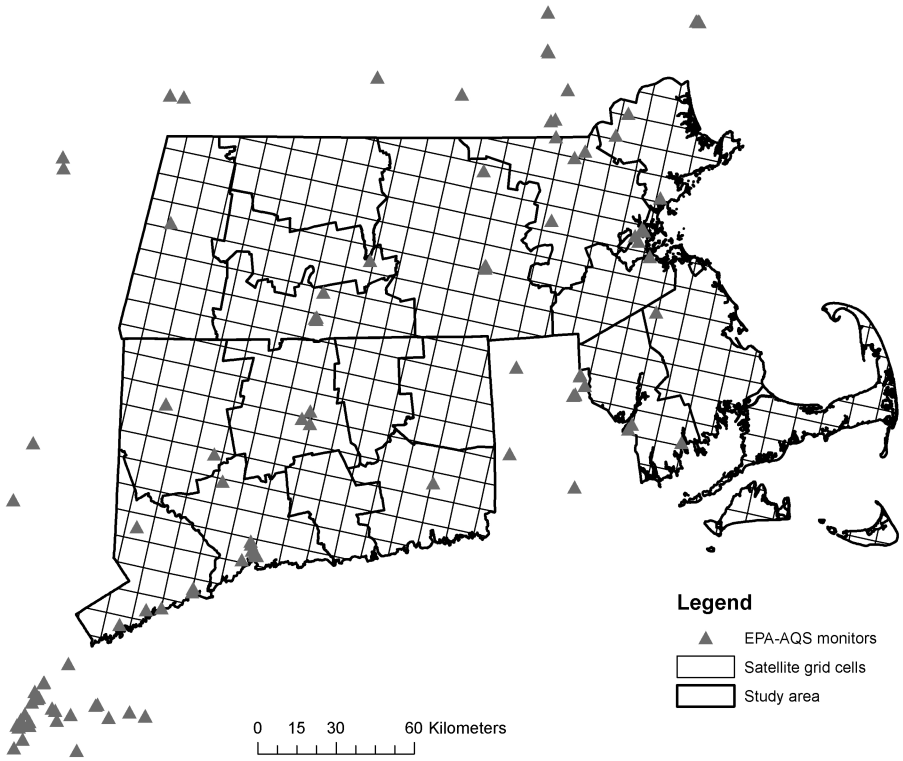

Figure.

Map of the study area, which includes counties in Connecticut and Massachusetts (thick black lines). Environmental Protection Agency – Air Quality System (EPA-AQS) monitoring sites located within 50km of the state boundary are shown in grey triangles. Grid cells (10x10km; thin black lines) for satellite methods are overlaid on the study area. Note that not all monitors and grid cells were used in exposure assessment due to data quality and availability issues.

Table 1

Descriptive statistics of maternal and child characteristics and birth outcomes from birth certificate data in Connecticut and Massachusetts (2000-2006). N=662,921 for all variables except where limited to births in a specific ranges of gestational length (e.g., term births or small for gestational age). Percentages are rounded to whole numbers.

Variables	No. (%)[a]
Birth outcomes	
Birth weight (in grams, for term births only); mean (SD)	3,449 (472)
Term low birth weight (term births <2500g)	11,641 (2)
Preterm birth (gestational age <37 weeks)	41,868 (6)
Small for gestational age (birth weight <10th percentile for gestational age and sex)	67,842 (10)
Baby's sex	
Boy	338,957 (51)
Girl	323,964 (49)
Type of birth	
Vaginal/Vaginal birth after cesarean birth	482,358 (73)
Cesarean/Repeated cesarean	180,563 (27)
Adequacy of Prenatal Care Utilization Index[64]	
Unknown/Missing	6,518 (1)
Inadequate	51,826 (8)
Intermediate	57,471 (9)
Adequate (Basic or Intensive)	547,106 (82)
Average number of cigarettes per day	
None	613,155 (93)
1-9	28,025 (4)
10-20	21,025 (3)
>20	716 (0.1)
Mother's education (years)	
<12	82,526 (12)
12	165,549 (25)
13-15	142,460 (22)
≥ 16	272,386 (41)
Mother's race/ethnicity	
White/non-Hispanic	448,330 (68)
Black/non-Hispanic	60,463 (9)
Asian/non-Hispanic	40,698 (6)
Hispanic/other-Hispanic	99,211 (15)
Other/non-Hispanic or unknown ethnicity	14,219 (2)
Mother's marital status	
Married	464,155 (70)
Unmarried	198,766 (30)
Mother's age (years)	

Variables	No. (%)[a]
<20	43,535 (6)
20-24	106,454 (16)
25-29	156,967 (23)
30-34	210,351 (31)
35-39	119,400 (18)
≥ 40	26,214 (4)
Season and weather	
Season of conception	
Winter	173,499 (26)
Spring	160,963 (24)
Summer	162,735 (25)
Fall	165,724 (25)
Apparent temperature (°C); mean (SD)	48.2 (7.2)
Parity (number of previous births)	
0	290,134 (44)
1	228,434 (34)
2	97,127 (15)
≥ 3	47,226 (7)
Previous preterm birth or small-for-gestational-age birth	6,090 (1)
Gestational age (weeks); mean (SD)	39.0 ± 1.6

[a]Except where otherwise specified.

Table 2

Descriptive statistics for exposure data for $PM_{2.5}$ ($\mu g/m^3$), based on 3 exposure methods.

Duration of exposure	Mean	SD	Min	Lower Quartile	Upper Quartile	Max	IQR
Monitor							
Entire pregnancy	11.91	1.89	4.02	10.66	13.07	19.97	2.41
1st trimester	12.03	2.66	3.24	10.19	13.66	24.50	3.46
2nd trimester	11.93	2.58	3.24	10.13	13.57	24.50	3.44
3rd trimester	11.81	2.55	0.50	10.02	13.58	43.30	3.56
Satellite (1)[a]							
Entire pregnancy	11.15	0.75	8.77	10.66	11.70	13.75	1.04
1st trimester	11.17	1.48	6.76	10.20	12.03	15.84	1.83
2nd trimester	11.16	1.49	6.75	10.19	12.04	15.75	1.86
3rd trimester	11.11	1.59	4.09	10.08	12.10	24.63	2.02
Satellite (2)[a]							
Entire pregnancy	11.36	0.85	8.82	10.79	11.92	14.81	1.12
1st trimester	11.38	1.59	6.73	10.28	12.34	17.09	2.06
2nd trimester	11.36	1.60	6.71	10.27	12.35	17.09	2.08
3rd trimester	11.32	1.70	4.23	10.18	12.40	31.59	2.22

IQR indicates interquartile range.

[a] see main text for differences in Satellite(1) and Satellite(2)

Table 3

Adjusted[a] association between $PM_{2.5}$ exposure over the entire pregnancy and birth outcomes, by exposure data source and by type of birth outcomes. Effect estimates (95%CI) are reported as per inter-quartile range (2.41 μg/m^3) increase in $PM_{2.5}$.

Model[b]			No.
Data source	**Observations**	**OR of term LBW**	
Monitor	**All**	1.01 (0.98 to 1.04)	619,675
	Joint	1.01 (0.98 to 1.04)	609,813
Satellite (1)	**All**	1.07 (0.99 to 1.17)	628,131
	Joint	1.06 (0.97 to 1.16)	609,813
Satellite (2)	**All**	1.09 (1.02 to 1.17)	628,131
	Joint	1.08 (1.01 to 1.16)	609,813
OR of SGA			
Monitor	**All**	1.03 (1.01 to 1.04)	654,193
	Joint	1.03 (1.01 to 1.04)	643,839
Satellite (1)	**All**	1.07 (1.03 to 1.11)	662,921
	Joint	1.06 (1.03 to 1.10)	643,839
Satellite (2)	**All**	1.08 (1.05 to 1.11)	662,921
	Joint	1.08 (1.04 to 1.11)	643,839
Change in birth weight (g)			
Monitor	**All**	−6.2 (−7.9 to −4.6)	619,675
	Joint	−6.2 (−7.9 to −4.6)	609,813
Satellite (1)	**All**	−14.6 (−19.4 to −9.8)	628,131
	Joint	−15.7 (−20.5 to −10.8)	609,813
Satellite (2)	**All**	−19.1 (−23.1 to −15.1)	628,131
	Joint	−19.0 (−23.0 to −14.9)	609,813
OR of preterm birth			
Monitor	**All**	1.00 (0.99 to 1.02)	647,942
	Joint	1.00 (0.99 to 1.02)	637,586
Satellite (1)	**All**	0.98 (0.93 to 1.02)	656,769
	Joint	0.98 (0.94 to 1.03)	637,586
Satellite (2)	**All**	1.00 (0.96 to 1.04)	656,769
	Joint	0.99 (0.95 to 1.03)	637,586

[a] All models controlled for the following confounders mother's age, marital status, education, race/ethnicity, prenatal care, smoking, type of birth, parity, season of conception, medical risk factors, medical risk due to previous preterm birth and/or small for gestational age, baby's sex, and gestational length. Gestational length and baby's sex were not included in the models for SGA. Gestational length was not included in the models for preterm birth.

[b] See main text for explanation of models.

Table 4

Adjusted[a] association between $PM_{2.5}$ exposure during each trimester and birth outcomes. Effect estimates with 95%CI are reported as per inter-quartile range (2.41 μg/m^3) increase in $PM_{2.5}$

Model[b]		Trimester of exposure		
Data Source	**Observations**	**First**	**Second**	**Third**
		OR of term LBW		
Monitor	**All**	1.01 (0.99 to 1.03)	1.00 (0.98 to 1.02)	1.01 (0.99 to 1.03)
	Joint	1.01 (0.99 to 1.03)	1.00 (0.98 to 1.02)	1.01 (0.99 to 1.03)
Satellite (1)	**All**	1.04 (1.01 to 1.08)	0.99 (0.96 to 1.02)	1.02 (0.98 to 1.05)
	Joint	1.04 (1.00 to 1.08)	0.99 (0.95 to 1.02)	1.01 (0.98 to 1.05)
Satellite (2)	**All**	1.05 (1.01 to 1.08)	1.00 (0.97 to 1.03)	1.02 (0.99 to 1.06)
	Joint	1.04 (1.01 to 1.08)	1.00 (0.97 to 1.03)	1.02 (0.99 to 1.05)
		OR of SGA		
Monitor	**All**	1.03 (1.01 to 1.04)	1.02 (1.01 to 1.02)	1.02 (1.01 to 1.02)
	Joint	1.03 (1.01 to 1.04)	1.02 (1.01 to 1.02)	1.02 (1.01 to 1.02)
Satellite (1)	**All**	1.02 (1.01 to 1.03)	1.02 (1.01 to 1.04)	1.02 (1.00 to 1.03)
	Joint	1.02 (1.00 to 1.03)	1.02 (1.00 to 1.04)	1.02 (1.01 to 1.04)
Satellite (2)	**All**	1.01 (1.01 to 1.02)	1.03 (1.01 to 1.04)	1.02 (1.01 to 1.04)
	Joint	1.01 (1.01 to 1.02)	1.02 (1.01 to 1.04)	1.02 (1.01 to 1.04)
		Change in birth weight (g)		
Monitor	**All**	−6.2 (−7.9 to −4.6)	−3.5 (−4.6 to −2.3)	−2.4 (−3.6 to −1.3)
	Joint	−6.2 (−7.9 to −4.6)	−3.5 (−4.7 to −2.4)	−2.5 (−3.7 to −1.4)
Satellite (1)	**All**	−6.5 (−8.3 to −4.6)	−5.1 (−7.1 to −3.1)	−1.4 (−3.3 to 0.4)
	Joint	−6.3 (−8.1 to −4.4)	−5.5 (−7.5 to −3.4)	−1.9 (−3.8 to 0.0)
Satellite (2)	**All**	−4.1 (−5.2 to −2.9)	−6.8 (−8.6 to −4.9)	−3.1 (−4.8 to −1.4)
	Joint	−4.0 (−5.2 to −2.8)	−6.8 (−8.6 to −4.9)	−3.2 (−4.9 to −1.5)
		OR of preterm birth		
Monitor	**All**	1.00 (0.99 to 1.02)	1.01 (1.00 to 1.02)	1.00 (0.99 to 1.01)
	Joint	1.00 (0.99 to 1.02)	1.01 (1.00 to 1.02)	1.00 (0.99 to 1.01)
Satellite (1)	**All**	1.00 (0.98 to 1.01)	0.99 (0.97 to 1.01)	0.99 (0.97 to 1.01)
	Joint	0.99 (0.98 to 1.01)	0.99 (0.97 to 1.01)	0.99 (0.97 to 1.01)
Satellite (2)	**All**	1.00 (0.99 to 1.01)	1.00 (0.98 to 1.02)	1.00 (0.98 to 1.01)
	Joint	1.00 (0.99 to 1.01)	1.00 (0.98 to 1.02)	0.99 (0.98 to 1.01)

[a] All models controlled for the following confounders mother's age, marital status, education, race/ethnicity, prenatal care, smoking, type of birth, parity, season of conception, medical risk factors, medical risk due to previous preterm birth and/or small for gestational age, baby's sex, and gestational length. Gestational length and baby's sex were not included in the models for SGA. Gestational length was not included in the models for preterm birth.

[b] See main text for explanation of models.