Air Quality Effects on Health-Indicator Data in Disease Outbreak Surveillance

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Utilizing the concept that air quality has predictable impacts on certain disease patterns enables better detection of unexpected fluctuations in community health trends and thereby enhances earlier detection of disease outbreaks. This study illustrates that increases in daily outdoor ozone concentrations are associated with quantifiable short-term increases in hospital emergency department visits for asthma exacerbations among Medicaid patients, especially among 5–12 year olds. Spatial variation in asthma visits did not appear to be completely explained by spatial variations either in pollutant level or in Medicaid population. Recognizing air quality impacts in health data will enable disease surveillance systems to rule out relatively common air quality problems in monitoring for the effects of a bioterrorist attack. Routine monitoring of air quality indicators along with the corresponding health-indicator effects also can assist in establishing expected ranges for disease levels to establish alerting thresholds for disease outbreak surveillance.

INTRODUCTION

Air quality impacts on public health can help explain certain seasonal and daily variations in health care data. In surveillance for bioterrorist attacks, diseases such as asthma may act as confounders because they demonstrate significant responses to environmental factors. Automated disease outbreak detection systems,[1] such as the Electronic Surveillance System for the Early Notification of Community-based Epidemics (ESSENCE),[2] collect public health data such as daily hospital emergency department (ED) visits and provide alerts to public health officials based on anomalies detected by using a variety of statistical algorithms.[3] To avoid false alarms or the masking of infectious respiratory disease outbreaks, it is important to understand how asthma exacerbations present in these community data are related to temporal and spatial variation in air quality parameters.

Therefore, the motivation for this study is to understand some of the environmentally related components of public health data to minimize confounding of the alerting algorithms.

The goal of this study was to determine the degree to which short-term increases in Medicaid patient hospital emergency room visits for asthma exacerbations are associated with high ozone and particulate concentrations, taking into account environmental effects of pollen, mold, and ambient temperature. The District of Columbia Department of Health (DC DOH), under a grant from the U.S. Centers for Disease Control and Prevention (CDC), established an Environmental Public Health Tracking Program to quantify possible relationships between ambient air quality and health resource usage for asthma exacerbations. As part of this task, concentrations of the air pollutants ozone, particulates of aerodynamic diameter <2.5 μm (PM2.5), and particulates of aerodynamic diameter ≤10 μm (PM10) were obtained from measurements taken in DC from 1994 through 2005 (Table 1). Records of asthma-related hospital ED visits under the Medicaid program, for the period between 1 October 1994 and 22 November 2005, were obtained from the DC DOH and tabulated on a daily basis. For the purposes of this study, asthma-related data are defined as those records for which an asthma code number was listed in one of the first three of nine possible diagnosis fields. These Medicaid record diagnosis fields contain numbers based on the International Classification of Diseases, Ninth Revision (commonly called ICD-9) codes used by hospitals and physicians' office personnel to report billing information to insurance companies and Medicaid.[4] ICD-9 codes may indicate either symptoms or specific diseases, and those beginning with 493 indicate an asthma diagnosis. Based on discussions with medical personnel about ED coding practices among different DC hospitals, the criterion of an asthma code in one of the first three ED record diagnosis fields was chosen as an indication that an asthma exacerbation was a principal reason for the visit. Data on daily concentrations of ozone and particulates were then evaluated as predictors of increases in these daily asthma-related visit counts.

The U.S. age-adjusted rates of ED visits for asthma have risen from 56 to >60 per 10,000 population from 1992 to 1999.[5] Many epidemiological studies have shown that increases in ground-level ozone and particulate concentrations are associated with increased occurrences of acute asthma exacerbations.[6–8] However, the relationships between air quality parameters and asthma vary among different localities. Some localities (such as DC) may have lower particulate levels than those with more smokestack industry (such as Baltimore or Philadelphia). Furthermore, localities with greater traffic congestion tend to have higher ozone levels.

Ground-level ozone is primarily produced photochemically from automobile and power-plant nitrogen oxide emissions. Because sunlight causes chemical reactions that result in ozone formation, concentrations are typically higher during the summer season, or approximately May through September in the Northern Hemisphere. Ozone is an oxidizing agent that acts as a respiratory tract irritant. Particulates (mixtures of solid particles and liquid droplets) small enough to enter the lungs also may act as respiratory irritants. Inhalable particulates may be produced chemically in the atmosphere from reactions with sulfur dioxide, nitrogen oxides, and semivolatile organic compounds that are found in gasoline and diesel engine exhaust and power-plant emissions. Alternatively, these particulates may be emitted directly into the atmosphere, as in the case of dust from traffic and construction sites. Such particulates include coarse particles that range in aerodynamic diameter from 2.5 to 10 μm and fine particles with aerodynamic diameters of ≤2.5 μm.

In addition to outdoor air pollutants, there are many other factors that may influence asthma exacerbations.

Table 1. Summary of ozone, PM2.5, and PM10 measurement locations and dates.

EPA Site ID	Location	Ozone	PM2.5	PM10
DC17	West End Neighborhood Library	01/01/94 to 06/30/96	None	01/01/94 to 05/30/99, 01/01/01 to 06/30/01
DC25	Takoma Elementary School	01/01/94 to 12/31/05	None	None
DC27	Chevy Chase Neighborhood Library	None	None	01/01/94 to 05/30/99, 01/01/01 to 06/30/01
DC41	River Terrace Elementary School	01/31/94 to 12/31/05	02/21/99 to 12/31/05	01/01/94 to 12/31/96, 01/01/98 to 06/28/98, 04/08/01 to 06/19/01, 01/01/02 to 12/31/05
DC42	National Park Service, Haines Point	None	03/20/99 to 12/31/05	None
DC43	McMillan Reservoir	06/20/94 to 12/31/05	01/15/99 to 12/31/05	None

Extreme ambient temperatures may result in asthma exacerbations in two different ways. High temperatures are associated with asthma exacerbation because of the increased sunlight-induced ozone production rather than as a direct effect of temperature. At the opposite temperature extreme, studies have suggested that very cold, dry air may act as an airway irritant, resulting in asthma exacerbations,[9,10] although this effect has been documented principally with exercise-induced asthma. Additionally, aeroallergens, such as pollen and mold, may trigger allergy-induced asthma symptoms. Although whole pollen grains are unable to enter the lower respiratory system, tiny pieces (~0.6–2.5 μm) of pollen grains, called amyloplasts, are small enough to enter and induce an asthmatic response.[11] Given that neural reflexes connect the nose and lungs, nasal provocation by larger allergens also may result in bronchoconstriction.[12] Plants that produce allergenic pollen are typically divided into three types: trees, weeds, and grasses. In Washington, DC, the customary seasons for these pollen types are as follows[13]:

- Tree pollen: February through June
- Grass pollen: May through August
- Weed pollen: July through October

The beginning, peak, end, and severity of these pollen seasons are influenced by preseason weather, diurnal cycle fluctuations, and land use.[14–16] Airborne pollen concentration and size fluctuate as plants respond to current weather conditions. Whole pollen particles produced by trees, weeds, and grasses can be dispersed up to 400 miles in windy, warm, and low-humidity conditions.[14,17] When humidity increases, plants may close their anthers to prevent pollen grains from being washed away by precipitation.[11] However, heavy thunderstorms may fracture grass pollen into amyloplasts even while contained within the closed anther.[11] Amyloplasts are then dispersed into the air when the anther reopens as a result of decreasing relative humidity after the thunderstorm.[17] Airborne pollen concentrations will not increase after rainstorms until plants reopen their anthers when the humidity decreases.[18]

Some recent studies have noted that, compared with those with private insurance, Medicaid enrollees have higher risks of respiratory hospitalizations from increases in ambient air pollution.[8,19] Medicaid, a locally administered and federally assisted program, pays for the health care of pregnant women, low-income families with children, permanently disabled individuals, and elderly individuals who cannot pay all of their medical costs. The cost of Medicaid in DC is shared equally by local and federal governments. The DC government has been expanding Medicaid eligibility for certain segments of the population over the last few years. In 2003, eligibility for the Medicaid program was extended to childless adults ages 50–64 who earn up to 50% of the U.S. federal poverty level. Over the last few years, there has also been a shift in Medicaid services from institutional-based to managed care and home- and community-based programs.

METHODS

Data Characterization

The DC DOH provided air quality data measured at different locations within DC in the form of hourly concentrations of ozone in parts per million (ppm) and daily concentrations of PM2.5 and PM10 in μg/m^3. The hourly ozone data were converted into daily averages by using standard 8-h daily maximum ozone conversion calculations from the U.S. Environmental Protection Agency (EPA). The PM2.5 and PM10 data were already in the form of daily averages. Table 1 lists the sites, the air pollutants measured, and the date ranges in which measurements were made. Table 2 shows how daily concentrations are correlated with health effects according to the EPA's air quality index as indicated by color codes. The colors toward the bottom of the table correlate with progressively worse effects on respiratory health. There was a relative lack of significant spatial variation in pollutant values (Fig. 1) among measurement sites (Fig. 2) during the time period of the study, consistent with the primary source being exhaust from vehicular traffic that is almost uniformly congested within the relatively compact 159-km^2 land area of DC. Because of this lack of spatial variation and because there were commonly days in which one or more of the sites had missing data, it was decided to use the maximum daily concentration of

Table 2. EPA air quality index code colors and pollutant concentrations.

Code Color	Ozone (ppm)	PM2.5 (μg/m^3)	PM10 (μg/m^3)
Green	0	0	0
	0.064	15.4	54.9
Yellow	0.065	15.5	55
	0.084	40.4	154.9
Orange	0.085	40.5	155
	0.104	65.4	254.9
Red	0.105	65.5	255
	0.124	150.4	354.9
Purple	0.125	150.5	355
	0.374	250.4	424.9
Maroon	>0.374	>250.4	>424.9

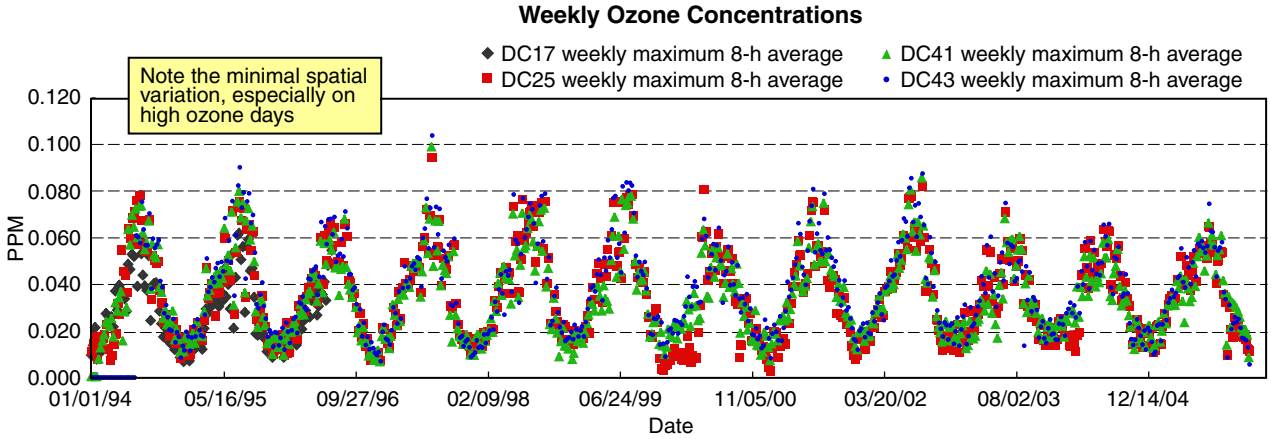

Figure 1. Weekly average ozone concentrations among different measurement sites (see also Table 1 and Fig. 2) within DC.

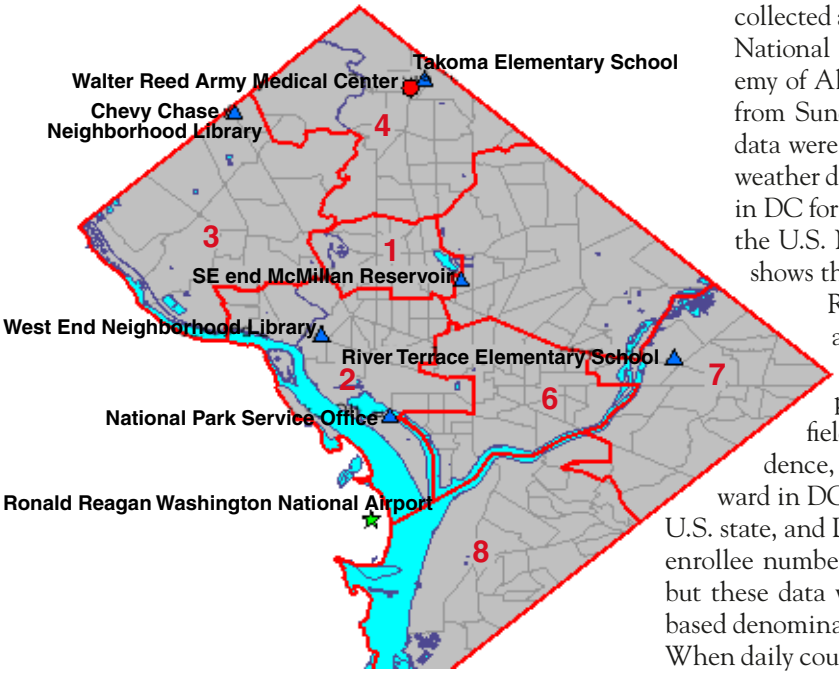

Figure 2. Map of DC showing ward boundaries (ward numbers are in red) as well as locations of weather measurements (green star), pollen and mold measurements (red circle), and air pollutant measurements (blue triangles).

each pollutant across the measurement sites to represent that pollutant's daily value. This approach thereby eliminated problems attributable to missing measurements. The maximum daily pollutant concentrations typically occurred during the summer months (June through August), similar to variations found in other studies.

Pollen and mold counts (in units of grains and spores m^{-3}, respectively) for Washington, DC, were collected at a single location within DC and were provided by the Department of Allergy and Immunology at the Walter Reed Army Medical Center. Pollen and mold counts are gathered by using a Rotorod Sampler and a Burkhard Spore Trap over a 24-hour period. Samples are collected at least 3 days per week, as directed by the National Allergy Bureau of the American Academy of Allergy, Asthma, and Immunology, usually from Sunday through Thursday. Pollen and mold data were available for the years 1998–2005. Daily weather data measured at Reagan National Airport in DC for the years 1994–2005 were obtained from the U.S. National Climatic Data Center. Figure 2 shows the locations of the measurement sites.

Records of Medicaid patient daily asthma-related hospital ED visits of DC residents were made anonymous and provided by the DC DOH. The record fields included patient age, ZIP code of residence, date of visit, and ward of residence. A ward in DC is somewhat analogous to a county in a U.S. state, and DC is divided into eight wards. Medicaid enrollee numbers also were provided by the DC DOH, but these data were available only by ward, so a ward-based denominator was used to determine ED visit rates. When daily counts of ED visits were calculated for use in the analysis, multiple records for the same patient on the same day of service were counted as a single visit. From analysis of these data using census population figures, the Medicaid patient age group with the highest rate for asthma-related ED visits was the 50- to 64-year-old group, followed by the 0- to 4-year-old group, and then the 21- to 49-year-old group (Fig. 3). The daily number of visits was observed to be highly variable over time, with the highest ED visit rates occurring before 1998 and a significant decrease after 1997. When these ED visit rates were stratified by age group (Fig. 3), it was seen that these changes in rates were predominantly in children. This post-1997 drop appears to result from implementation of the State Children's Health Insurance Program (SCHIP, authorized under U.S. Title XXI of the Balanced Budget Act of 1997 for all states and DC to provide health insurance to eligible uninsured children). This program reduced the number of Medicaid-billed

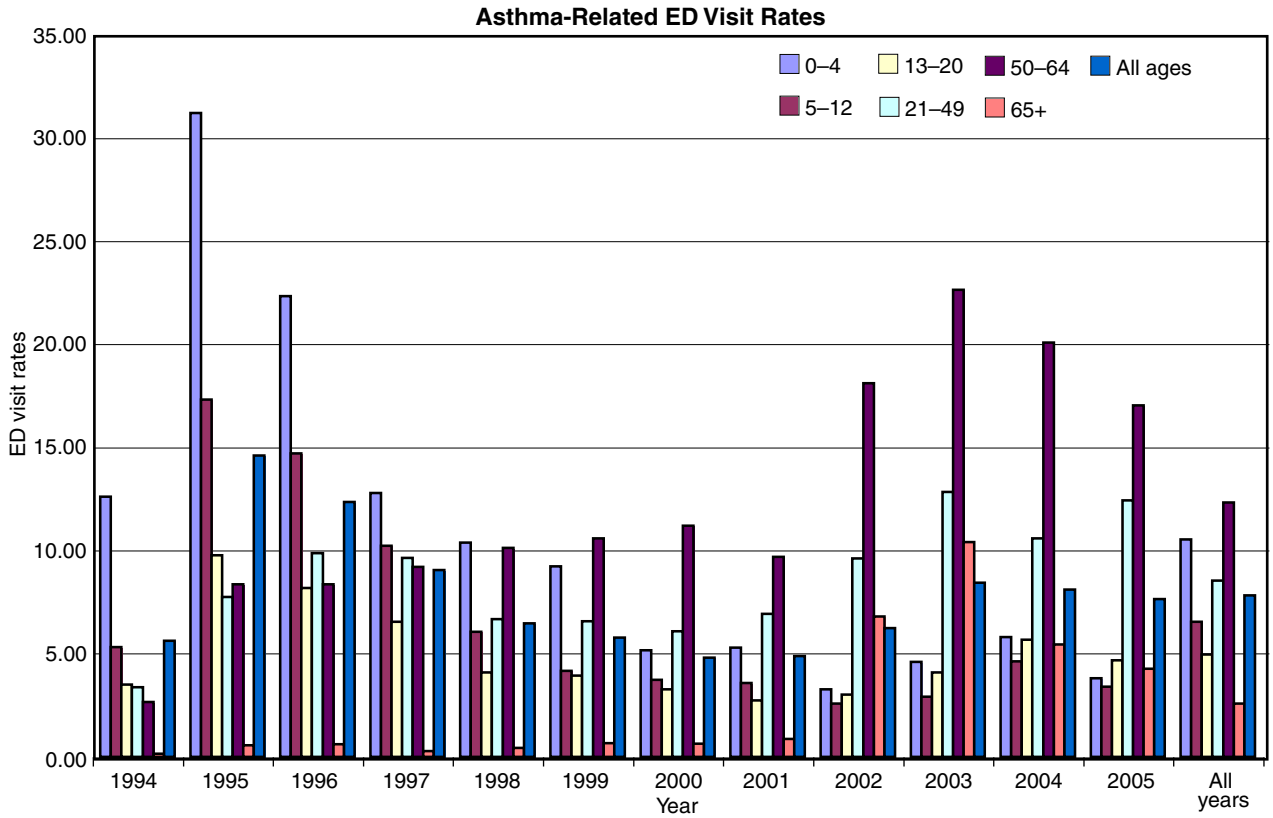

Figure 3. Asthma-related ED visit rates for Medicaid patients by age group and year.

services by providing more primary health care coverage for children. The implementation of SCHIP would be expected to reduce the number of children using the ED for primary care. After 1997, the years with the highest rates of asthma-related ED visits were 2003 and 2004, while 2000 and 2001 had the lowest rates.

The Medicaid data generally had two annual peaks in asthma-related ED visits: the highest peak in the fall (September to December) and the second-highest peak in late spring (May). Because peaks in ozone, PM2.5, and PM10 occurred in June through August, the peaks in Medicaid patient asthma data did not correspond to peaks in the air-pollutant concentrations. This lack of agreement between peak dates does not mean that there is no short-term relationship between increases in air-pollutant levels and asthma exacerbations because strong seasonal effects associated with other factors[20] obscure this relationship. For example, there is ample biological and statistical evidence (e.g., see the review by Gern and Busse[21]) that asthma attacks are triggered by the respiratory viral infections that occur during the autumn cold season. Air quality effects on asthma exacerbations are difficult to discern because of masking by these seasonal effects over long time scales.

Therefore, we used a long-term trend curve-fitting approach[22–24] to control both for strong seasonal variations in asthma-related health care visits and for temporal variations in Medicaid enrollment, so that the short-term impacts of ozone, PM2.5, and PM10 concentrations might be revealed. We examined several techniques for controlling for known confounders such as day-of-week effect, Medicaid eligibility changes, and seasonal effects. Different covariates were used to model these longer-term variations. Because the asthma data for the 5- to 12-year-old age group showed all of the long-term effects most clearly (Fig. 4), data from this age group were used as the basis of the modeling efforts to control for confounding.

Statistical Methods

After collecting all of the above data and creating a database in an integrative statistical software package,[25] we classified each variable as either an independent variable or a dependent variable. Concentrations of tree pollen, grass pollen, weed pollen, mold spores, ozone, PM2.5, and PM10; maximum and minimum daily temperature; and daily average dew point temperature were categorized as independent variables. For the dependent variables, ED daily visit counts were further tabulated by the following age groups based on the patient's age on the visit date: 0–4 years, 5–12 years, 13–20 years, 21–49 years, 50–64 years, >65 years, and all ages combined. Based on similar previous studies,[22,23] we chose a Poisson regression analysis to seek associations of asthma-related visits with the environmental data. This regression assumes that counts of independent, rare events follow a Poisson

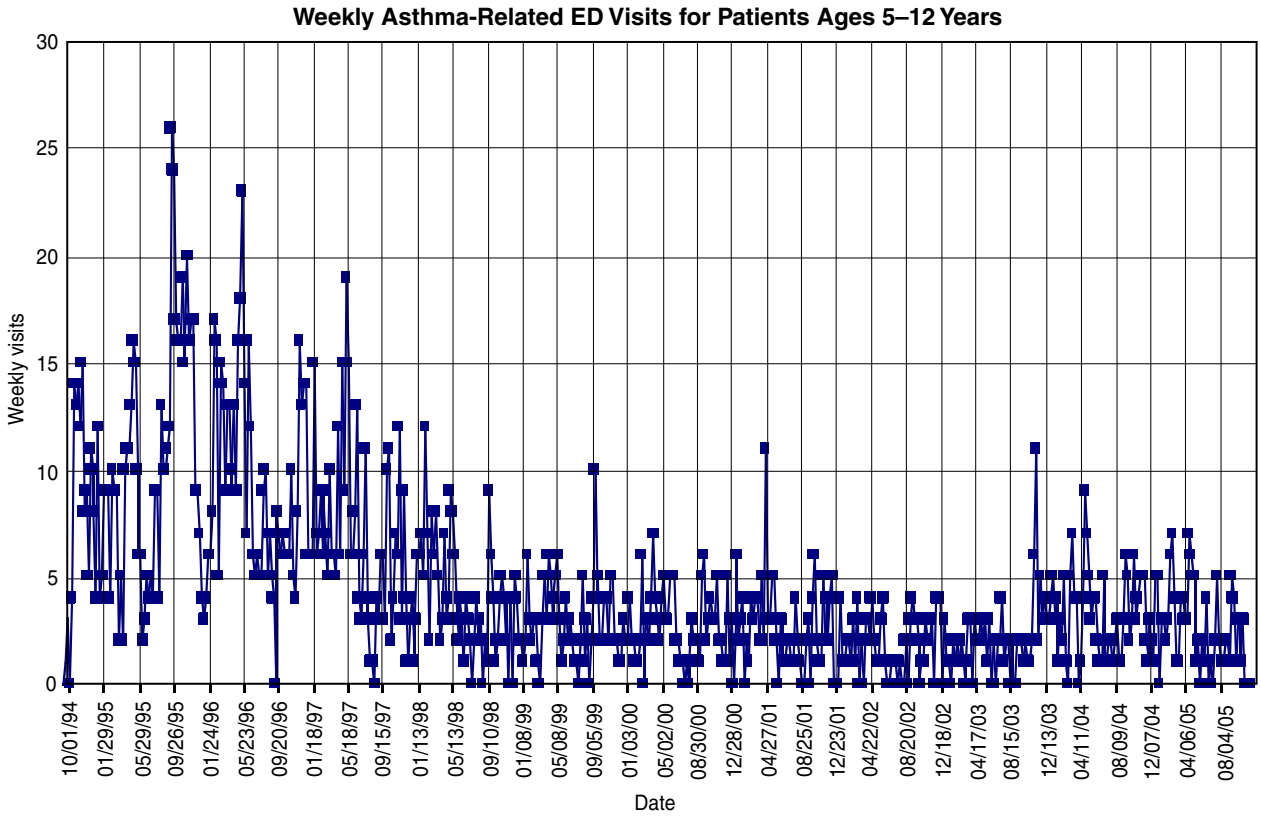

Figure 4. Weekly Medicaid patient asthma-related ED visits for 5- to 12-year-old patients. The dates of major turning points in the plot were used to create the knots used in fitting the spline curves.

distribution and that the logarithm of daily visit counts is a linear function of the explanatory variables.

Before this Poisson analysis could be applied, the longer-term effects mentioned previously had to be taken into account in order for the shorter-term air quality effects to be revealed. Several data-fitting approaches were tried. One approach was to fit the data by using a cubic spline[24,26] with the spline knot (i.e., turning point) dates chosen from the most significant long-term turning points in data for the 5- to 12-year-old age group (Fig. 4). The selection of turning-point dates reflected both year-to-year variation in long-term health trends and significant Medicaid eligibility changes, so that not every year had the same number of knots nor were the knots evenly spaced in time. Using this cubic spline approach meant that the same knots were used for curve fitting regardless of which variables were being compared in the Poisson regression.

Another approach was to use a set of linear spline functions (with each linear spline section fitted to data between two knots) to create new variables that served to create continuous functions of time (i.e., date). These continuous functions of time were different depending on which variables were being compared in the Poisson regression because the actual data fitting was done for each regression. Once selected, the knots for these splines were kept constant for all regressions using the corresponding variables. By using the turning-point dates derived for the 5- to 12-year-old age group described above, 68 knots were chosen to create a set of 69 variables for the continuous functions of time (i.e., date) used in the custom spline covariate. Using this approach meant a refitting of long-term effects for each analysis relative to the specific daily visit counts and risk factors analyzed.

To decide objectively the best approach to modeling long-term data trends, we applied McFadden's R^2 and the Bayesian Information Criterion (BIC) to residuals obtained by using the different modeling approaches. The McFadden's R^2 statistic is a nonlinear generalization of the R^2 goodness-of-fit statistic of ordinary least-squares regression, and this statistic is similarly measured on a scale from 0 to 1, with a value near 1 indicating a good fit. The BIC, also called the Schwarz's Bayesian criterion,[27] provides another relative measure of goodness-of-fit but also takes into account the complexity of the model. The BIC is a large negative number, and the farther it is from zero, the better the model fit, with a bias toward simpler models. The BIC is used to determine when additional model complexity is not justified by corresponding improvement in the capability of the model to explain the data. Based on these two objective criteria, the least complicated model that best fits the data was chosen. The chosen model was a linear spline/

continuous time approach that took into account day-of-week effects. Therefore, these covariates were used to remove known confounding effects for the remainder of the analysis. This approach generates a different modeled function of time as a baseline for each analysis, depending on the variables being compared in the Poisson regression. Note that each analysis is performed separately, with no statistical combining of the results.

RESULTS

For same-day effects (i.e., no time lag in days between increases in air quality risk factors and in daily ED visits), we determined the statistically significant associations among the various risk factors (ozone, PM2.5, PM10, tree pollen, grass pollen, weed pollen, mold, temperature, dew point). No statistically significant effects of dew point were observed except that dew point appeared to be negatively correlated with pollen, consistent with the studies described earlier.[11,18] Furthermore, when all seasons and all age groups were combined, no statistically significant associations with the above risk factors were found.

As noted earlier, the spring and summer months typically had the highest daily values of ozone, PM2.5, and PM10, and these months also have the lowest incidence of viral respiratory infections, an important risk factor unavailable in our data. When only spring and summer seasons were examined, statistically significant relationships were found, but only for the 5- to 12-year-old age group. The results are shown in Table 3. The first column is the risk factor (e.g., ozone), and the second column is the reference unit of increase in this risk factor, based on the data scale and EPA risk levels (Table 2). These reference units were used to calculate the mean percentage change in the daily ED visits per unit change in the risk factor (column three). The third column also parenthetically lists the upper and lower 95% confidence limits for the percentage change. Column four lists the *P* values from Student's *t* test, with values ≤0.05 representing a statistically significant relationship (95% probability of null hypothesis rejection). It is important to note both the *P* value and the sign and magnitude of the mean percentage change in daily visits per unit change in risk factor. While a *P* value may be low and therefore significant, the percentage change in daily visits may be almost zero or even slightly negative. We considered these results to show a significant positive association when both the percentage change in daily visits was relatively large (e.g., a few percent) for a unit risk factor increase and the *P* value was significant. From Table 3, a 0.01-ppm increase in ozone was associated with a 4.6% increase in the number of asthma-related ED visits by Medicaid patients in the 5- to 12-year-old age group.

We also investigated associations between counts of asthma-related Medicaid visits by residents of particular wards (see Fig. 2 for ward boundaries) and the ambient ozone, PM2.5, and PM10 concentrations. Ward-specific associations may be weaker than district-wide ones because of the fewer number of patients. In this partially ecological study, it was impossible to determine whether individuals with pollutant exposure were the same people seeking care for asthma exacerbations, so there were other possible factors involved in ward-specific associations. Note in Fig. 5 that Ward 8 has the highest Medicaid enrollment, followed by Wards 7, 2, 5, 6, etc., and that these enrollment differences among wards can be large. Ward-specific associations also may be confounded by the presence of homeless populations and the presence of long-term care facilities such as hospices and nursing homes. Ward 6 had the highest rates of asthma-related ED visits for all years combined (Fig. 6). When individual years were examined, Ward 6 had the highest rates except for 1996–1997, when Ward 8 surpassed those rates. It should be noted that Ward 6 contains some large homeless shelters with many Medicaid enrollees. Wards 2 and 3 had the lowest rates of ED visits for all years.

Table 3. Results for asthma-related ED visits for 5- to 12-year-old Medicaid patients, spring and summer seasons only (95% confidence interval is given in parentheses).

Risk factor	Unit of increment	Mean % change in daily visits per unit of increment (95% confidence interval)	Student's *t* test *P* value
Ozone	0.01 ppm	4.6 (0.9, 8.4)	0.015
PM2.5	1 mg m^{-3}	–0.2 (–1.3, 0.9)	0.733
PM10	1 mg m^{-3}	–0.1 (–1.4, 1.2)	0.885
Grass pollen	10 grains m^{-3}	0.8 (–0.2, 1.8)	0.112
Tree pollen	100 grains m^{-3}	2.4 (–0.5, 5.4)	0.111
Weed pollen	10 grains m^{-3}	7.1 (–6.5, 22.6)	0.323
Mold	1000 spores m^{-3}	–0.8 (–4.8, 3.4)	0.704

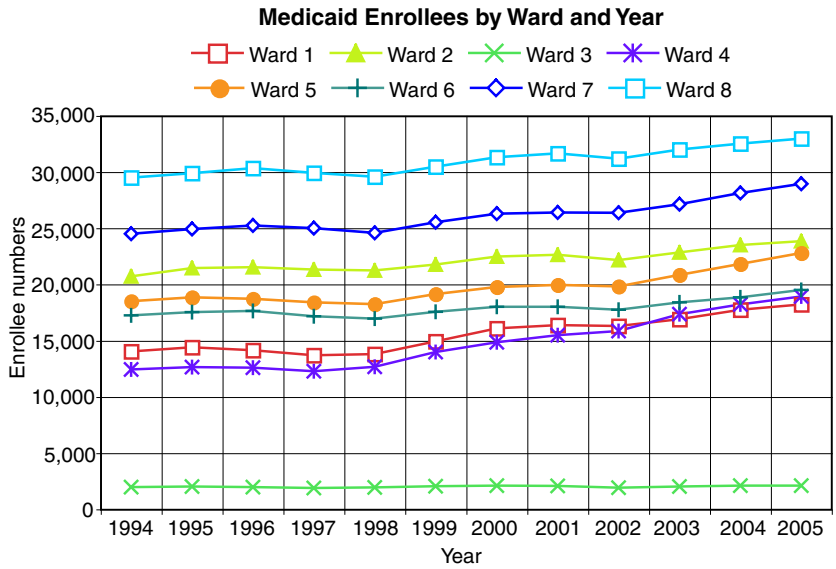

Figure 5. Annual numbers of Medicaid enrollees by ward.

In addition, lagged effects were examined. When asthma-related ED visits were lagged behind ozone, PM2.5, and PM10 levels by 1–7 days, no statistically significant associations were found with any of the covariates.

CONCLUSIONS

We examined daily time series of Medicaid patient asthma-related ED visits from October 1994 through November 2005 for DC residents. Associations of these data with environmental variables were tested for various age groups. The environmental variables included ozone, PM2.5, and PM10 measurements, as well as aeroallergen and weather measurements.

When all seasons were considered together for the entire DC area, we found no significant ozone or particulate associations with the Medicaid patient asthma-related ED visits. A plausible explanation for this finding is that other risk factors mask environmental effects so completely that only an individual-based case control or longitudinal study with appropriate statistical power could extract associations of air quality effects.

When we examined ozone effects only during the spring and summer seasons, we found statistically significant associations with daily asthma-related ED visits only for the 5- to 12-year-old age group and only with daily ozone concentrations. The 5- to 12-year-old age group showed that a 0.01-ppm daily ozone concentration increase was significantly correlated with a 4.6% increase in daily ED visits.

Because there is significant variation in Medicaid enrollment (Fig. 5), and therefore in socioeconomic status by ward within DC, we also examined air quality effects by ward on asthma-related ED visits by Medicaid patients. While Ward 8 always had higher numbers of Medicaid enrollees, Ward 6 showed the largest rate of asthma-related ED visits over the study period (Fig. 6). This result may be attributable, at least in part, to the presence of large homeless shelters in Ward 6.

For DC, spatial variation in daily air quality measurements among different locations did not appear to be significant for the years of this study. Also, during the study period, daily PM10 never reached EPA Code Red levels (Table 2), and we found no statistically significant association between PM10 and Medicaid patient asthma-related ED visits. Daily PM2.5 concentrations reached EPA Code Red levels for 3 days during this same period. The 8-hour daily maximum ozone concentrations reached EPA Code Red levels (Table 2) for 21 days during the 134-month study period. During this period, the facts that particulate levels were not very high and that ozone was the most frequent high-level pollutant suggest why we only found significant associations with ozone.

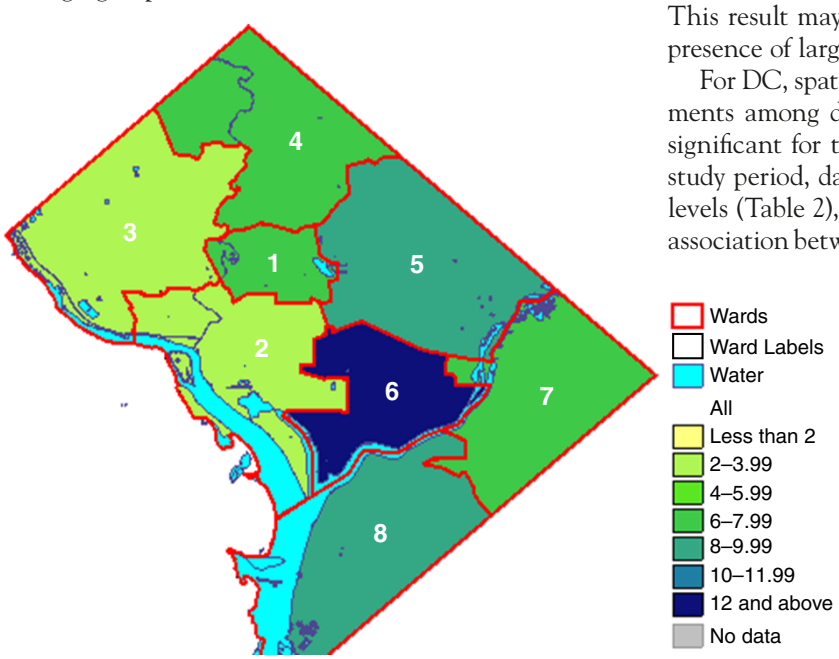

Figure 6. Map of DC showing asthma-related Medicaid patient ED visit rates (visits divided by Medicaid enrollment of ward residents) over all of the years of the study. Wards are indicated by red boundaries and white numbers.

Several additional limitations of this study should be noted. Because of the lack of any capability to track

individual exposures in these data, investigation was limited to a partially ecological study with no confirmation that patients represented by the hospital visit records were outside on days when the measured air quality was low. Thus, patient-based odds ratios estimating relative risks could not be calculated by comparing, for example, visit rates of asthma patients exposed to the effects of air pollution with rates of unexposed patients. The patient database included only Medicaid patients who had an asthma ICD-9 code listed in one of the first three diagnosis fields in their Medicaid records. Because our sample included only Medicaid patients, it represents a specific population with potentially unique characteristics, such as level of exposure to outdoor and indoor air quality, health-seeking behavior, and susceptibility to asthma. Therefore, our findings should not be generalized to represent the entire population. Medicaid eligibility and enrollment varied considerably during the 134-month period of this study (Fig. 5). The ozone, PM2.5, and PM10 data were measured at only three stations within DC during the study period, thereby limiting the spatial resolution of outdoor air quality. The available weather data were measured only at a single location, so spatial variations could not be analyzed.

Our data consisted only of asthma-related visits by Medicaid enrollees, and the Medicaid program is targeted toward those with lower-than-average socioeconomic status. Although some studies have suggested that asthma prevalence is higher among those of low socioeconomic status,[28] there are conflicting reports in the literature (see the review by Rona[29]). Finkelstein et al.[30] concluded that underuse of asthma-controlling medications among Medicaid-insured children is widespread. It is possible that, in general, the DC Medicaid population similarly undercontrols their asthma and postpones seeking treatment of asthma-related symptoms until they become relatively serious. Although this partially ecological study has the limitations described above, these results should be useful in hypothesis generation and designing future individual-based, epidemiological cross-sectional and case-control studies aimed at refinement of program interventions. From the broader health surveillance perspective, knowledge of the spatiotemporal variations in daily asthma-related ED visits should be useful to public health surveillance programs designed to target infectious disease outbreaks or bioterrorist attacks.

ACKNOWLEDGMENTS: We express our gratitude to Dr. Walter Faggett and Kerda DeHaan of the DC DOH for their assistance in obtaining and interpreting the Medicaid health data and to Susan Kosisky and her staff at the U.S. Army Centralized Allergen Extract Laboratory, Department of Allergy and Immunology, Walter Reed Medical Center, for their assistance in obtaining and interpreting the pollen and mold data. This article was prepared under a grant from the Office of State and Local Government Coordination and Preparedness (SLGCP), U.S. Department of Homeland Security. Points of view or opinions expressed in this document are those of the authors and do not necessarily represent the official position or policies of SLGCP or the U.S. Department of Homeland Security.

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