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An Assessment of Air Pollutant Exposure Methods in Mexico City, Mexico

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Introduction

Air pollution is a major public health problem, with growing numbers of urban residents living in areas with air pollution levels exceeding the World Health Organization (WHO) air quality guidelines (Cohen, Ross Anderson et al. 2005). Air pollution has been associated with mortality and morbidity (Borja-Aburto, Loomis et al. 1997; Brunekreef and Holgate 2002), cardiovascular disease (Künzli, Jerrett et al. 2005; Park, O'Neill et al. 2008), and adverse pregnancy outcomes (e.g. low birth weight, preterm birth, intrauterine growth retardation) (Slama, Darrow et al. 2008; Woodruff, Parker et al. 2009).

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Many previous epidemiological studies of air pollution have used data collected from central monitoring sites (Ozkaynak, Baxter et al. 2013). Recent advances in the availability of fine-resolution remote sensing data and application of methods that incorporate temporal and spatial variability have demonstrated that exposure measurement error from the use of central sites can influence pollutant-specific health effects estimates (Ozkaynak, Baxter et al. 2013). Several publications on outdoor air pollution and perinatal outcomes have used birth registries and air pollution data from government-run air quality monitors to create exposure estimates (Bell, Ebisu et al. 2007; Chang, Reich et al. 2012; Sagiv, Mendola et al. 2005). Other exposure assessment approaches (Jerrett, Arain et al. 2004) include methods that account for the mother's residential location (Nethery, Leckie et al. 2008), proximity to traffic or other sources of emission (Wilhelm and Ritz 2003; Yorifuji, Naruse et al. 2011), land-use regression models (Brauer, Lencar et al. 2008; Slama, Morgenstern et al. 2007), models to reduce exposure measurement error (Zou, Wilson et al. 2009), and even personal monitoring of mothers during pregnancy (Jedrychowski, Galas et al. 2005; Perera, Tang et al. 2005; Perera, Li et al. 2009).

The spatial distribution of air pollutants gives rise to special considerations in exposure assessment methods. For instance, spatial averaging of air pollution (i.e. averaging concentrations across all monitors in a given area or city) may adequately represent individual exposures to spatially homogeneous pollutants (Brunekreef and Holgate 2002). Alternatively, when the study participants' location is known or if exposures decline with distance from a pollution source due to mixing and dilution effects, other methods can be used. Nearest monitor, inverse distance weighting, and ordinary Kriging use distance to estimate exposure to outdoor air pollution. (Brauer, Lencar et al. 2008; Janssen, van Vliet et al. 2001; Wyler, Braun-Fahrländer et al. 2000). In particular, Kriging is an interpolation technique that estimates values at unsampled locations based on concentrations sampled spatially (e.g. a network of monitors within an urban area) and has been used for exposure estimates (Iñiguez, Ballester et al. 2009; Jerrett, Burnett et al. 2005; Leem, Kaplan et al. 2006; Liao, Peuquet et al. 2006; Ross, Ito et al. 2013; Shad, Mesgari et al. 2009). Additionally, Kriging allows calculation of uncertainty in the estimated values, essential to quantify the potential bias caused by air pollution exposure measurement error (Gryparis, Paciorek et al. 2009; Marshall, Nethery et al. 2008; Woodruff, Parker et al. 2009).

Although interpolation methods have many advantages, no published studies to our knowledge have used them to estimate individual air pollution exposure in Mexico City, a place with significant air pollution and one of the world's top ten mega-cities. We used 2008 daily ambient air pollution data from metropolitan Mexico City to construct and compare different exposure assessment methods (citywide average (CWA), nearest monitor (NM), inverse distance weighting (IDW), and ordinary Kriging (OK)) for application in perinatal epidemiology studies where mothers' residential locations are known. The differences among these methods were evaluated in a simulated population from various regions of metropolitan Mexico City. We compared daily predicted air pollutant concentrations for this population by various methods to guide assessment of associations between air pollution and preterm birth in a mother-infant pair cohort recruited from 1994–2005 (Ettinger, Lamadrid-Figueroa et al. 2008), and for an ongoing study in Mexico City (O'Neill, Osornio-Vargas et al. 2013).

METHODS

Study location

The Federal District of Mexico (Mexico City) has an estimated population of 8.9 million (INEGI 2010) and is located in a valley surrounded by mountains reaching elevations of 2,240 meters above sea level. The area is impacted by pollution sources ranging from industrial refineries to traffic emissions and wind-blown dust from a dry lake basin. Although the metropolitan area often meets daily standards for six regulated pollutants (carbon monoxide (CO), particulate matter with aerodynamic diameter ≤ 10 and ≤ 2.5 micrometers respectively, (PM₁₀; PM_{2.5}), ozone (O₃), sulfur dioxide (SO₂), and nitrogen dioxide (NO₂), it does not meet the annual standards, with concentrations almost double the limits for many pollutants (Hamilton, Hoyert et al. 2013). The Mexico City air quality standards are as follows: PM₁₀ (annual mean: 50 $\mu\text{g}/\text{m}^3$; daily average: 120 $\mu\text{g}/\text{m}^3$); PM_{2.5} (annual mean: 15 $\mu\text{g}/\text{m}^3$; daily average: 65 $\mu\text{g}/\text{m}^3$); O₃ (1 hour average: 110 ppb; 8 hour average: 80 ppb); SO₂ (annual mean: 30 ppb; daily average: 130 ppb); NO₂ (1 hour average: 210 ppb); CO (8 hour average: 11 ppm).

Air pollution data

The air quality monitoring network in Mexico City (“Sistema de Monitoreo Atmosférico”, SIMAT by its acronym in Spanish) provides hourly data on the six pollutants from 34 stations. Of these 34 sites, 22 sample for O₃; 26 for SO₂; 18 for NO₂; 18 for CO; 14 for PM₁₀, and 9 for PM_{2.5} (Zuk, Tzintzun Cervantes et al. 2007). We downloaded the data on April 19, 2011 for the whole calendar year of 2008 from the SIMAT website (<http://www.sma.df.gob.mx>). We chose 2008 because this is a relatively recent year with measurements representative of improvements to the network and validation methods, but also a year which has had adequate time for any corrections to be made. Prior to posting on the website, SIMAT staff clean and validate the data (Retama-Hernandez 2011; Zuk, Tzintzun Cervantes et al. 2007). PM₁₀ and PM_{2.5} were reported in micrograms per cubic meter ($\mu\text{g}/\text{m}^3$), whereas O₃, CO, NO₂, and SO₂ were reported in parts-per-million (ppm). O₃, NO₂, and SO₂ data were transformed from ppm to ppb to facilitate comparison of concentration levels with Mexico City air pollution standards. PM₁₀, PM_{2.5}, and CO retained the originally reported units. Although data are available hourly for most pollutants, we summarized data as daily concentrations (24 hour averages) for particulates (PM₁₀ and PM_{2.5}), SO₂, and NO₂; and the daily 8 hour maximum running average for CO and O₃, from all available monitoring stations. These concentration averaging times match the Mexican health-based regulatory standards (Zuk, Tzintzun Cervantes et al. 2007). If more than 25% of the hourly values in a given day were missing, the daily concentration was coded as ‘missing’. The term ‘daily value’ or ‘pollutant concentration’ refers to these summaries.

Simulated population location data for exposure estimation

Our goal was to construct and compare exposure metrics and eventually assign them to participants in a pregnancy cohort in Mexico (O’Neill, Osornio-Vargas et al. 2013). To evaluate these metrics, we simulated a population of 1,000 women with residential locations distributed across the metropolitan area. To restrict the area of simulated residences to a zone within which we could perform Kriging, we created a polygon surrounding the

perimeter of the entire air monitoring network (i.e., the convex hull) using ArcGIS 9.3.1 (ESRI, Redlands, CA) (Figure 1). Then, we mapped the location of five monitoring stations at which we also deployed our own equipment and sampled particulate matter for toxicological and chemical compositional evaluation (Manzano-León, Quintana et al. 2013). These locations also informed our recruiting of participants for our pregnancy cohort study (Vadillo-Ortega, Osornio-Vargas et al.), and enabled us to divide Mexico City into north, south, east, west and center zones with potentially distinct pollution sources and mixtures. Thiessen polygons, which describe ‘areas of influence’ within which any given location is closer to its corresponding monitor than any of the other four monitors, were created to subdivide the convex hull into five zones surrounding these stations (Figure 1). The Hawth’s tools extension to ArcGIS ((Beyer 2004) was used to generate 200 random locations according to population density (from Mexico City’s 2005 census data (<http://www.inegi.org.mx/>)) within each of the five polygons, omitting areas known to be uninhabited or where people probably do not live (e.g., parks, industrial, non-residential areas). This simulation mimics the spatial distribution of potential future study participants.

Exposure assessment methods

Citywide averaging (CWA)—City-wide or spatial averaging uses a simple average of a given pollutant across all monitors within an identified geographic region to estimate an individual’s exposure. Estimates thus will not reflect spatial gradients of concentration that may be present for certain air pollutants. Previous studies have used spatial averaging as a surrogate of personal exposure to outdoor pollution (Borja-Aburto, Castillejos et al. 1998; Brunekreef and Holgate 2002).

Nearest monitor (NM)—The NM method assigns pollutant concentration at the closest monitor to the study participant’s location as the exposure estimate. We defined distance as the shortest straight line from the air quality monitor to the simulated residential location using ArcGIS 9.3.1 Hawth’s Tools (Beyer 2004). The NM method relied on the three closest neighboring monitors, in case the nearest monitor was missing data for any given day. In that scenario, data from the second or the third closest monitor was used.

Inverse distance weighting (IDW)—IDW computes predicted concentrations at a location as a weighted average of concentrations at neighboring monitors. Weights are a function of the inverse of the distance between the location and each monitor; for example, $1/\text{distance}^5$ or $1/\text{distance}^2$. Higher values of the power applied to the inverse distance emphasize the contribution of the nearest points to the location and interpolated values. The higher the value of the exponent, the less influence from distant points is exerted. We selected the square of the inverse distance ($1/\text{distance}^2$) to create a smoother surface across simulated locations. The square is also one of the default parameters commonly used in this method. We used at least five monitors closest to the residence location to calculate the IDW exposure estimates, with a maximum of 12 monitors for each pollutant.

Ordinary Kriging (OK)—Several forms of Kriging (simple Kriging, block Kriging, universal Kriging, ordinary Kriging), have been used to estimate air pollution exposure (Brauer, Lencar et al. 2008; Leem, Kaplan et al. 2006; Wong, Yuan et al. 2004). Similar to

IDW, OK calculates a weighted average of concentrations at monitoring stations to estimate a participant's exposure. However, OK uses weights derived from a function of distance referred to as a variogram, which describes the degree of spatial dependence or autocorrelation. A positive-definite model of the variogram is fitted to a plot of semivariance (a measure of deviation between pairs of sample points) and distance, calculated from observed data. OK assumes that the variogram model describing the spatial dependence is constant across the region being mapped.

The OK operation yields a continuous surface of estimated pollution concentrations within a defined geographical area, which can be mapped to grid cells. At any given location or grid cell, the value of the surface (i.e., a predicted concentration for the location) can be estimated, along with its estimation variance (or standard error). The standard error will be lower for points closer to the actual monitors, since the standard error represents the estimation error due to location, sampling error, and measurement error. An advantage of OK over other interpolation methods is that the weights assigned to the data are computed to minimize the standard error, whereas IDW assigns weights to neighboring locations in a way that is not informed by the observed spatial correlation of the sampled data (i.e., the variogram)..

Variogram modeling—Spherical, Gaussian, and exponential models were used to model the variogram. R statistical software (version 2.12.1) and the gstat package (Pebesma 2004; Szpiro, Sampson et al. 2010) were used to estimate the optimal model parameters. Because variogram parameters are affected by positive skewness in the air pollution data, data were log-transformed to facilitate estimation. Results from the spherical model are presented because it had the lowest root mean squared error (RMSE), described later, meaning it fit the empirical variogram best. The nugget, which is related to the short range variability of the data due to measurement error, was set to zero.]

Creating the metrics—Daily exposure estimates for calendar year 2008 were constructed for all 1,000 locations using the exposure methods above described. Because outdoor pollution in Mexico City, a relatively temperate climate, varies seasonally, we used rainy (May through October) or dry season (November through April) periods for calculating longer-term averages and comparing exposure metrics, in addition to year-long summary calculations.

Statistical analysis

We produced descriptive statistics on daily measured pollutant concentrations in 2008 and the exposure estimates, overall; by season; and by region. For the OK estimates, we chose to assign a concentration and its corresponding standard error for a given pollutant only to those residences within each pollutant-specific polygon, because outside these polygons, the method is essentially extrapolating, and standard errors are generally large. We then calculated Pearson correlation coefficients among pollutants for 2008 based on pollutant daily values, and, for each pollutant, correlations were then calculated daily across exposure assessment methods for each of the 1,000 locations, both citywide and in five zones. The mean differences in exposure estimates across methods for the 200 participants in each of

the five Thiessen polygons (zones) were also calculated to assess regional differences and method performance.

Model evaluation—We compared CWA, IDW, and NM methods to OK by computing the absolute value of the difference between each method and OK, and by comparing root mean square error (RMSE) of the estimated values from the NM, IDW to the OK estimates' RMSEs. In theory, estimates of air pollution exposure produced by Kriging better reflect spatial variability and provide a proxy of individual-level exposure with less measurement error than the other three methods. Thus, in subsequent comparisons we used the values and variances of the Kriging estimates as the point of reference for comparing the performance of each method, in the absence of a true 'gold standard' (measured concentration at the location of simulated participants' homes).

Kriging offers an additional opportunity for evaluating potential error in estimating pollution exposure, since the standard error of the OK estimate reflects estimation error due to location, sampling error, and measurement error. Regarding measurement error, comparisons between personally monitored exposures and ambient monitor data indicate that fine particles are more spatially homogenous than gaseous pollutants and thus better represent overall exposure (Sarnat, Klein et al. 2009). Air pollutants with fewer sample points (so average distance is greater, increasing error due to location) would have higher standard errors, on average, for the Kriging estimates. The Kriging standard error also depends on the nugget, so pollutants with higher measurement/sampling error (we cannot be sure what the nugget is representing) would also have greater overall standard errors when summarized across all the estimates, and give an indication of which pollutants are harder to estimate with spatial interpolation. To evaluate whether some pollutants had more estimation error than others, we calculated a version of a coefficient of variation for each of the six pollutants by dividing the mean of the daily-predicted Kriging standard errors by the standard deviation of all the Kriging-estimated daily pollution concentrations. This ratio can be thought of as the proportion of the variance in the estimated pollutant due to measurement, location, and sampling error (versus true variation), and the higher the dimensionless number, the greater the error associated with the estimated pollutant concentration (Shechtman 2013).

Finally, we used cross-validation to assess the performance of interpolation methods. In cross-validation, commonly referred to as the "leave-one-out" approach, each sampling site was removed from the dataset one at a time, and the remaining data were used to predict the pollutant concentration at that particular site. The predicted value for the monitor was then compared to the true observed value at that site. Equation 1 was used to compute RMSE from the daily cross validations was used to compare method performance and precision in terms of predicting the monitored concentration:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (z_i - \hat{z}_i)^2} \quad (1)$$

where $\hat{z}_i$ = the estimated pollutant concentration at location i ; z_i = the air pollutant concentration at location i , and n = number of pollutant-specific monitoring sites, which varies depending on the pollutant. An RMSE of zero means the prediction of the parameter of interest (air pollution concentration) matches the observation perfectly, although such values are practically impossible to achieve.

The Statistical Analysis System (SAS version 9.3; SAS Institute, Inc. Cary, NC) was used for estimating CWA, NM, and IDW concentrations, whereas R, Version 2.11.0, package 'gstat' (Pebesma 2004) was used for estimating OK.

Results

Table 1 presents summary descriptive statistics for the four air pollutant metrics estimated for the 1000 simulated study participants during all of 2008 and within the dry and wet seasons. Overall, means and standard deviations from the different methods were similar within each pollutant across the 2008 study period. However, the ranges of estimated concentrations determined by NM, IDW, and OK were always wider than the ranges for CWA. Seasonally, days with maximum pollutant concentrations occurred during the dry season for all exposure assessment methods. Overall, estimated pollutant concentrations, with the exception of SO₂ and CO, sometimes surpassed air quality standards established by U. S. and Mexican regulations.

Maximum PM₁₀ concentrations were higher in northern Mexico City, and O₃ concentrations were higher in the south. By contrast, PM_{2.5} concentrations were spatially invariant. All other pollutants had a relatively low level of spatial variation across the area and across estimates produced for the overall study period (data not shown).

The correlation coefficients across pairs of exposure methods and all air pollutants were generally high (0.77 to 0.99; Table 2). As expected, the two weighted averaging methods, IDW and OK, were the most highly correlated. NM correlations with other methods were always the smallest, since no averaging with data from other monitors is employed in that method. All pollutant estimates produced by CWA, with the exception of SO₂, were highly correlated with OK estimates.

The strength of the correlations across pairs of exposure methods varied across five zones depicted in Figure 1. Supplemental tables S-1(a–f) shows Pearson correlation coefficients between exposure assessment methods for each air pollutant for the five zones. Correlation coefficients were relatively high between methods for all pollutants, except for between CWA and NM. In all except the southern zone, CO showed high correlations between methods (r values ranging from 0.77 to 0.96). NO₂ exhibited high correlations between methods, except for CWA and NM, for all zones. Correlation coefficients for O₃ estimated by CWA and NM in the north and center zones were relatively lower than for other zones. Methods had high correlations for PM₁₀ and PM_{2.5}, when all zones were examined, although for PM_{2.5}, the CWA, NM, and OK methods had lower correlations in the southeast and west zones. Lastly, methods were less correlated for SO₂ in the southeast, south, west,

and northwest zones than for other pollutants, where CWA had higher correlation with IDW than with either NM or OK.

Table 3 shows the mean and standard deviations of differences in estimates by method, using OK as the ‘gold standard’, across all pollutants and zones. In northern Mexico City (Zone 5, with typically high PM₁₀ levels), CWA and IDW underestimated PM₁₀ on average, relative to OK, by 4.17 µg/m³ and 1.80 µg/m³, respectively, and NM overestimated the exposure by 4.11 µg/m³ when compared to OK. In the south (Zone 3), CWA overestimated PM₁₀ exposure by 7.49 µg/m³, whereas NM and IDW underestimated the exposure by 3.09 µg/m³ and 7.21 µg/m³, respectively. IDW produced lower standard deviations of the mean difference for the north and south zones. The center and eastern zones (zones 1 and 2, respectively) exhibited minimal differences in PM₁₀ estimates for the four methods. For PM_{2.5}, methods produced relatively similar results across zones. In the southern zone (high O₃), CWA underestimated the exposure by 0.91 and IDW by 3.29 ppb, whereas NM overestimated the exposure by 4.18 ppb. IDW estimates produced higher standard deviations of the mean difference between methods. Applied to NO₂, CO, and SO₂, all three methods produced similar estimates. Estimates produced by IDW showed higher standard deviations than other methods.

Descriptive statistics for all pollutants for individuals who reside within pollutant-specific polygons, along with the standard error and coefficients of variation (COV) for Kriging estimates, are shown in Table 4. The number of participants living within these polygons varies by pollutant, since the number and locations of monitors with available measures (and the corresponding convex hull polygon) of a given pollutant are different. The mean concentrations calculated within these polygons by the study methods were relatively similar to mean concentrations produced for all 1,000 individuals across Mexico City. Maximum concentrations estimated by OK were lower than for the two other interpolation methods, except for NO₂. PM₁₀ and PM_{2.5} showed significantly lower predicted maximum concentrations using OK compared to NM and IDW.

As previously noted, OK produces both a concentration estimate and its corresponding standard error for individuals living within pollutant-specific polygons. The range of the OK standard errors varied considerably between pollutants and the computed coefficients of variation ranged from 0.46 (least error) for SO₂ and PM₁₀ to 3.91 (most error) for PM_{2.5}, the pollutant with only 9 monitoring sites (Table 4).

Results from the cross-validation are shown in Table 5. The RMSEs for OK were consistently equal to or lower than for the other two methods, and only for non-log-transformed O₃ and NO₂ did IDW have RMSE’s equal to those of OK. This suggests that the OK method did the best overall job of predicting the actual measured concentrations at monitoring sites.

Discussion

This study compared daily exposure estimates derived from using four exposure assessment methods (CWA, NM, IDW, and OK) for 1,000 simulated women in Mexico City during

2008, to help guide selection of exposure metrics in perinatal epidemiological studies. We evaluated differences in the metrics produced and the accuracy of prediction of actual measured values by descriptive statistics, correlations, and cross-validation statistics. Air pollution exposure assessment in epidemiological studies on birth outcomes has sometimes relied on simple spatial averaging methods for estimation of individual exposure to airborne contaminants; this study provides insights into the extent to which the temporal and spatial variation of air pollution exposures may affect estimated exposure. Estimating exposure by taking location within this megacity into account can reduce the likelihood for exposure misclassification in health studies, increasing power to detect associations by capturing an adequate gradient of exposure in the study population (Navidi, Thomas et al. 1999).

The four exposure assessment methods yielded similar, but not identical, results for the air pollutants examined. The ranges of exposure estimates produced by methods incorporating location were significantly wider than for estimates produced by CWA. A cohort study in a Korean population utilized similar exposure assessment methods to our study and found similar estimates for different air pollutants, and that concentration ranges from methods accounting for geographical location were greater than those from spatial averaging (Son, Bell et al. 2010). A study comparing kriging and nearest monitor methods in estimating health effects associated with long-term pollution exposures concluded that kriging was generally better due to lower bias and better coverage of health effect parameter estimates. (Kim, Sheppard et al. 2009) In addition, researchers found that different interpolation methods produced similar estimates when monitor density was low, whereas when monitor density was high the differences were much greater (Kim, Sheppard et al. 2009; Wong, Yuan et al. 2004). High correlation coefficients between OK and IDW in our study suggest that these two interpolation methods were similarly able to predict spatial variation in concentrations of air pollutants in Mexico City, and the cross-validation suggested that IDW was a close second in predictive ability.

Regarding ease of use, the NM and IDW methods are simpler to calculate than OK. Air pollution exposure estimation by OK poses several challenges. One involves empirical and experimental variogram estimation. To automate and optimize the daily estimation of variogram parameters (range, sill, and nugget), skewed air pollution data must be log-transformed (Liao, Peuquet et al. 2006). Also, to select the best-fitting model, based on cross validation, variogram parameters needed to be determined by exploring their RMSE values under different covariance models (spherical, exponential, and Gaussian). For all air pollutants, the spherical covariance model showed the lowest RMSE. Similarly, other researchers experimented with model fit and selected the spherical model (Son, Bell et al. 2010). In spite of the more labor-intensive calculation, the advantage of Kriging is that standard errors for the estimated exposures can be calculated, unlike for IDW and NM. With these standard errors, one could use inverse variance weighting to give more precise Kriged exposure estimates a greater contribution when estimating epidemiologic associations, or use available measurement error models (Gryparis, Paciorek et al. 2009; Madsen, Ruppert et al. 2008; Spiegelman, Logan et al. 2011; Wannemuehler, Lyles et al. 2009).

We recommend that Kriged exposure estimates be employed in future epidemiological studies in Mexico City. However, one caveat is illustrated by the coefficient of variation

calculation we made with the Kriging standard errors and standard deviation. This suggested that estimation error relative to true variance is much greater in the PM_{2.5} Kriged estimates than for the other five pollutants. This is likely because PM_{2.5} is monitored at only 9 sites in Mexico City, and PM_{2.5} is known to be a spatially homogeneous pollutant that represents individual exposure well (Sarnat 2005). Including PM_{2.5} estimated by several exposure assessment methods in epidemiologic models may yield relatively consistent effect estimates, or, in other words, the specific exposure metric used for PM_{2.5} may be less critical than for other pollutants that have more geographical variation.

Strengths of this study include inclusion and comparison of methods that address both temporal and spatial scales of the air pollution data derived from the monitoring network and the creation of future capacity for linking estimates with an ongoing birth cohort. Moreover, because daily exposure was calculated using different exposure methods, we have the flexibility to construct multiple windows of exposure during pregnancy, not limited to trimesters or overall pregnancy windows, allowing us to capture all the biologically relevant times of exposure. Further, considering that Mexico City is a megacity, geocoding positional errors, more likely in rural settings, are of little concern in our study population or in future geo-referenced data from the city (Ward, Nuckols et al. 2005).

Limitations include the fixed number of available monitors (notably for PM_{2.5}), because a denser network would improve model performance, and variability in the numbers of reporting monitors by day, which changes the shape of the daily polygon. Additionally, we lacked personal exposure measurements as a gold standard in the simulated locations. However, previous work suggests that outdoor monitor concentrations are well-correlated with indoor and personal measures of exposure to air pollution in Mexico City (O'Neill, Ramirez-Aguilar et al. 2003; Rojas-Bracho 1994). Lastly, polygon shape is defined by the monitors reporting in a given day, and variations in the number and location of these monitors can shift the interpolation area relative to the residence location and increase prediction errors of interpolated data.

Nevertheless, our work adds to the growing literature comparing air pollution exposure assessment methods (Kim, Sheppard et al. 2009; Ross, Ito et al. 2013; Szpiro, Paciorek et al. 2011). A logical next step is to link the estimates from these models with health outcomes data to evaluate whether the pollution effect estimates differ by metric used, which may not always be the case (Szpiro, Paciorek et al. 2011) (Gryparis, Paciorek et al. 2009; Madsen, Ruppert et al. 2008).

Examining spatial variation in air pollution exposure, especially in Mexico City where “bowl-shape” topography promotes the accumulation of pollutants and the formation of air pollution concentration gradients, is important for epidemiological studies. Earlier and recent studies examining particulate exposure have shown variation by size and chemical composition in different zones within Mexico City (Manzano-León, Quintana et al. 2013; Osornio-Vargas, Bonner et al. 2003).

Conclusions

The power of perinatal epidemiology studies in Mexico City can be enhanced by knowing the location where pregnant women spend their time, enabling exposure estimation in both temporal and spatial domains, and thus maximizing exposure contrasts. Second, OK and IDW interpolation methods yielded similar estimated exposures among the simulated residences, so use of these metrics in studies with health outcomes may yield similar associations. If epidemiologic effect estimates do not differ significantly among the four exposure estimation metrics, using OK may be a recommended approach due to the available standard errors. Third, the zone of Mexico City in which women live can affect how well different exposure metrics correlate. This suggests that measurement error may have variable magnitude depending on zone of residence, especially when using a method like CWA.

Application of the exposure estimation methods we described in perinatal epidemiology may help clarify controversies about the role of exposure to air pollutants and the development of specific conditions, such as preterm labor, as limited and inconclusive evidence has been found by researchers (Liu, Krewski et al. 2003; Simpson, Williams et al. 1997; Vadillo-Ortega, Osornio-Vargas et al. 2014). However, factors relevant to preterm risk could also differ by zone of residence, so disentangling the contribution of exposure measurement error from confounding by these other factors could present a challenge.

Our plans to combine the estimated exposures from outdoor monitors with biomarker data, reports on personal activities and exposure, and detailed clinical data, will improve our ability to understand how air pollution influences perinatal health, in Mexico City and elsewhere, and to set control and prevention priorities.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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Implications

Many studies evaluating associations between outdoor air pollution and adverse pregnancy outcomes rely on outdoor air pollution monitoring data linked to information gathered from large birth registries, and often lack residence location information needed to estimate individual exposure. This study simulated 1,000 residential locations to evaluate four air pollution exposure assessment methods, and describes possible exposure misclassification from using spatial averaging versus geo-statistical interpolation models. Implications of this work are that policies to reduce air pollution and exposure among pregnant women based on epidemiologic literature should take into account possible error in estimates of effect when spatial averages alone are evaluated.

Figure 1.
Location of simulated subjects' residences, Thiessen polygons and air quality monitors in Mexico City.

Descriptive statistics for four exposure metrics calculated for 1,000 simulated residents of Mexico City using daily concentrations of air pollutants during calendar year 2008.

Table 1

Pollutant (Monitors)	Method	Entire year 2008			Dry Season ^a			Wet Season ^b		
		Mean±(SD) ^c	Range	Mean±(SD) ^c	Range	Mean±(SD) ^c	Range	Mean±(SD) ^c	Range	Mean±(SD) ^c
PM ₁₀ (µg/m ³) 14 Sites	CWA	53.2 (20.6)	14.4 – 109.7	67.8 (15.4)	20.7 – 109.7	38.8 (13.9)	14.4 – 88.0	38.8 (13.9)	14.4 – 88.0	38.8 (13.9)
	NM	53.7 (25.4)	8.0 – 214.1	68.9 (23.8)	15.1 – 214.1	38.7 (16.6)	8.0 – 122.5	38.7 (16.6)	8.0 – 122.5	38.7 (16.6)
	IDW	54.1 (22.6)	8.2 – 209.8	68.8 (19.2)	15.3 – 209.7	39.4 (15.2)	8.2 – 120.6	39.4 (15.2)	8.2 – 120.6	39.4 (15.2)
	OK	52.9 (22.8)	8.4 – 206.7	67.8 (19.5)	15.7 – 206.7	38.1 (14.8)	8.4 – 113.2	38.1 (14.8)	8.4 – 113.2	38.1 (14.8)
PM _{2.5} (µg/m ³) 9 Sites	CWA	26.8 (10.1)	7.7 – 67.0	32.4 (8.3)	9.2 – 67.0	21.4 (8.7)	7.7 – 52.5	21.4 (8.7)	7.7 – 52.5	21.4 (8.7)
	NM	27.6 (13.0)	4.5 – 110.3	33.7 (12.5)	6.2 – 110.3	21.6 (10.5)	4.5 – 91.3	21.6 (10.5)	4.5 – 91.3	21.6 (10.5)
	IDW	27.4 (11.3)	4.6 – 110.2	33.1 (10.0)	6.2 – 110.2	21.7 (9.4)	4.6 – 91.1	21.7 (9.4)	4.6 – 91.1	21.7 (9.4)
	OK	26.3 (10.0)	5.6 – 102.4	31.6 (8.2)	6.5 – 102.4	21 (8.6)	5.6 – 82.6	21 (8.6)	5.6 – 82.6	21 (8.6)
O ₃ (ppb) 22 Sites	CWA	58.0 (18.5)	12.7 – 113.3	61.6 (16.5)	22.7 – 98.3	54.4 (19.6)	12.7 – 113.3	54.4 (19.6)	12.7 – 113.3	54.4 (19.6)
	NM	56.8 (21.3)	3.50 – 160.3	60.5 (20)	3.50 – 127.4	53.1 (21.9)	4.0 – 160.3	53.1 (21.9)	4.0 – 160.3	53.1 (21.9)
	IDW	56.9 (19.6)	4.5 – 151.5	60.6 (17.7)	4.50 – 124.7	53.3 (20.6)	4.7 – 151.5	53.3 (20.6)	4.7 – 151.5	53.3 (20.6)
	OK	56.6 (19.0)	5.4 – 134.5	60.3 (17.1)	6.70 – 127.3	52.9 (20.0)	5.4 – 134.5	52.9 (20.0)	5.4 – 134.5	52.9 (20.0)
NO ₂ (ppb) 18 Sites	CWA	30.6 (9.3)	10.7 – 62.4	35.6 (9.4)	16.1 – 62.4	25.7 (6.0)	10.7 – 48.8	25.7 (6.0)	10.7 – 48.8	25.7 (6.0)
	NM	30.3 (10.9)	3.2 – 79.2	35.0 (11.2)	3.50 – 79.2	25.7 (8.2)	3.2 – 70.7	25.7 (8.2)	3.2 – 70.7	25.7 (8.2)
	IDW	31.4 (9.9)	3.6 – 78.6	36.2 (10.0)	4.20 – 78.6	26.6 (7.1)	3.6 – 70.0	26.6 (7.1)	3.6 – 70.0	26.6 (7.1)
	OK	29.7 (10.0)	3.5 – 78.9	34.8 (9.9)	4.80 – 78.9	24.7 (7.0)	3.5 – 70.0	24.7 (7.0)	3.5 – 70.0	24.7 (7.0)
CO (ppm) 17 Sites	CWA	1.54 (0.58)	0.40 – 3.45	1.88 (0.58)	0.55 – 3.45	1.21 (0.36)	0.44 – 2.30	1.21 (0.36)	0.44 – 2.30	1.21 (0.36)
	NM	1.57 (0.75)	0.07 – 5.47	1.92 (0.76)	0.09 – 5.47	1.22 (0.56)	0.07 – 3.59	1.22 (0.56)	0.07 – 3.59	1.22 (0.56)
	IDW	1.59 (0.63)	0.08 – 5.39	1.92 (0.64)	0.13 – 5.39	1.26 (0.44)	0.08 – 3.53	1.26 (0.44)	0.08 – 3.53	1.26 (0.44)
	OK	1.50 (0.60)	0.20 – 5.00	1.90 (0.60)	0.20 – 5.00	1.20 (0.4)	0.10 – 3.6	1.20 (0.4)	0.10 – 3.6	1.20 (0.4)
SO ₂ (ppb) 26 Sites	CWA	6.67 (5.12)	2.29 – 33.9	8.00 (6.10)	2.50 – 33.9	5.37 (3.45)	2.29 – 22.1	5.37 (3.45)	2.29 – 22.1	5.37 (3.45)
	NM	6.38 (6.30)	1.00 – 164.3	7.50 (7.58)	1.00 – 164.3	5.27 (4.41)	1.00 – 49.1	5.27 (4.41)	1.00 – 49.1	5.27 (4.41)
	IDW	6.56 (5.65)	1.02 – 163.0	7.82 (6.76)	1.02 – 163.0	5.32 (3.90)	1.00 – 46.3	5.32 (3.90)	1.00 – 46.3	5.32 (3.90)
	OK	6.00 (5.3)	0.91 – 153.0	7.00 (6.3)	1.00 – 153.0	4.90 (3.7)	0.90 – 43.3	4.90 (3.7)	0.90 – 43.3	4.90 (3.7)

^a Dry Season (November – April);

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Wet Season (May – October),
Standard deviation

Table 2

Pearson correlation coefficients among four metrics estimating the exposure of 1,000 simulated women to six different air pollutants in Mexico City, 2008. All p values <0.05. N's range from 140,910 to 319,860, due to missing data and OK estimates being restricted to locations within pollutant specific polygons.

	CWA (N)	NM (N)	IDW (N)
	<u>PM₁₀</u>		
NM	0.83		
IDW	0.92	0.95	
OK	0.92	0.94	0.98
	<u>PM_{2.5}</u>		
NM	0.83		
IDW	0.93	0.95	
OK	0.99	0.84	0.94
	<u>O₃</u>		
NM	0.85		
IDW	0.94	0.95	
OK	0.96	0.91	0.97
	<u>NO₂</u>		
NM	0.82		
IDW	0.93	0.94	
OK	0.93	0.91	0.97
	<u>CO</u>		
NM	0.77		
IDW	0.91	0.92	
OK	0.94	0.85	0.96
	<u>SO₂</u>		
NM	0.77		
IDW	0.88	0.95	
OK	0.83	0.93	0.97

Table 3

Mean differences and standard deviations (SD) of the differences in air pollution exposure estimates produced by three exposure assessment methodologies for 1,000 simulated women in Mexico City during 2008, with ordinary Kriging used as reference method.

Zone	Model	Mean Difference (SD)					
		PM ₁₀ (µg/m ³)	PM _{2.5} (µg/m ³)	O ₃ (ppb)	NO ₂ (ppb)	CO (ppm)	SO ₂ (ppb)
All Zones	CWA	0.34 (9.03)	0.56 (1.04)	1.40 (5.43)	0.88 (3.61)	-0.03 (0.20)	0.71 (3.03)
	NM	0.84 (8.96)	1.36 (7.10)	0.20 (9.06)	0.59 (4.53)	0.02 (0.40)	0.42 (2.44)
	IDW	-2.30 (12.2)	0.38 (5.10)	-2.68 (8.29)	-0.07 (6.02)	-0.10 (0.34)	-0.18 (1.97)
1	CWA	-1.14 (5.83)	0.61 (0.94)	1.94 (4.67)	-1.53 (3.77)	-0.11 (0.24)	0.59 (2.19)
	NM	1.75 (7.37)	0.13 (3.57)	-1.30 (8.17)	1.69 (5.07)	0.18 (0.40)	0.21 (2.02)
	IDW	-3.40 (10.8)	-0.12 (3.11)	-2.62 (5.85)	1.03 (3.42)	0.01 (0.22)	-0.27 (1.75)
2	CWA	0.94 (5.52)	0.43 (1.48)	0.97 (4.68)	1.05 (2.71)	-0.01 (0.14)	1.57 (2.81)
	NM	0.08 (7.99)	4.95 (10.23)	1.57 (9.25)	1.14 (4.54)	0.08 (0.40)	0.24 (2.15)
	IDW	-2.50 (9.83)	2.46 (7.52)	-4.22 (8.71)	0.19 (6.54)	-0.13 (0.36)	-0.21 (1.71)
3	CWA	7.49 (7.47)	0.76 (0.90)	-0.91 (5.82)	0.72 (3.67)	0.09 (0.24)	0.97 (2.37)
	NM	-3.09 (5.91)	-2.78 (3.87)	4.18 (8.54)	0.94 (4.55)	-0.20 (0.45)	0.41 (1.86)
	IDW	-7.21 (14.0)	-2.31 (3.49)	-3.29 (13.2)	-2.40 (11.1)	-0.30 (0.55)	-0.64 (2.35)
4	CWA	7.26 (7.95)	0.65 (0.49)	-0.23 (4.82)	1.18 (2.83)	0.03 (0.22)	0.18 (2.76)
	NM	-3.62 (6.31)	-0.92 (4.69)	2.56 (7.64)	0.71 (3.28)	0.05 (0.40)	0.64 (2.24)
	IDW	-3.40 (5.57)	-1.22 (2.96)	0.33 (6.4)	0.76 (3.04)	-0.05 (0.26)	0.14 (1.75)
5	CWA	-4.17 (10.5)	0.58 (0.71)	2.83 (6.03)	1.70 (4.02)	0.01 (0.19)	0.12 (3.55)
	NM	4.11 (10.5)	-0.59 (4.24)	-2.39 (9.05)	-0.54 (4.45)	-0.05 (0.32)	0.59 (3.55)
	IDW	-1.80 (15.5)	0.01 (2.84)	-2.30 (7.36)	-0.50 (5.08)	0.10 (0.29)	-0.12 (2.22)

Note: Zone 1=Center; Zone 2=East; Zone 3=South; Zone 4=West; Zone 5=North. Negative values reflect underestimation by the exposure method being compared to ordinary Kriging. Mean differences were calculated as CWAconcentration - OKconcentration for each day and then averaged for the whole year for each woman, and then the mean and SD across all women calculated for each pollutant; identical calculations done for IDW and NM.

Table 4

Descriptive statistics for estimated concentrations of each pollutant for locations inside pollutant specific polygons in 2008 in Mexico City, and standard errors (*SE*) and coefficient of variation (*COV*)^a for OK estimates.

Pollutant	Method	N	Mean	SD	Range
PM ₁₀ (µg/m ³) 14 Sites	CWA	189,222	53.2	20.6	14.4, 109.7
	NM	189,210	55.1	25.7	8.0, 214.1
	IDW	189,222	50.6	21.9	8.2, 206.4
	OK	189,222	53.6	22.8	8.4, 194.4
	OK (<i>SE</i>)		10.5		0.5, 66.0
	OK (<i>COV</i>)	0.46			
PM _{2.5} (µg/m ³) 9 Sites	CWA	154,452	26.8	10.1	7.7, 67.0
	NM	154,452	27.0	12.0	4.5, 110.3
	IDW	154,452	26.2	10.8	4.6, 108.8
	OK	154,452	26.2	9.9	5.6, 88.2
	OK (<i>SE</i>)		38.7		3.2, 100.0
	OK (<i>COV</i>)	3.9			
O ₃ (ppb) 22 Sites	CWA	319,884	58.0	18.5	12.7, 113.3
	NM	319,860	57.1	21.4	3.5, 160.3
	IDW	319,518	53.8	20.0	4.5, 151.5
	OK	319,884	56.7	19.0	5.4, 134.5
	OK (<i>SE</i>)		10.4		0.6, 107.5
	OK (<i>COV</i>)	0.55			
CO (ppm) 17 Sites	CWA	140,910	1.54	0.58	0.44, 3.45
	NM	140,886	1.66	0.77	0.07, 5.47
	IDW	140,910	1.53	0.68	0.08, 5.39
	OK	140,910	1.58	0.64	0.19, 4.99
	OK (<i>SE</i>)		0.45		0.07, 1.19
	OK (<i>COV</i>)	0.70			
NO ₂ (ppb) 18 Sites	CWA	163,236	30.6	9.3	10.7, 62.4
	NM	163,223	32.3	11.6	3.2, 79.2
	IDW	163,236	30.4	10.6	3.6, 78.6

Pollutant	Method	N	Mean	SD	Range
SO ₂ (ppb) 26 Sites	OK	163,236	31.0	10.4	3.5, 78.9
	OK (SE)		5.0		0.5, 18.0
	OK (COV)	0.48			
	CWA	308,904	6.67	5.12	2.29, 33.89
	NM	308,461	6.30	6.32	1.00, 16.43
	IDW	308,904	5.72	5.36	1.00, 16.27
	OK	308,904	5.92	5.28	0.09, 15.30
	OK (SE)		2.44		0.11, 53.8
	OK (COV)	0.46			

Note: The sample sizes used to calculate these summary statistics differ by pollutant and method because 1) differing subsets of the 1,000 locations fell inside pollutant specific polygons (PM₁₀: 517; PM_{2.5}: 422; O₃: 874; CO: 385; NO₂: 446 and SO₂: 844) and 2) some daily pollutant concentrations were missing on certain days.

^a Coefficient of variation (COV) for OK = (mean standard error of estimates/mean standard deviation of concentrations/)

Root mean square errors (RMSE) by exposure method when data are cross-validated with the actual concentrations measured at Mexico City air pollution monitors during 2008.

Table 5

Pollutant	Exposure Method	RMSE	Range ^a
PM ₁₀ (µg/m ³) 14 Sites	Nearest Monitor	0.281	0.092 – 0.555
	IDW	0.226	0.091 – 0.395
PM _{2.5} (µg/m ³) 9 Sites	Ordinary Kriging	0.218	0.077 – 0.463
	Nearest Monitor	0.247	0.087 – 0.738
	IDW	0.229	0.076 – 0.535
O ₃ (ppb) 22 Sites	Ordinary Kriging	0.230	0.082 – 0.508
	Nearest Monitor	0.320	0.084 – 1.280
	IDW	0.235	0.071 – 0.710
CO (ppm) 17 Sites	Ordinary Kriging	0.210	0.066 – 0.660
	Nearest Monitor	0.513	0.180 – 1.220
	IDW	0.402	0.153 – 0.900
NO ₂ (ppb) 18 Sites	Ordinary Kriging	0.380	0.150 – 0.890
	Nearest Monitor	0.271	0.088 – 0.598
	IDW	0.235	0.080 – 0.499
SO ₂ (ppb) 26 Sites	Ordinary Kriging	0.230	0.081 – 0.510
	Nearest Monitor	0.611	0.267 – 1.010
	IDW	0.495	0.285 – 0.820
	Ordinary Kriging	0.476	0.260 – 0.900

^aRange (Minimum – Maximum)