MONITORING VS. MODELED EXPOSURE DATA IN TIME-SERIES STUDIES OF AMBIENT AIR POLLUTION AND ACUTE HEALTH OUTCOMES

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Abstract

Background.—Population-based short-term air pollution health studies often have limited spatiotemporally representative exposure data, leading to concerns of exposure measurement error.

Objective.—To compare the use of monitoring and modeled exposure metrics in time-series analyses of air pollution and cardiorespiratory emergency department (ED) visits.

Methods.—We obtained daily counts of ED visits for Atlanta, GA during 2009–2013. We leveraged daily ZIP code level concentration estimates for eight pollutants from nine exposure metrics. Metrics included central monitor (CM), monitor-based (inverse distance weighting, kriging), model-based [community multiscale air quality (CMAQ), land use regression (LUR)], and satellite-based measures. We used Poisson models to estimate air pollution health associations using the different exposure metrics. The approach involved: (1) assessing CM-based associations, (2) determining if non-CM metrics can reproduce CM-based associations, and (3) identifying potential value added of incorporating full spatiotemporal information provided by non-CM metrics.

Results.—Using CM exposures, we observed associations between cardiovascular ED visits and carbon monoxide, nitrogen dioxide, fine particulate matter, elemental and organic carbon,

and between respiratory ED visits and ozone. Non-CM metrics were largely able to reproduce CM-based associations, although some unexpected results using CMAQ- and LUR-based metrics reduced confidence in these data for some spatiotemporally-variable pollutants. Associations with nitrogen dioxide and sulfur dioxide were only detected, or were stronger, when using metrics that incorporate all available monitoring data (i.e., inverse distance weighting and kriging).

Significance.—The use of routinely-collected ambient monitoring data for exposure assignment in time-series studies of large metropolitan areas is a sound approach, particularly when data from multiple monitors are available. More sophisticated approaches derived from CMAQ, LUR, or satellites may add value when monitoring data are inadequate and if paired with thorough data characterization. These results are useful for interpretation of existing literature and for improving exposure assessment in future studies.

Keywords

Air pollution; criteria pollutants; epidemiology; exposure modeling; particulate matter; population-based studies

INTRODUCTION

Substantial evidence supports short-term associations of ambient air pollution and health, including cardiovascular and respiratory illnesses (1, 2). Contributing to this body of evidence are population-based studies that relate day-to-day changes in ambient concentrations to indicators of population health for a community, such as daily counts of deaths or hospitalizations. These studies have had considerable weight in setting of National Ambient Air Quality Standards (NAAQS) in the US (3). Ideally, communities represented in these studies are reflective of all populations of concern; this includes populations of different geographic extents ranging from those living in specific neighborhoods within a city, to entire metropolitan statistical areas, and rural regions.

A common challenge in short-term health effect studies is the limited availability of spatially representative air pollution exposure data for the study population. The most commonly available data are compliance monitoring data routinely-collected by state and federal agencies. Monitoring data provide highly accurate time series of pollutant concentrations at the monitoring site, and thus make these data highly relevant for temporal studies. However, these measurements are inherently limited in that they may not represent concentrations across space. Their ability to reflect population-level exposure for a given study area depends on the density (numbers and placement) of the monitors and pollutant variability over space. For pollutants that vary little over space [e.g., ozone (O_3), a secondary pollutant, or fine particulate matter ($PM_{2.5}$), which has predominant contributions from secondary particle components, such as sulfate and nitrate] (4), limited monitors may represent concentrations across a large study area reasonably well. For pollutants that vary substantially over space such as primary pollutants emitted directly from mobile or stationary sources [e.g., nitrogen dioxide (NO_2) or sulfur dioxide (SO_2)] (4), limited measurement locations are unlikely to accurately represent concentrations across a large study area over which health outcomes are aggregated.

For studies relying on air monitoring alone, the exposure and health outcome data are often misaligned in space, leading to concerns of exposure measurement error (5). Spatial misalignment can contribute to exposure measurement error that biases observed health effect associations to different degrees for different pollutants (5–7). Simulation studies in the Atlanta metropolitan area have estimated that error due to uncaptured pollutant spatial variability leads to 43–68% reductions in observed health effect estimates for primary pollutants (e.g., NO_2, SO_2) compared to only 16% for secondary pollutants (e.g., O_3) when assigning exposures based on central monitors (6). Exposure measurement error due to spatial misalignment is likely to be non-constant across days; for example, the higher spatial contrast in traffic pollutant concentrations when traffic pollution is high will result in greater measurement error compared to when traffic pollution is low.

Approaches to handle such measurement error include: 1) restriction of study areas to specific distances from monitors (8–10); 2) application of statistical methods to estimate and adjust health effects estimates for spatial misalignment error (5, 11); and 3) application of modeled daily air pollution estimates that provide greater study area coverage (12–19). The latter presents opportunities for directly limiting exposure measurement error in population-based time-series studies with geographically expansive study areas. However, the impact on epidemiologic findings of different types of exposure metrics across different patient populations with varying spatiotemporal profiles is understudied. Specifically, few studies to our knowledge have compared and interpreted the use of different types of exposure metrics in time-series analyses of multiple pollutants and outcomes (15, 20, 21).

To address this gap, we leveraged a long-standing study of air pollution and emergency department (ED) visits in Atlanta, Georgia (22–27). Our study area includes the 20-county Atlanta metropolitan statistical area (1999 definition), comprising 15,790 square kilometers and a population of 5,110,183 persons in 2010 (28). While we do not include rural counties outside of the MSA, the Atlanta MSA includes territories and populations that may be rural. County population density ranges from relatively high (e.g., 2,586 persons/sq. mile in DeKalb County) to relatively low (126 persons/sq. mile in Pickens County). While the majority of the population (66%) resides in the five most densely populated central counties of the city (Clayton, Cobb, DeKalb, Fulton, Gwinnett), a sizeable percent of the population (44%) resides in outer counties.

Building on previous exposure modeling efforts (29, 30), Yu and colleagues developed a set of nine daily exposure metrics, using a range of monitoring- and model-based approaches, for eight pollutants for the 2009–2013 period for our study area (31). Here, we applied these outputs to epidemiologic analyses of cardiorespiratory ED visits, and compared the resulting health effect estimates across exposure metrics. Our assessment involved a 3-step approach: (1) estimating associations using concentrations from a central monitor (CM), a common method for characterizing daily air pollution in time-series studies (32); (2) determining if non-CM exposure metrics can reproduce CM-based associations; and (3) identifying potential value added of incorporating the full spatiotemporal information provided by non-CM exposure metrics.

MATERIALS AND METHODS

Emergency Department Visit Data

We obtained daily counts of cardiorespiratory ED visits for patients living in 192 residential ZIP codes located wholly or partially within the 20-county Atlanta area for the period January 1, 2009 to December 15, 2013 (n=1800 days). Data were aggregated from individual-level hospital billing records obtained through the Georgia Hospital Association (26, 33). During the 2009–2013 time period, 38 of 39 hospitals were represented, capturing over 95% of all ED visits in the study area. We identified outcomes based on patient billing records with primary International Classification of Diseases, 9th Revision (ICD-9) diagnosis codes for: cardiovascular disease (CVD, ICD-9 codes: 410–414, 427, 428, 433–437, 440, 443–445, 447) and respiratory disease (RESP, ICD-9 codes 460–519).

Air Pollution Exposure Metrics

Air pollution exposure metric estimation approaches are provided in detail by Dharmalingam and colleagues (31). Brief descriptions of the nine metrics and how we applied them for this analysis, are provided below. Daily pollutant measures from each metric included 1-hour maximum concentrations of carbon monoxide (CO), NO_2, and SO_2; 8-hour average maximum O_3; and 24-hour average $PM_{2.5}$, $PM_{2.5}$ sulfate (SO_4), $PM_{2.5}$ elemental carbon (EC), and $PM_{2.5}$ organic carbon (OC).

1. Central Monitor (CM).—The Jefferson St. (JST) site, part of the SouthEastern Aerosol Research and Characterization (SEARCH) network, was selected as the central monitoring site. The JST site is located in a central urbanized area of Atlanta approximately 2.3 km away from the nearest major roadway and provided daily concentrations for all pollutants of interest.

2. Site Average (SA).—The SA metric averaged daily concentration data from all monitors located inside the 20-county Atlanta region, obtained from the U.S. Environmental Protection Agency (USEPA) and the Southeastern Aerosol Research and Characterization (SEARCH) study (34, 35). Data were available from 19 monitors, with the number of monitors per pollutant varying: CO=4, NO_2=5, SO_2=5, O_3=10, $PM_{2.5}$=14, SO_4=3, EC=3, and OC=3 [Supplemental Table S1; see also Dharmalingam et al. (2022) Figure S2 (31)].

3. Inverse Distance Weighting (IDW).—IDW is a spatial interpolation method in which pollutant concentrations are inferred at unknown locations. In this study, daily pollutant concentration data were interpolated to the centroids of each of the 192 Atlanta study area ZIP codes using observations collected from all USEPA and SEARCH monitors located within the 200 km radius of the study area. Data were available from 141 monitors, with the number of monitors per pollutant varying: CO=12, NO_2=12, SO_2=23, O_3=76, $PM_{2.5}$=88, SO_4=27, EC=27, and OC=24 [see Dharmalingam et al. (2022) Figure S2 (31)].

4. Kriging (KRIG).—Kriging is also a spatial interpolation method, which unlike IDW, uses optimal weights derived from observed spatial dependence. For each pollutant, Kriging prediction was based on a parametric variogram, estimated using binned empirical

semivariance. The fitted variogram model for each pollutant was then used to estimate daily pollutant concentrations at ZIP code centroids.

5.   Community Multiscale Air Quality Model (CMAQ).—CMAQ is a chemical transport air quality model driven by emissions and meteorology. Here, we used a 12 km gridded product generated by the USEPA and the Centers for Disease Control and Prevention as part of the Public Health Air Surveillance Evaluation study (36, 37). The 12 km resolution CMAQ data were mapped to ZIP codes via area-weighting to obtain daily concentrations for each pollutant at each ZIP code. Since the CMAQ model itself generally does not incorporate observations, daily temporal variability in pollutant concentrations is purely modeled and is generally not reproduced well (31). As a result, we do not consider raw CMAQ as a directly suitable metric for daily time-series applications, however we include it as a comparison with the next two CMAQ-based metrics that do incorporate monitoring information.

6.   CMAQ-Kriging (CMAQKR).—The CMAQKR approach uses observations and Kriging to adjust CMAQ model outputs. Specifically, daily ratios of CMAQ/observations were calculated at all monitor locations within the 200 km radius study domain. These ratios were then interpolated to all 12 km CMAQ grid cell centroids using Kriging. Daily CMAQ concentrations at each grid cell were adjusted proportionately using the interpolated ratios, and then mapped to ZIP codes via area-weighting to obtain daily concentrations for each pollutant at each ZIP code.

7.   CMAQ Data Fusion (CMAQDF).—We collected a ready-to-use CMAQDF data product (developed by the Georgia Institute of Technology) for this study for 2009–2013 (29, 38). The CMAQDF approach is designed to correct for modeling biases/errors within CMAQ data. It also accounts for the potential for specific locations being consistently impacted by very local sources leading to observations higher than surrounding areas. In CMAQDF, two concentration fields were developed. The first field assimilated temporal variations of observation data and spatial structure from CMAQ results, and the second field incorporated spatial and temporal variations of CMAQ data which were also scaled using observation data to correct for modeling biases. The two developed fields were then fused together using weighting factors that vary over space based on their ability to predict temporal variations.

8.   Land Use Regression (LUR) – NO_2 and $PM_{2.5}$ only.—LUR is a potentially computationally-intensive empirical supervised multiple regression approach to simulate traffic-related pollutant concentration fields when sufficient measurement locations are available. Here, sufficient locations and computing resources were available to estimate NO_2 and $PM_{2.5}$. In LUR, concentration measurement data are related to spatially or temporally varying candidate predictor variables. Candidate predictor variables included land use (elevation, population, land cover types and roadway types), meteorological parameters (visibility, boundary layer height, precipitation, radiations, pressure, humidity, temperature, wind), pollutant emission data and output data from the CMAQ model. Using LUR, we

estimated daily concentrations of NO_2 and $PM_{2.5}$ at 1 km grid cells covering the study area, and then mapped concentrations to ZIP codes via area-weighting.

9.   Aerosol Optical Depth (AOD) – PM$_{2.5}$ only.—Use of satellite observational data has gained popularity in exposure modeling over the past decade due to their broad spatial coverage (39–41). Essentially, the AOD approach is based on a regression that associates satellite AOD data with available ground-based observational data. In this study, we applied a Bayesian-based calibration method (42) with 1-km resolution AOD data obtained from the Multiangle Implementation of Atmospheric Correction (MAIAC) (43) downscaled from MODIS data. Using this approach, we estimated daily concentrations of $PM_{2.5}$ at 1 km grid cells covering the study area, and then mapped concentrations to ZIP codes via area-weighting.

Epidemiological Study Approach

The goal of this study was to estimate and compare associations of air pollution and cardiorespiratory ED visits across exposure metrics. The epidemiologic model used to estimate the associations is described below. The study approach consisted of three steps that facilitated the comparison of effect estimates across exposure metrics.

Step 1. CM Analysis.—First, we estimated the pollutant-outcome relationships for the central monitor. The daily CM value of each pollutant, from the JST monitoring station, was assigned to all 192 study area ZIP codes (i.e., same daily values for each ZIP code). With the CM metric, any potential spatiotemporal concentration variability in the study area is neglected.

Step 2. Central ZIP Analysis.—Second, we determined if the non-CM exposure metrics were able to reproduce the CM-based associations. For this analysis, we assigned the daily value of each pollutant from the non-CM exposure metrics at the ZIP code that houses the JST central monitor (ZIP code 30318) to all 192 ZIP codes (i.e., same daily values for each ZIP code). Therefore, this approach again neglects any potential spatiotemporal concentration variabilities. This step is analogous to Step 1, but with exposures assigned using each of the non-CM metrics estimated at the same location. If the non-CM metrics estimate daily concentrations near the CM well, observed health effect estimates should be similar.

Step 3. Full Spatial Analysis.—Finally, to assess potential value added of utilizing exposure metrics with spatial information, for each non-CM exposure metric we assigned the daily ZIP code-specific pollution value to each study area ZIP code (i.e., allowing different daily values for each ZIP code). Unlike the previous two steps, this approach incorporates spatiotemporal information in health effects estimation and therefore we anticipated either similar or stronger health effect estimates compared to the previous two steps. [Note that the SA metric results from this approach were identical to those from the Central ZIP approach (Step 2) given that the SA provided only one value per day for the entire study area].

To facilitate comparisons, exposure metrics were matched for missing values by pollutant. For example, if data for a certain pollutant (e.g., NO_2) were missing for one exposure metric (e.g., CM) for a specific date, the data for the other exposure metrics for that pollutant were also set to missing for that date; the resulting sample size (ZIP code-days) was the same for all metrics for a given pollutant.

Epidemiologic Model

Main Model.—We used Poisson generalized linear models to estimate associations between daily measures of air pollution and daily counts of ED visits for cardiovascular and respiratory outcomes, following the 3-step epidemiological study approach. For each study approach, the form of the model was the same:

$$
\begin{aligned}
\log\left(E(Y_{kt})\right) &= \beta_0 + \beta_1 pollution_{kt} + \sum_k \beta_{2k} Zip_k + \sum_n \beta_{3n} hospital_{nt} \\
&+ \sum_m \beta_{4m} dow\_h_{mt} + \sum_o \beta_{5o} season_{ot} + \sum_{mo} \beta_{6mo}(dow_{h_{mt}} * season_{ot}) \\
&+ \sum_{7p} \beta_{7p} holiday_{oth_{pt}} + \sum_q \beta_{8q} maxT\_l0_{qt} + \beta_9 minT\_ma17_t + \beta_{10} minT\_ma17_t^2 \\
&+ \beta_{11} minT\_ma17_t^3 + \beta_{12} meanDT\_ma07_t + \beta_{13} meanDT\_ma07_t^2 + \beta_{14} meanDT \\
&\_ma07_t^3 + g(\gamma_1, \ldots, \gamma_N; time_t)
\end{aligned}
\qquad \text{Eq. 1}
$$

where Y_{kt} was the count of ED visits in ZIP code k on day t for CVD or RESP. *Pollution* referred to the moving average (of lag days 0–7) concentrations for a given pollutant-metric-assignment of interest in ZIP code k on day t. The geographical area (*zip*) from which ED counts were spatially aggregated was represented by indicator variables, to control for spatially-varying factors and enable the analysis to rely solely on temporal contrasts; this also stringently controlled for spatial autocorrelation in the baseline ED visits across ZIP codes. The models included indicator variables for *hospital* to account for any entry and exit of hospitals during the study period, day of week and federal holidays (*dow_h*), *season* (Winter=Dec-Feb, Spring=Mar-May, Summer=June-Aug, Autumn=Sep-Nov), an interaction between *dow_h* and *season*, and additional holiday indicators (*holiday_oth*) for New Year's Day, Independence Day, Veterans Day, Thanksgiving, and Christmas Day when different from the date of the federal holiday. Meteorology was controlled using indicator variables for same-day (lag 0) maximum temperature (*maxT_l0*, for each degree Celsius), and cubic terms for the moving averages of minimum temperature (lags 1–7, *minT_ma17*) and mean dew point temperature (lags 0–7, *meanDT_ma07*). Finally, long-term trends in case presentation rates (*time*) were controlled with parametric cubic splines with monthly knots for CVD ED visits and bi-monthly (2 knots per month) for RESP ED visits. Variance estimates were scaled to account for Poisson overdispersion. These modeling decisions (e.g., choice of *a priori* lags, meteorological control, and time trend control) were derived largely from our previous analyses (15, 22, 23, 45–47). We ran this model for each outcome, pollutant, exposure metric, and study approach combination. We scaled rate ratios (RR) and 95% confidence intervals (CI) to increases in pollutant concentrations as follows: 250 ppb for CO; 10 ppb for NO_2; 4 ppb for SO_2; 15 ppb for O_3; 5 μg/m^3 for $PM_{2.5}$; 1 μg/m^3 for SO_4; 0.5 μg/m^3 for EC; and 1 μg/m^3 for OC.

Sensitivity Analyses.—To assess robustness of our results to different model specifications, we considered two sets of sensitivity analyses based on the 'Full Spatial

Analysis' approach. We tested different lag structures for air pollution: lag 0, moving average of lag days 0–2, and moving average of lag days 0–5, and compared the results to the moving average of lag days 0–7 in our base model (Eq. 1). Meteorological controls were adjusted to match the lag structure of air pollution exposure in these analyses. In addition, we tested different specifications of temporal controls compared to our base model (Eq. 1): controlling for time using parametric cubic splines with two knots per month (for CVD ED visits) and one knot per month (for RESP ED visits); controlling for temperature with cubic terms for the moving average of mean temperature (lag days 0–7); and adding product terms for season*temperature. All epidemiological analyses were conducted in SAS V9.4 (SAS Institute, Inc., Cary, NC, USA).

RESULTS

ED Visit Summary

During 2009–2013, there were 230,718 ED visits (average of 128 visits/day) for CVD and 1,068,026 ED visits (average of 593 visits/day) for RESP. Figure 1 presents time-series plots of daily visit counts for each outcome. The visits were made by patients residing across the 192 ZIP codes, with ZIP code-level daily averages ranging from <1 to 2 for CVD and <1 to 11 for RESP. ED visit counts among the outcomes were similarly distributed over the study area (Supplemental Figure S1), with a high spatial correlation of total ZIP code-level visit counts between the two outcomes (r = 0.896). While similarly distributed over space, the outcomes were weakly correlated over time; the average ZIP code-level Pearson correlation of daily CVD and RESP ED visit counts was 0.016 (Supplemental Figure S1).

Air Pollution Levels

Table 1 presents summary concentrations for each pollutant-metric combination. Median levels and IQRs of primary pollutants (e.g., CO, NO_2, SO_2) differed across metrics more than for pollutants with secondary contributions (e.g., O_3, $PM_{2.5}$). Maps of ZIP code average pollutant concentrations by exposure metric are presented by Dharmalingam et al. (31). Note that data availability for OC (N of 86,976 ZIP code-days) was less than for other pollutants (N>340,000 ZIP code-days), due to lower monitoring coverage.

At the Central ZIP code (ZIP 30318), pollutant concentrations from the different exposure metrics were generally well correlated with the CM (Supplemental Table S2, blue shading). IDW, KRIG, and CMAQKR values were the most correlated with CM values for all pollutants (r>0.97). SA values were also correlated with CM values for all pollutants (r>0.80), but at slightly lower levels due to the influence of monitors located away from the CM. CMAQ values were least correlated with CM values (r = 0.47–0.79).

When considering the full spatial information of the exposure metrics data, pollutant concentrations from the different exposure metrics were also well correlated (Supplemental Table S2, red shading), although not as strongly as at the Central ZIP code. ZIP code-level correlations previously reported by Dharmalingam et al. (31) showed that for many pollutants, correlations were strongest in the city center and weakest towards the outskirts. In general, for spatiotemporally heterogeneous pollutants (such as CO, NO_2, SO_2,

EC), correlations among exposure metrics were more variable than for spatiotemporally homogeneous pollutants (such as O_3, $PM_{2.5}$, SO_4^{2-}, and OC).

Associations of Air Pollution and Cardiovascular ED Visits

Estimated associations of air pollution and ED visits for cardiovascular diseases are presented in Figure 2 and Supplemental Table S3. Rate ratios from models using the CM analysis approach (Figure 2, black RRs) were positive for several pollutants (i.e., CO, NO_2, $PM_{2.5}$, EC and OC).

When applying Central ZIP values from the non-CM exposure metrics, models largely reproduced the CM-based associations (Figure 2, blue RRs). For NO_2, for example, all RRs were positive and ranged from 1.010 (95% CI: 0.999–1.021) to 1.018 (95% CI: 0.996–1.040) per 10 ppb increase across metrics. The reproducibility of CM-based associations lend support to the non-CM exposure metrics in their ability to capture health-relevant temporal contrasts similar to the CM. The only exception was for CMAQ SO_2, for which Central ZIP exposures showed a positive association with CVD ED visits; given the lack of observed association using CM SO_2 data, this result was unexpected and reduces our confidence in the use of CMAQ SO_2 in this health study application.

When utilizing the full spatial information of exposure metrics (Figure 2, red RRs), estimated associations were largely similar to those estimated with Central ZIP data. However, for several pollutants (CO, NO_2, and EC), estimated associations – especially the three CMAQ-derived estimates and LUR – were considerably weaker when utilizing the full spatial data.

Associations of Air Pollution and Respiratory ED Visits

Estimated associations of air pollution and ED visits for respiratory diseases are presented in Figure 3 and Supplemental Table S3. Rate ratios from models using the CM analysis approach were positive only for O_3 (Figure 3, black RRs).

When applying Central ZIP values from the non-CM exposure metrics, models again largely reproduced the CM-based associations (Figure 3, blue RRs). For some pollutant-metrics (i.e., CMAQ NO_2, CMAQDF NO_2, LUR NO_2, CMAQ SO_2, and CMAQ EC), estimated associations were unexpectedly different from the CM-based associations. For example, while the RR for CM NO_2 [0.996 (95% CI: 0.989–1.002) per 10 ppb increase] was consistent with the null, RRs for NO_2 when using CMAQ [1.010 (95% CI: 1.003–1.016)], CMAQDF [1.012 (95% CI: 1.005–1.019)], and LUR [1.023 (95% CI: 1.010–1.036)] were considerably stronger. Again, these results reduce our confidence in the CMAQ- and LUR-based metrics for these pollutants in this health study application.

When utilizing the full spatial resolution of exposure metrics (Figure 3, red RRs), estimated associations showed largely similar patterns across exposure metrics as those using Central ZIP code assignment. Some important differences were noted. In particular, associations with NO_2 and SO_2 were only detected when assigning IDW and KRIG exposures utilizing their full spatial information; associations with O_3 were also stronger when utilizing these metrics. For example, the RR for full spatial KRIG NO_2 [1.026 (95% CI: 1.018–1.034) per

10 ppb increase] was considerably stronger than that for Central ZIP KRIG NO_2 [0.996 (95% CI: 0.989–1.002)].

Sensitivity Analyses

The observed pattern of associations across exposure metrics for both outcomes was largely unchanged when considering different exposure windows (Supplemental Figures S2 and S3), with the moving average of lag days 0–7 exposure window generally providing the strongest estimated association among different outcome-pollutant-exposure metric combinations. Similarly, the observed pattern of associations across exposure metrics was largely unchanged when considering different temporal control specifications in the model (Supplemental Figures S4 and S5). In general, less stringent time control (monthly knots for splines) led to stronger observed outcome-pollutant associations for RESP, and less stringent temperature control (moving average of mean temperature for lag days 0–7) also led to stronger observed outcome-pollutant associations.

DISCUSSION

In this study, we compared associations of cardiorespiratory ED visits and exposure to 8 ambient air pollutants estimated using multiple approaches in 20-county Atlanta, GA during 2009–2013. We utilized exposure metrics that varied considerably in complexity, both in terms of inputs required, computational resources needed, ease of implementation, and availability and ease of use to public health researchers (31). Using central monitor data, the simplest and common metric for characterizing daily air pollution in time-series studies (32), we observed a number of anticipated associations, including between CVD and combustion-related gases and particles (CO, NO_2, $PM_{2.5}$, EC and OC) as well as between RESP and O_3. To understand whether the effort and resources required for more complex exposure metrics development is warranted for the purpose of short-term air pollution health effects studies, we compared the use of the CM metric to non-CM metrics in a step-wise approach.

In the Central ZIP analysis, we conducted analyses with exposures for all 192 study area ZIP codes assigned using values from the ZIP code that houses the JST central monitor. We anticipated similar health effect estimates for a given pollutant comparing results using non-CM exposures metrics from this approach to those using CM exposure data. That is, if the non-CM metrics estimate daily concentrations near the CM well, observed health effect estimates should be similar. More specifically, this approach enabled an assessment of whether temporal over-smoothing, a recognized concern for predictions from statistical models (e.g., KRIG, CMAQ) because of regression to the mean (44), affected health effect estimates compared to the CM that reflects accurate temporal variability in its specific location. Indeed, estimated associations were largely similar across metrics at the Central ZIP. The reproducibility of CM-based associations lend support to the non-CM exposure metrics in their ability to capture health-relevant temporal contrasts similar to the CM for most pollutants.

Exceptions to this were several unexpected results for both CVD and RESP associations with NO_2, SO_2, and EC exposures from CMAQ, CMAQDF, and LUR metrics. CMAQ and

LUR data in this study were developed at 12 km and 1 km grid cell resolutions, respectively, thus providing good spatial characterization of pollutant concentrations (31). However, the ability of CMAQ and LUR to capture daily variation in pollutant concentrations at ZIP codes relies mostly on input emissions and meteorology data (and associated chemical transport and transformation processes for CMAQ), all of which are expected to contain considerable uncertainties; hence their estimated temporal concentration variability may be poor. In previous work, for example, we found that raw CMAQ data do not perform as well in reproducing temporal pollutant concentration variations in the study region due to modeling biases and errors (31). Given that CMAQ and LUR in this study would not be anticipated to provide good estimates of temporal variability (30, 31), we would have expected similar or weaker health effect associations compared with those of other metrics. However, we in fact observed stronger associations of CVD-SO_2, RESP-NO_2, RESP-SO_2, and RESP-EC with these metrics. While epidemiologic models of this study controlled strictly for time, the results may be highlighting complex temporal confounding, when pairing ED visit outcomes with modeled exposure metrics that have poor estimated temporal concentration variability. As such, health effect estimates derived from raw CMAQ and LUR data should be interpreted with caution. We note that CMAQKR and CMAQDF may partially overcome this shortfall when paired with rigorous time control in epidemiologic models, given their fusion to monitoring data, and were among the metrics with better performance in the evaluation by Dharmalingam et al. (31).

The Full Spatial analysis enabled a qualitative assessment of the potential value added in health effect estimation when incorporating the full spatial information provided by non-CM exposure metrics. We anticipated that use of full spatial data from the more complex multi-monitor and model-based exposure metrics would result in stronger health effect estimates compared to CM or Central ZIP exposure assignment, as these were specifically developed to provide a better estimate of population exposure for our large study area. We observed some anticipated results. In particular, associations for RESP and NO_2, SO_2, and O_3 were only detected or stronger when using IDW and KRIG full spatial data than when utilizing Central ZIP estimates for these pollutants. These results suggest that use of data from all monitors in and extended beyond the study area to generate ZIP code-specific concentration estimates, compared to relying on just on the central monitor may be important in observing health effects in some cases. We also observed some unanticipated results, most strikingly the weaker estimated associations for CVD when using full spatial CO, NO_2, and EC CMAQ-based and LUR metrics compared to those from the Central ZIP approach. It is possible that relatively low pollution levels with less variation in the outskirts of the city (31) contributed to the weaker observed health effect associations for CVD when using full spatial resolution data, and the results may be indicative of non-linear pollutant-CVD health associations.

There are several limitations to consider in this study. Some differences in associations observed among pollutants and metrics may be impacted by uncertainties in scaling to some degree; we selected a common increment by which to standardize rate ratios for each pollutant. However, because of different exposure distributions by different metrics, the scaling may not reflect expected changes in exposure equally well. It is important to note that scaling does not impact direction of effects (i.e., positive vs. negative) or significance.

It is also important to note that this particular analysis focused on time-series design, where minimizing temporal errors in the metrics is the most important, and other study designs may be more affected by spatial errors.

Conclusions

We conducted a time-series study of cardiorespiratory ED visits and ambient air pollutants estimated using a variety of approaches in 20-county Atlanta, GA during 2009–2013. Ultimately, associations observed with using the simplest CM exposure assignment were largely similar to those using more complex metrics. We found some evidence of better representation, in particular for NO_2 and SO_2, by monitoring-based metrics that incorporate all available monitoring data and interpolate to locations between monitors (i.e., IDW, KRIG). These findings are likely driven by the ability of air monitors to accurately characterize temporal contrasts at their location, which is the key exposure contrast for time-series health studies. Even though air monitors for most pollutants are often sparsely distributed over metropolitan regions in the US, our results suggest monitoring-based metrics are a sound exposure assignment approach. In locations where monitoring data are inadequate, our results provide some support for the use of CMAQ-, LUR-, and satellite-based metrics in time-series health studies. However, unexpected results using CMAQ- and LUR-based metrics for some pollutants (in particular, NO_2, SO_2, and EC) in their inability to reproduce associations observed using CM data temper our confidence. Use of these exposure metrics should be paired with thorough data characterization and validation within health analyses. We anticipate that the results of this research will be useful for interpretation of existing health effects literature and for improving exposure assessment in future air pollution epidemiology studies. Additional studies in other locations are warranted, especially for locations with different population spatial structures and monitoring availability and placement.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

DATA AVAILABILITY

This study was based on air pollution data from a variety of sources and on hospital billing records. We will make the air pollution exposure metrics data applied in this study, and

relevant documentation and metadata available without cost to researchers. Individuals and parties must agree to the conditions of use governing access to the public release data, including reporting responsibilities, restrictions on redistribution of the data to third parties, proper acknowledgement of the data resource, and restrictions on use for commercial purposes. We will not be able to make the hospital records data (neither patient-level nor aggregate forms) available to external investigators given restrictions in our data use agreements between Emory University and the Georgia Hospital Association. The exposure-response functions generated in this study are available in the Supplemental Material for incorporation into meta-analyses, health impact assessments, or other analyses by external investigators.

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IMPACT STATEMENT

This study compared and interpreted the use of monitoring and modeled exposure metrics in a daily time-series analysis of air pollution and cardiorespiratory emergency department visits. The results suggest that the use of routinely-collected ambient monitoring data in population-based short-term air pollution and health studies is a sound approach for exposure assignment in large metropolitan regions. CMAQ-, LUR-, and satellite-based metrics may allow for health effects estimation when monitoring data are sparse, if paired with thorough data characterization. These results are useful for interpretation of existing health effects literature and for improving exposure assessment in future air pollution epidemiology studies.
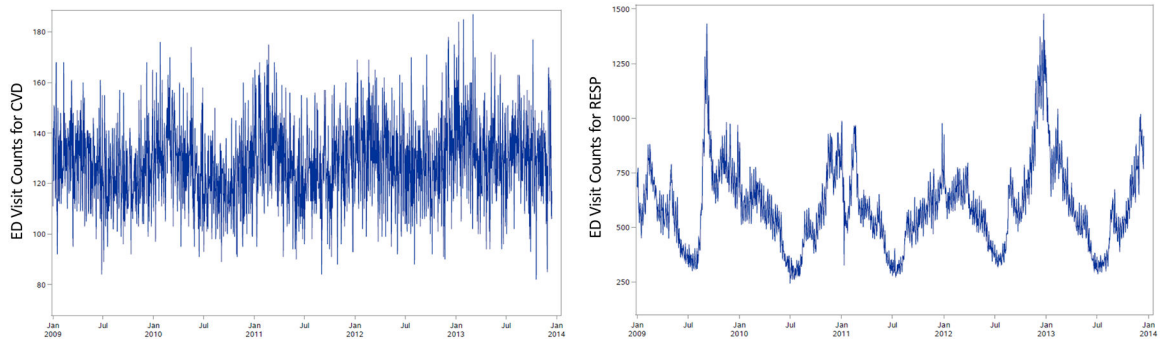
Figure 1.
Time-series plots of daily ED visit counts for cardiovascular diseases (left) and respiratory diseases (right) in 20-county Atlanta during January 1, 2009 to December 15, 2013.
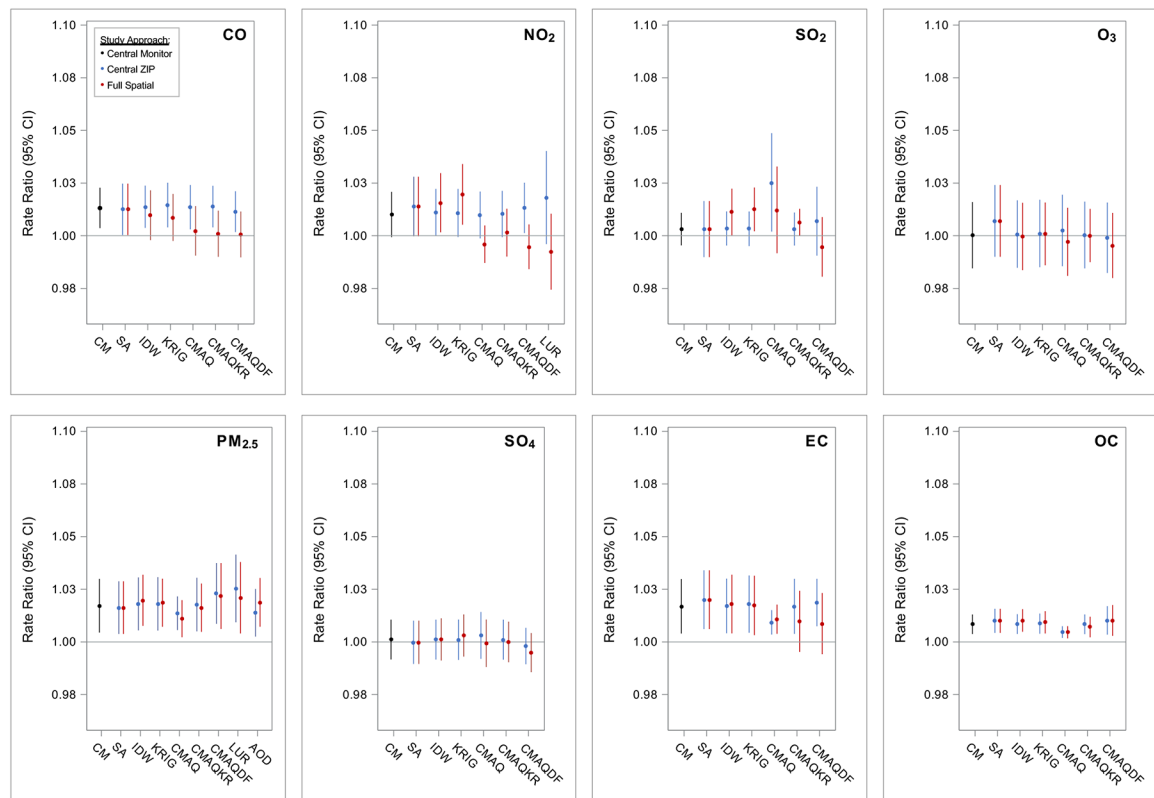
Figure 2. Associations of air pollution and ED visits for cardiovascular diseases, comparing among pollutants, exposure metrics, and study approaches.

Exposure metrics included: Central Monitor (CM), Site Average (SA), Inverse Distance Weighting (IDW), Kriging (KRIG), Community Multiscale Air Quality model (CMAQ), CMAQ-kriging adjustment with observations (CMAQKR), CMAQ combined with monitoring data in a data fusion (CMAQDF), Land Use Regression (LUR), and satellite Aerosol Optical Depth (AOD). Study approaches included assigning: Central Monitor values to all 192 ZIP codes by day (black), Central ZIP Code values for each exposure metric to all 192 ZIP codes by day (blue), and the Full Spatial information of the exposure metrics to the 192 ZIP codes by day (red). All models controlled for time and meteorology as specified by the base model. Rate ratios (RR) and confidence intervals (CI) scaled to standard units: per 250 ppb CO, 10 ppb NO_2, 4 ppb SO_2, 15 ppb O_3, 5 μg/m^3 $PM_{2.5}$, 1 μg/m^3 SO_4^{2-}, 0.5 μg/m^3 EC, and 1 μg/m^3 OC.
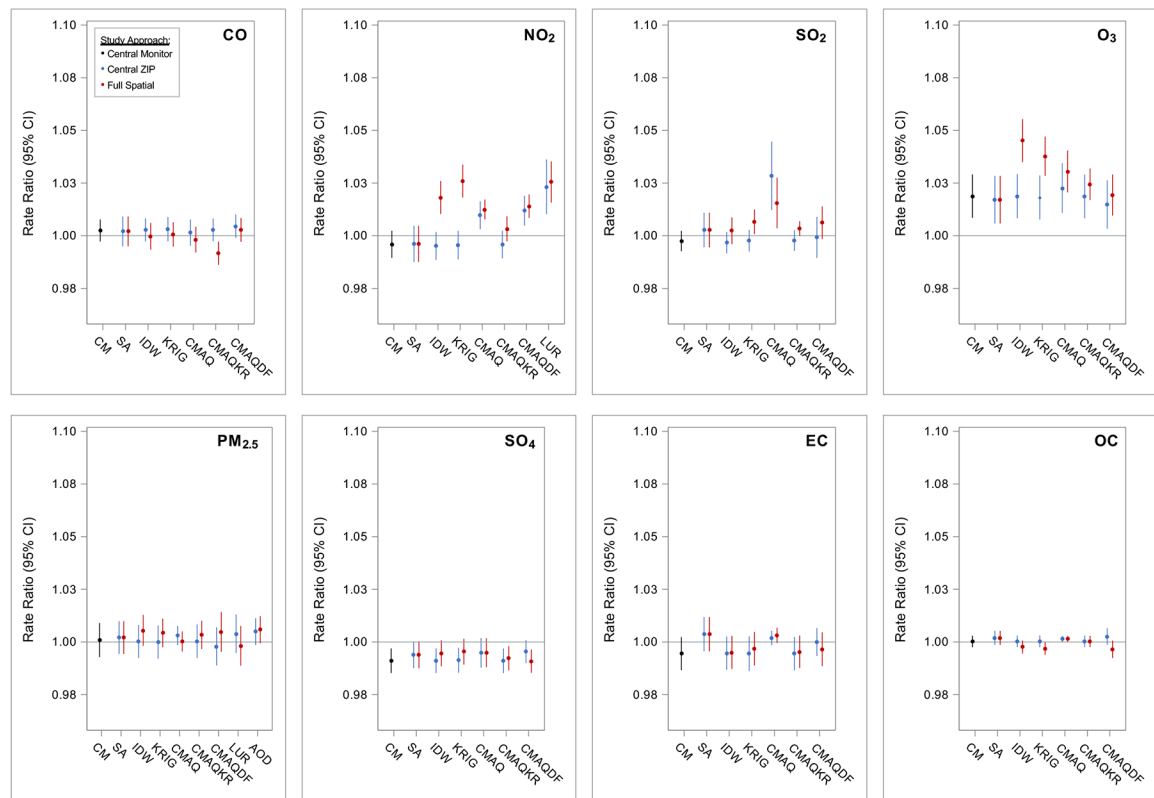
Figure 3. Associations of air pollution and ED visits for respiratory diseases, comparing among pollutants, exposure metrics, and study approaches.

Exposure metrics included: Central Monitor (CM), Site Average (SA), Inverse Distance Weighting (IDW), Kriging (KRIG), Community Multiscale Air Quality model (CMAQ), CMAQ-kriging adjustment with observations (CMAQKR), CMAQ combined with monitoring data in a data fusion (CMAQDF), Land Use Regression (LUR), and satellite Aerosol Optical Depth (AOD). Study approaches included assigning: Central Monitor values to all 192 ZIP codes by day (black), Central ZIP Code values for each exposure metric to all 192 ZIP codes by day (blue), and the Full Spatial information of the exposure metrics to the 192 ZIP codes by day (red). All models controlled for time and meteorology as specified by the base model. Rate ratios (RR) and confidence intervals (CI) scaled to standard units: per 250 ppb CO, 10 ppb NO_2, 4 ppb SO_2, 15 ppb O_3, 5 μg/m^3 $PM_{2.5}$, 1 μg/m^3 SO_4^{2-}, 0.5 μg/m^3 EC, and 1 μg/m^3 OC.

Table 1.

Summary of pollutant concentrations across all ZIP code-days for each exposure metric.[1]

Metric	1-hr max CO (ppb) N=345,600			1-hr max NO$_2$ (ppb) N=343,680			1-hr max SO$_2$ (ppb) N=345,216			8-hr max O$_3$ (ppb) N=344,640			24-hr avg PM$_{2.5}$ (µg/m^3) N=345,216			24-hr avg SO$_4$ (µg/m^3) N=342,528			24-hr avg EC (µg/m^3) N=340,608			24-hr avg OC (µg/m^3) N=86,976		
	Median	IQR	Max	Median	IQR	Max	Median	IQR	Max	Median	IQR	Max	Median	IQR	Max	Median	IQR	Max	Median	IQR	Max	Median	IQR	Max
CM	378.5	326.2	2309.6	29.7	17.9	82.5	3.0	7.4	86.3	39.6	22.6	103.6	9.7	5.9	39.8	2.1	1.5	11.0	0.67	0.48	4.32	2.6	1.6	12.2
SA	458.2	332.6	1879.3	16.8	14.3	70.8	2.6	5.1	64.9	39.9	18.6	89.0	10.2	6.4	31.6	2.0	1.5	7.4	0.59	0.56	3.57	2.4	1.5	8.5
IDW	490.9	315.0	3287.1	19.5	14.2	82.2	2.8	4.8	128.3	39.4	19.3	120.1	10.2	6.3	62.1	2.0	1.5	11.0	0.61	0.45	4.31	2.4	1.5	12.2
KRIG	472.6	335.1	4287.8	17.3	13.5	79.5	2.6	4.6	122.5	39.3	19.4	118.4	10.1	6.5	63.3	2.0	1.5	11.0	0.61	0.44	4.28	2.3	1.5	12.1
CMAQ	359.2	340.1	2516.7	20.9	22.8	119.9	1.6	1.9	46.3	41.6	20.8	108.6	9.1	6.8	121.0	1.7	1.3	10.1	0.83	0.89	11.53	1.8	1.9	38.1
CMAQKR	373.0	325.0	4051.8	12.8	16.0	88.7	2.5	4.6	575.9	41.0	19.0	272.5	9.5	6.5	57.2	1.9	1.5	12.4	0.47	0.42	4.52	2.2	1.7	13.1
CMAQDF	490.7	318.8	3559.8	16.7	15.4	117.3	2.1	2.6	177.9	40.2	18.7	118.6	9.1	4.5	63.5	1.9	1.3	10.1	0.51	0.37	2.80	2.0	1.0	8.9
LUR				13.1	14.7	75.9							10.2	4.0	57.3									
AOD													10.4	6.0	47.6									

exposure metrics include: Central Monitor (CM), Site Average (SA), Inverse Distance Weighting (IDW), Kriging (KRIG), Community Multiscale Air Quality model (CMAQ), CMAQ-kriging adjustment with observations (CMAQKR), CMAQ combined with monitoring data in a data fusion (CMAQDF), Land Use Regression (LUR), and satellite Aerosol Optical Depth (AOD).