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Loose-coupling an air dispersion model and a geographic information system (GIS) for studying air pollution and asthma in the Bronx, New York City

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This study developed new procedures to loosely integrate an air dispersion model, AERMOD, and a geographic information system (GIS) package, ArcGIS, to simulate air dispersion from stationary sources in the Bronx, New York City, for five pollutants: PM_{10}, $PM_{2.5}$, NO_x, CO, and SO_2. Plume buffers created from the model results were used as proxies of human exposure to the pollution from the sources and they modified the commonly used fixed-distance proximity buffers by considering the realities of air dispersion. The application of the plume buffers confirmed that the higher asthma hospitalization rates were associated with the higher potential exposure to local air pollution. The air dispersion modeling exhibited advantages over proximity analysis and geostatistical methods for environmental health research. The loose integration provides a relatively simple and feasible method for health scientists to take advantage of both air dispersion modeling and GIS by avoiding the need for intensive programming and substantial GIS expertise.

Keywords: asthma; air pollution; geographic information system; air dispersion model; proximity analysis; loose coupling

Introduction

Asthma is a serious environmental health and justice issue in New York City (NYC), USA. According to the New York City Department of Health and Mental Hygiene's report, *Asthma Facts*, in 2000 the asthma hospitalization rate for children in New York City was 6.06 per 1000 children, which was 1.8 times the rate in U.S. and 3.4 times the rate in the rest of New York State (excluding New York City); asthma was the leading cause of hospitalization for children in this city; the asthma hospitalization rate for children aged 0–4 living in low-income neighborhoods was more than four times the rate for children from high-income neighborhoods (New York City Department of Health and Mental Hygiene [NYC DOHMH] 2003). This issue has obtained increasing attention from government and scientists.

A number of research studies have explored the spatial distribution of asthma hospitalizations, and the association of asthma hospitalization rate with

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socioeconomic factors, land use, and air pollution in New York City (Luttinger and Wilson 2003; Claudio et al. 2006; Corburn et al. 2006). The Bronx, one of the five boroughs of NYC, figures prominently in these studies, because it has the highest asthma hospitalization rate, highest percentage of minority population, lowest mean household income, and lowest average educational attainment level, compared to the city's other boroughs. Additionally, the Bronx contains a dense network of highways and truck routes, and other noxious land uses, including Toxic Release Inventory (TRI) facilities and other stationary pollution sources (Luttinger and Wilson 2003; Maciejczyk et al. 2004; Claudio et al. 2006; Corburn et al. 2006; Maantay 2007). The Bronx is the NYC borough with the highest overall asthma hospitalization rates, asthma death rates, and asthma prevalence among children as well as adults. In 2000, the asthma hospitalization rate for children in Bronx was 9.16 per 1000 children, which is 1.51 times the rate of NYC and 2.73 times the rate of U.S. (NYC DOHMH 2003).

Therefore, our objective was to study the impact of environmental and socioeconomic factors on asthma in the Bronx. This project explored the spatial relationship between asthma rates and air pollution in the Bronx using different methodologies, including fixed-distance buffer analysis (Phase I), multiple regression analysis (Phase II), dasymetric mapping (Phase III), and air dispersion modeling (Phase IV). This paper describes and reports the methodology and the findings of the integration of the air dispersion modeling with the GIS.

Although the precise causes of asthma are unknown, and may include multiple factors such as outdoor air pollution, indoor air pollution, pollen, allergies, family history, and behavioral causes (Guo et al. 1999), the Phase I portion of our study already found considerable spatial correspondence between asthma hospitalization rates and local air pollution sources in the Bronx using "proximity analysis" with fixed distance buffers (Maantay 2007). In that study, distance to the locations of air pollution sources in the Bronx, including Toxic Release Inventory (TRI) facilities, limited access highways, major truck routes, and National Emissions Inventory (NEI) stationary point sources, were used as a proxy for human exposure to air pollution. Proximity buffers are created based on a fixed distance to each of the types of pollution sources. The areas inside the buffers are assumed to be associated with poorer air quality compared to the places outside. The Phase I study found that the people living within the boundaries of the proximity buffers were up to 60% more likely to be hospitalized for asthma, depending on the particular pollution source, than those living outside the buffers; thus the higher asthma hospitalization rates were associated with the closer proximity to local air pollution sources (Maantay 2007). In Phase II, multiple regression analysis of asthma hospitalization and proximity to major pollution sources found that environmental factors remained significant, even when controlling for race/ethnicity and poverty status.

Proximity analysis is a leading and frequently-used method to study the association between air pollution and environmental health and justice (Chakraborty and Armstrong 1997; van Vliet et al. 1997; Lin et al. 2002; Jerrett et al. 2005; Hodgson et al. 2007; Maantay 2007; Ryan et al. 2007). The basic assumption of this method is that distance to emission sources is an appropriate surrogate for human exposure to air pollution (Jerrett et al. 2005). Proximity analysis is straightforward and easy to use. However, it has some drawbacks. First, it assumes that air pollution disperses equally in all directions from a source. It only considers the absolute, fixed distance of pollutant dispersion, but not the physical properties of pollutants (e.g. density), characteristics of sources (e.g. emission rate, velocity, and temperature), local meteorological conditions (e.g. wind direction, wind speed, and temperature), topographical features, and effect of the surrounding built environment, all of which may strongly influence the actual areal extent of pollutant exposure. Secondly, the distances considered are usually somewhat subjective, most commonly based on best estimates of general pollutant fate and transport, as determined by environmental scientists, but are not derived from the actual measured concentrations or specific emission data. The population considered as exposed varies using different distances, which might affect the association found between air pollution and health. Thirdly, the differentiation between areas, cases, and population outside and inside a proximity buffer is binary, which is not able to represent the continuous spatial process of air pollution dispersion. Thus, an application of proximity analysis might not realistically reflect the complexities inherent in the relationship between air pollution exposure and human health.

In recent years, a more sophisticated method, air dispersion modeling, has been employed to study the relationship between air pollution and human health (Bellander et al. 2001; Hrubá et al. 2001; Poulstrup and Hansen 2004; Hodgson et al. 2007). Air dispersion modeling uses mathematical equations, which consider emission quantities, meteorological and topographical factors, and describes chemical and physical processes within the plume over time and space, in order to calculate concentrations of air pollutants at different receptors. If sufficient data for pollution sources and emissions, meteorological conditions, and topographical features are available, air dispersion modeling can provide a more accurate assessment of potential exposure without the need for extensive monitoring networks (Dent et al. 1998; Jerrett et al. 2005; Hodgson et al. 2007).

A widely-used air dispersion model is AERMOD (American Meteorological Society/Environmental Protection Agency Regulatory Model), which has been validated and frequently used to simulate air dispersion of pollutants from industrial, mining, landfill, and road sources (Cimorelli et al. 2005; Perry et al. 2005; Macleod et al. 2006; Singh et al. 2006; Kesarkar et al. 2007; Touma et al. 2007). It is an advanced steady-state plume model that aims to simulate the air dispersion from sources to a distance up to 50 km. It incorporates the boundary layer theory and an understanding of turbulence and dispersion, and also considers the influence of building wakes on plume rise and dispersion (Perry et al. 2005). AERMOD is listed as a preferred and recommended model by the US Environmental Protection Agency (US EPA) and its accuracy is well-tested and documented (US EPA 2005). However, it is rarely used for studying the association between air pollution and human health mainly due to the lack of available health data at the appropriate scales for fine-grained analysis, and the relatively costly air dispersion modeling data inputs, including source locations, source release parameters, meteorological parameters, terrain, and building locations and heights. Furthermore, a full implementation of this model for air pollution and environmental health study requires an integration of specialized software, including a dispersion model and a geographic information system (GIS). The process of integration usually involves intensive expertise in computer programming, GIS, and meteorology, any one or all of which may be unfamiliar to health scientists (Jerrett et al. 2005).

Even though the inputs to AERMOD are mostly spatial data, and therefore should be able to be processed and stored in a GIS, AERMOD requires different formats for some inputs and thus cannot import some GIS data directly. Moreover, the concentration values in the outputs of AERMOD cannot be exported directly as GIS point shapefiles, which limits further analyses on the model results. Since GIS is a necessary tool to study the spatial correspondence between air pollution and environmental health (Nyberg et al. 2000; Bellander et al. 2001; Hrubá et al. 2001; Poulstrup and Hansen 2004; Hodgson et al. 2007) we need to develop a set of new procedures integrating AERMOD with GIS to take advantage of both, while reducing the complexity of the integration by avoiding intensive programming and making it more accessible for health researchers.

In this study, we integrated AERMOD and GIS to study the association between asthma hospitalizations and air pollution sources in the Bronx. We first developed a series of procedures to integrate AERMOD and GIS in a loosely-coupled system. Secondly, we simulated air dispersion from US EPA National Emission Inventory (NEI) stationary sources for five criteria pollutants: PM_{10}, $PM_{2.5}$, NO_x, CO, and SO_2. Thirdly, we created plume buffers based on the modeled concentrations as a proxy for exposure, to modify the fixed distance proximity buffers. Fourthly, we compared the association between asthma hospitalizations and air pollution generated from the plume buffers with that of the proximity buffers.

Methods

Loosely-coupled model

Loose-coupling is an important method used to integrate a GIS and an environmental modeling program where the two systems have been designed separately (Maantay 1995). Usually the GIS acts as a preprocessor and/or postprocessor, executing such tasks as preparing and supplying input data, further analyzing data using GIS functions during or after execution of the model, and displaying and archiving output data for the modeling system, while environmental modeling simulates processes involving phenomena such as water, air, and soil across space.

We first preprocessed spatial data in GIS, then converted these data to the formats required by AERMOD, and then imported these data as inputs to AERMOD. After air dispersion was modeled, the outputs were exported and converted to GIS for further analyses.

The GIS software used in this study was ArcGIS 9.2, by Environmental Systems Research Institute. The air dispersion model was the Industrial Source Complex-AERMOD (ISC-AERMOD 5.6), by Lakes Environmental Ltd.

Data sources

Table 1 lists the data sources and preprocessing methods. The stationary point source data for the Bronx were extracted from the National Emissions Inventory (NEI) (US EPA 2006). Only stack emissions were used in the analysis; fugitive emissions were excluded because they account for a very small portion of the total emissions from the stationary sources (less than 3% of the total emissions of criteria pollutants), and including them would have dramatically increased the complexity of the model. Therefore, the analysis included 21 facilities having 33 emission release points (stacks). The 2002 annual emission data for five criteria air pollutants (PM_{10}, $PM_{2.5}$, NO_x, CO, and SO_2) were used in this study.

Table 1. Data sources and preprocessing methods.

Data		Source	Year	Preprocessing method
Meteorological data	Surface air data in Station 147321	National Climatic Data Center	1999	Preprocessed by Meteorological Solutions Inc., then by AERMET
	Upper air data in Station 94703			
Stationary source data	Location	US EPA 2002 National Emissions Inventory	2002	Geocoded and modified using Aerial photos and MapPLUTO in ArcGIS
	Source release parameters			Emission rate is calculated based on annual emission
Building data	Location	Building Footprints datasets provided by NYC DOITT	2005	Height is estimated based on the number of floor
	Height	MapPLUTO provided by NYC DCP	2003	Building shapefile is converted to DXF12 format using ArcV2CAD
Asthma hospitalization data		SPARCS	1995–1999	Geocoded in ArcGIS
Population data		US census 2000	2000	Disaggregated to tax lot level using CEDS

Asthma hospitalization data with the location of each patient's home address (in latitude and longitude) were from the New York State Department of Health's State Planning and Research Cooperative System (SPARCS). Five years of asthma hospitalization records for the Bronx (1995–1999) were selected and geocoded to generate the point shapefile of asthma hospitalizations. The detailed preprocessing of asthma data is described in Maantay (2007).

Population data were downloaded from census 2000 (U.S. Census Bureau 2000). The original population data by census block group were disaggregated to a much finer tax-lot level using the cadastral-based expert dasymetric system (CEDS). There are, on average, 150 tax lots per census block group in New York City. Because the data were disaggregated to a much finer spatial resolution than the unprocessed census data, this method provided a more realistic depiction of population distribution and hence a more accurate denominator for use in developing disease rates and estimates of total impacted population. The CEDS method and its validation (Phase III) are detailed in Maantay et al. (2007).

AERMOD and GIS loose-coupling

AERMOD is loosely integrated with GIS through a series of steps: input preprocessing in ArcGIS, air dispersion modeling in AERMOD, and output post-processing for further analyses in ArcGIS (Figure 1).

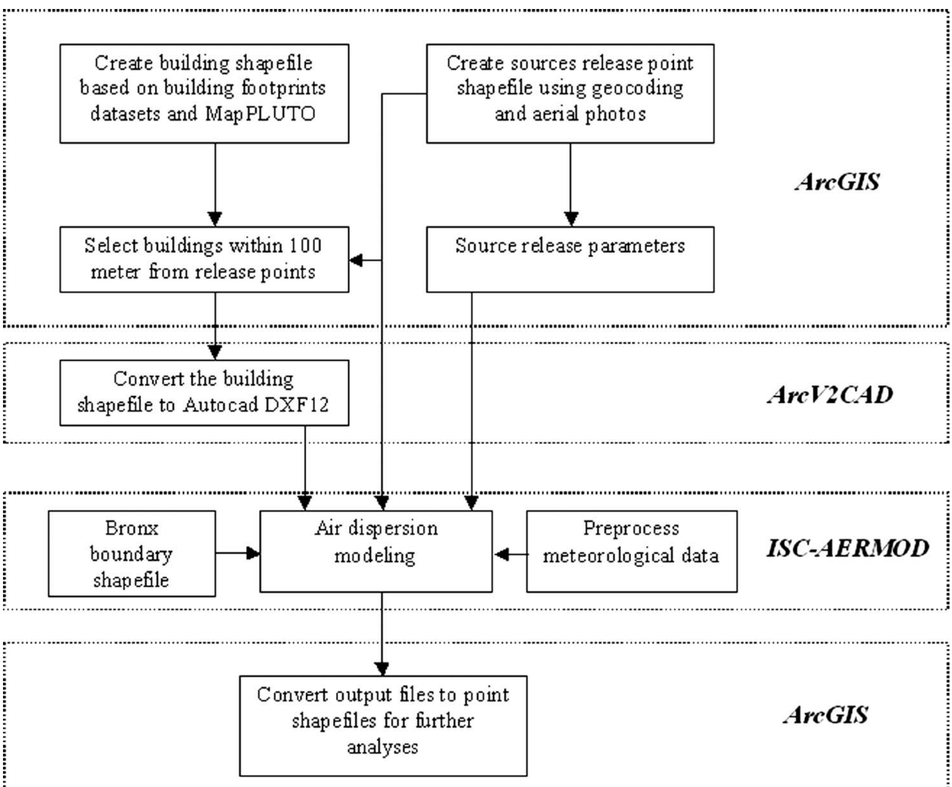

Figure 1. Flow chart of loose-coupling the air dispersion model and GIS.

Step 1 – input preprocessing in ArcGIS

A GIS shapefile showing the locations of the 21 NEI stationary point sources in the Bronx is created by geocoding in ArcGIS based on the street address of each facility. However, a street address is not enough to describe the location for a stack, and some facilities have multiple stacks. Based on the facility location shapefile, a Bronx aerial photo with a spatial resolution of 0.5 $\times$ 0.5 ft, and the MapPLUTO dataset, containing land-use data for each tax-lot, were used to locate each stack, then a GIS shapefile showing the locations of the 33 release points was created (Figure 2).

A GIS shapefile of building locations and heights was created in ArcGIS based on the Building Footprints and MapPLUTO data. The number of floors for each lot in MapPLUTO was used to estimate the height for each building, assuming the height of one floor is 11 feet. The aerial photo was used to correct some obvious errors in the location and height of housing.

Step 2 – air dispersion modeling in AERMOD

The meteorological data were first preprocessed to fit the study area using AERMOD Meteorological Preprocessor (AERMET), a component of ISC-AERMOD. Six source release parameters are required to be imported in AERMOD

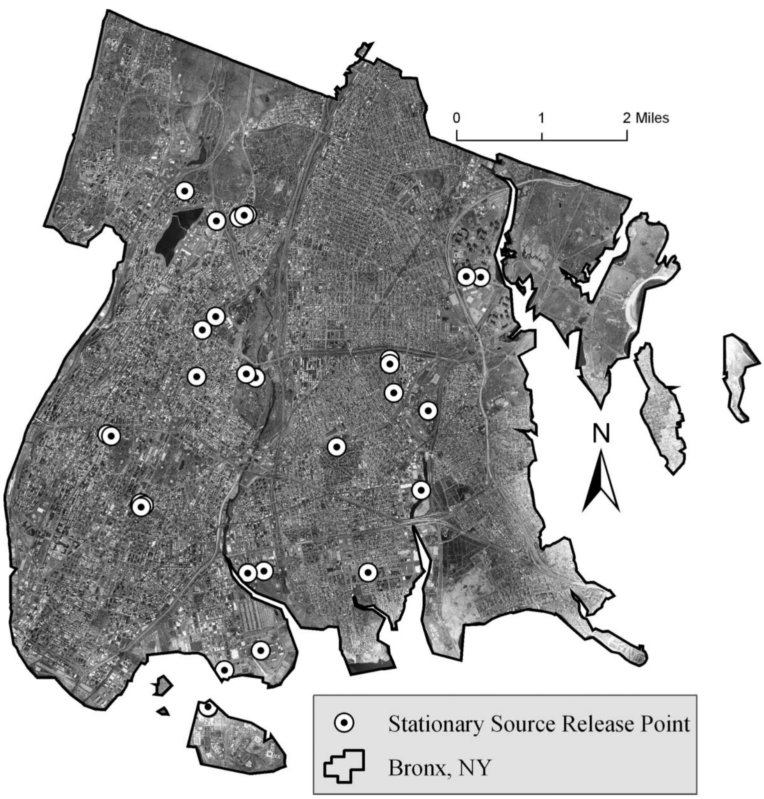

Figure 2. Locations of emission release points in the Bronx.

for each stack: release height, gas exit temperature, stack inside diameter, gas exit velocity, gas exit flow rate, and emission rate. The first five parameters, obtained from 2002 NEI, were assumed to be the same for all the air pollutants from a stack. However, emission rate, defined as the emission amount per second for a pollutant from a stack, is different for different air pollutants from the same stack. This was calculated based on the annual emission from 2002 NEI for each pollutant. The great variability in source release parameters among the 33 release points and air pollutants would have substantial impacts on the outputs of AERMOD (Table 2).

The AutoCAD building file was imported into ISC-AERMOD, and then it and meteorological data were used to run the BPIP (Building Profile Input Program) model to simulate downwash, the effect of buildings on the dispersion of air pollutants. A receptor grid with 500 × 500 ft (152 × 152 m) intervals was created resulting in 9120 receptors. The concentration of air pollutants for each receptor would be calculated in this model.

After the inputs were defined, AERMOD was run for each pollutant and facility. Two facilities which had no emissions for the pollutants of interest were excluded, leaving 19 facilities and five air pollutants to be modeled. Therefore, 95 model iterations were run in AERMOD. Two types of concentration values were generated for each air pollutant: annual average concentration and annual average highest hourly concentration over 24 h. Both were produced as two types of outputs. The first was a graphic, which showed the concentration contour produced from the simulated concentration data for all the receptors. It was not easy to use this for analyses in other programs since the graphical outputs only contained several concentration contour values, discarding the original more detailed point concentration information from AERMOD. The second was a digital file, containing the original simulated concentration and location data for the receptors, so the data could be extracted and converted to shapefiles for further analyses in ArcGIS.

Step 3 – output post-processing for further GIS analyses

SPSS software was used to extract the concentration and location data in the output file of ISC-AERMOD and convert it into a simple database format (i.e. dbf format). Then the dbf files were converted into point shapefiles in ArcGIS based on the coordinates for each receptor. One hundred and ninety point shapefiles (spatial

Table 2. Statistical summary of the source release parameters for the 33 release points.

Source release parameter	Unit	Max	Min	Mean
Release height	M	123.44	7.92	43.94
Stack inside diameter	M	4.72	0.24	1.54
Gas exit temperature	°C	343.33	21.67	191.46
Gas exit velocity	Ms^{-1}	21.64	2.44	8.99
Gas exit flow rate	$m^3 s^{-1}$	179.90	0.31	24.52
Emission rate of PM_{10}	gs^{-1}	0.36	0.00	0.05
Emission rate of $PM_{2.5}$	gs^{-1}	0.172	0.00	0.026
Emission rate of NO_x	gs^{-1}	10.59	0.00	0.85
Emission rate of CO	gs^{-1}	1.70	0.00	0.21
Emission rate of SO_2	gs^{-1}	3.93	0.00	0.42

datasets) were produced for both average and highest concentrations from the 95 model runs.

Source impact index (SII) calculation

The outputs of AERMOD are the concentrations contributed by the pollution sources used in the model, so they do not include the background concentration and cannot represent the ambient air quality or the total pollution burden. In this study we only analyzed the impact of a stationary source on its surrounding area. It is believed that the impact of air pollution on human health is from a contribution of multiple air pollutants, although the combined effect is at present not clear (Murena 2004; Wang and Lu 2006). Therefore, we analyzed the relationship between the asthma hospitalization rate and the combined impact of all selected criteria air pollutants contributed by each stationary source, instead of a single pollutant. In order to measure the impact of a stationary source on its surrounding area, we created a Source Impact Index (SII) to represent the combined contribution of the five air pollutants from a source to the ambient air, by following the EPA method of calculating the Air Quality Index (AQI) (US EPA 2006). The AQI is a useful method for reporting ambient air quality in respect to its health effects and for converting the relatively abstract scientific values (concentrations) to the numerical indices that are more understandable to the public. The AQI, sometimes called the Air Pollution Index (API), is widely used by government environmental protection agencies and scientists around the world, such as USA (US EPA 2006), Canada (Stieb et al. 2005), Italy (Murena 2004), Greece (Kyrkilis et al. 2007), India (Nagendra et al. 2007), Malaysia (Afroz et al. 2003), Mainland China (Jiang et al. 2004), Taiwan (Liu 2002), and Hong Kong (Wang and Lu 2006), to assess the ambient air quality and its health effects. Although differences exist in the included air pollutants and breakpoints used in AQI calculations among different countries or studies, the principles from which the calculations are derived are the same as the US EPA's method. The US EPA AQI converts the measured concentration of each of six air pollutants (O_3, PM_{10}, $PM_{2.5}$, NO_2, CO, and SO_2) to a sub-index on a scale of 0 to 500 using a linear interpolation method by setting up a series of breakpoints based on the National Ambient Air Quality Standards (NAAQS) and the results of epidemiological studies on the health effects of air pollution. The highest sub-index of the six air pollutants is reported as the AQI representing the ambient air quality over the measurement period (US EPA 2006).

We were not able to calculate the AQI for ambient air, because we were modeling only the air dispersion from the NEI stationary point sources. We focused on the contributions of air pollutant emissions from these stationary sources to the ambient air and their local impact on public health. Therefore, our index was entitled the "Source Impact Index", rather than the Air Quality or Pollution Index. We calculated and compared the sub-indices for the five air pollutants at each receptor (point), and the highest sub-index is used as the SII for that point. The equation followed that of the US EPA AQI, expressed below:

$$I_p = \frac{I_{Hi} - I_{Lo}}{BP_{Hi} - BP_{Lo}} \left(C_p - BP_{Lo} \right) + I_{Lo}$$

where I_p is the sub-index for pollutant p, C_p is the concentration of pollutant p, BP_{Hi} is the top breakpoint that is greater than or equal to C_p, BP_{Lo} is the bottom breakpoint that is less than or equal to C_p, I_{Hi} is the sub-index corresponding to BP_{Hi}, I_{Lo} is the sub-index corresponding to BP_{Lo}.

The breakpoints from US EPA AQI were modified to be used here (Table 3). However, the air pollutants in this study were PM_{10}, $PM_{2.5}$, NO_x, CO, and SO_2. US EPA AQI does not provide the breakpoints for NO_x, so we derived them from the method of State Environmental Protection Administration of China (Liu 2002).

Through this process, the five annual average concentration point shapefiles for the five air pollutants for each stationary source were converted to an annual average SII point shapefile. The five highest hourly concentration point shapefiles for each source were also converted to a corresponding SII shapefile.

Proximity and plume buffers generation

Plume buffers are created from the continuous pollutant surface (the SII values) in order to define the geographic impact extent of the highest pollutant values from each individual major stationary point source. These plume buffer polygons were designed to characterize the pollutant profile of each modeled facility.

In Phase I, fixed-distance proximity buffers were created for TRI facilities, limited access highways, major truck routes, and NEI stationary point sources and used as a proxy for human exposure to air pollution; 150 meters was used as the distance for proximity buffers of both limited access highways and major truck routes. Half-mile (800 m) and one-quarter mile (400 m) were used as the radius for proximity buffers of TRI facilities and NEI stationary point sources, respectively (Maantay 2007).

In the current Phase IV study, we conducted air dispersion modeling only for NEI stationary point sources, to compare, as a pilot study, proximity buffers to plume buffers. Thus, for the purpose of comparing proximity analysis and air dispersion modeling, we also created one-quarter mile (400 m) radius buffers around NEI stationary point sources. This buffer distance is based on established standards from environmental agencies as the area of greatest potential impact from such sources (New York City Mayor's Office of Environmental Coordination 2001).

We then created plume buffers to modify the proximity buffers based on the results of dispersion modeling. As in Phase I, the residents living inside of the buffers were assumed to be exposed to higher levels of air pollution than those living outside the buffers.

The plume buffers were created based on the SII shapefiles in ArcGIS. The highest SII for a source is usually at or close to the location of the source. In general, the SII decreases as the air pollutant disperses out from the source. We then created a

Table 3. Breakpoint concentrations and the corresponding sub-indices for SII calculation.

Sub-index	PM_{10} ($\mu g/m^3$)	$PM_{2.5}$ ($\mu g/m^3$)	NO_x ($\mu g/m^3$)	CO (ppm)	SO_2 (ppm)
0–50	0–54	0.0–15.4	0–50	0.0–4.4	0.000–0.034
51–100	55–154	15.5–40.4	51–100	4.5–9.4	0.035–0.144
101–200	155–354	40.5–150.4	101–150	9.5–15.4	0.145–0.304
201–300	355–424	150.5–250.4	151–565	15.5–30.4	0.305–0.604
301–400	425–504	250.5–350.4	566–750	30.5–40.4	0.605–0.804
401–500	505–604	350.5–500.4	751–940	40.5–50.4	0.805–1.004

series of contours surrounding the source, based on the SII value at each point over the study area. The values of contours decrease as distance increases away from the source. Thus, for each contour, the impact of the source on ambient air was higher inside the contour than outside. One contour can be used as a buffer to identify the difference in asthma hospitalizations inside and outside the buffer. However, those contours are not circular due to meteorological and building effects, which are the major differences from proximity buffers. The SII values for individual sources showed substantial difference due to the large variation in inputs to AERMOD for the stationary sources. (Table 2) As such, we were not able to select a single SII value applicable to all the sources.

We used 10% of the highest SII value for each source to define the boundary of its plume buffer. The areas with SII values higher than or equal to 10% of the highest value were considered to be inside the plume buffer, and the other areas were outside of the plume buffer. The reason we used this definition was that 10% of the highest value is considered as the plume edge by US EPA when simulated by a Gaussian modeling approach, as used in AERMOD (Cora and Hung 2003). The Gaussian approach assumes that the simulated concentration values follow a bell-shaped distribution. The concentration of a modeled pollutant is the highest at the center of the plume (the location of the source in this study), and then decreases exponentially approaching zero at the plume edge (Cora and Hung 2003). Thus, the areas beyond the plume edge (10% of the highest value) can be considered as free of the impact of the source.

Additionally, the plume buffers created by using 10% of the highest value capture approximately the same amount of area as the one-quarter mile proximity buffer, which avoids the impact of geographical scale on the results from the comparison of plume buffers and proximity buffers. We used and compared the plume and proximity buffers to examine the local effects of air pollution from major point sources, and to minimize the influences of other local- and regional-scale sources.

The plume buffers representing both average and highest concentrations depict nearly identical areal extents. Due to this similarity, only the plume buffers using the highest concentrations were used for calculating asthma rates and are reported in this paper.

Asthma rates calculations for inside and outside buffers

The proximity and plume buffers and the disaggregated population data at the tax-lot level are used to calculate the total population living inside and outside of the buffers. The population layer is overlain with the proximity and plume buffer layers. The population in tax lots whose centroids falls inside a buffer are summed to get the total population living inside of the buffer. The disaggregation of population data from the census block group to tax-lot level using CEDS significantly improves the accuracy of the total population count, as was described and validated in Maantay et al. (2007). The rest of the population is considered as living outside of the buffers.

The asthma hospitalization data layer was also overlain with each of the proximity and plume buffer layers. The number of asthma hospitalization cases inside a buffer was divided by the total population inside the buffer to derive the rate inside the buffer. The remaining asthma hospitalization cases were divided by the total population outside the buffer to get the corresponding asthma hospitalization rate.

Cumulative SII and its relationship with asthma rate

Besides the plume and proximity buffer analyses using the SII of individual sources, an analysis was conducted using a continuous and cumulative SII surface created from the combined concentration data of all sources. Hypothetically, a continuous-cumulative surface would be optimal; however, it is shown to have some shortcomings in the context of this study when analyzing asthma hospitalizations as a function of air pollution, due to two major reasons. Firstly, in this study only the NEI stationary point sources were considered due to a lack of available or reliable pollution data from other potential sources (e.g. toxic release inventory facilities, truck routes, limited access highways, etc.). This results in a pollution surface that does not account for many other sources that could have a greater effect on asthma rates as the distance from the measured NEI sources becomes greater. Secondly, certain measured stationary point sources result in far higher SII values, effectively obfuscating the effect of other sources when analyzed cumulatively.

To illustrate these phenomena, the cumulative SII data were aggregated into 20 quantiles (20 groups of five percentiles each arrayed in ascending order). The asthma hospitalizations and CEDS-derived population coinciding with the geographic area of each quantile group were used to calculate the asthma rate by dividing the number of hospitalizations by the population in ArcGIS. Figure 3 shows how the asthma hospitalization rates change among different cumulative SII quantile groups. An effect on the rates was clearly visible only in the highest (95th percentile), which is associated with the highest rate, and lowest ($<$10th percentile) groups, which is related to the lowest rate. This suggests that due to the exclusion of other sources and the uneven nature of SII concentrations from the modeled sources, the local effect [i.e. very close to the source (95th percentile) or very far from the source ($<$10th percentile)] has a more clearly defined relationship with asthma hospitalizations when analyzing this type of correlation. This finding was bolstered by regression analysis which demonstrated a statistically significant linear relationship between asthma hospitalization rates and the cumulative SII quantile groups ($R^2 = 0.305$, $\beta = 0.553$, $p < 0.05$). The "noise" associated with the middle values (between the 10th and 95th percentiles) was most likely a function of the issues listed above

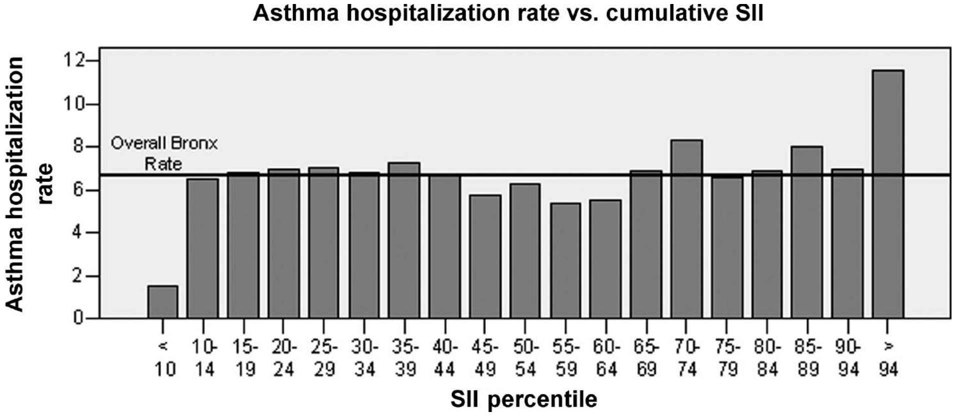

Figure 3. Asthma hospitalization rates in different SII percentile groups.

(e.g. the analysis not being able to take other pollution sources into account, and the masking or obliterating effect of a cumulative pollution surface on individual source impacts). When the extreme values (highest and lowest quantile groups) were removed from the regression, no linear relationship was detectable ($R^2 = 0.036$, $\beta = 0.190$, $p = 0.465$). These results strengthened the decision to use binary plume buffers, specifically designed to measure the effect of local sources while minimizing the influence of other local or regional pollution. Therefore, we report only the results of the plume and proximity buffer analyses in the following section.

Results and discussion

Results of AERMOD

AERMOD calculates the concentration contributed by a source for each receptor with certain intervals (e.g. 500 × 500 ft grid). This high density of data points (9120 for the Bronx) can be used to calculate a continuous surface of spatially varying pollutant concentrations by using interpolation techniques.

In contrast, the Bronx, with an area of 150 km^2, has only five ambient air quality monitoring stations, operated by the New York State Department of Environmental Conservation. Rather than statistically interpolating (e.g. Kriging, Inverse Distance Weighting) pollutant concentration levels using only the data from the five monitoring stations in the Bronx, AERMOD generates over 9000 data points (receptors) each with a modeled concentration value, from which the interstitial values are then interpolated. Since there are so many more data points, the AERMOD-GIS loose-coupling potentially yields far more realistic results.

Figure 4 shows a concentration surface for one sample pollution source created using Kriging interpolation based on the data from AERMOD. The concentrations were highest around the source, decreasing as distance increased from the source at different rates in different directions affected mainly by local meteorological conditions.

Comparison of proximity buffer and plume buffer

Figure 5 compares the proximity and plume buffers for one NEI stationary source. The circular shape of the proximity buffer was modified. For example, the plume buffer distance downwind of annual dominant wind directions, northeast and northwest, was longer than that in other directions. In addition to wind direction, the modification of shape was also influenced by other factors such as buildings. The spatial difference in exposure contributed by the source using air dispersion modeling would seem to be more accurate than that obtained in the proximity buffer analysis, because AERMOD considers the properties of the sources, meteorological conditions, and the building effect, instead of only a fixed, absolute distance.

Based on the asthma hospitalization data from 1995–1999, the rate inside the fixed-distance proximity buffers of the major stationary point sources was higher than that outside the buffer, and when air dispersion modeling was used, a similar spatial pattern was found (Table 4). For both plume and fixed-distance proximity buffers, the difference in the asthma rate between inside and outside buffers was statistically significant at $p < 0.05$, tested by an odds ratio analysis.

The results of the plume buffer analysis modified the findings of the Phase I study. Results of the current (Phase IV) study showed that the higher asthma hospitalization

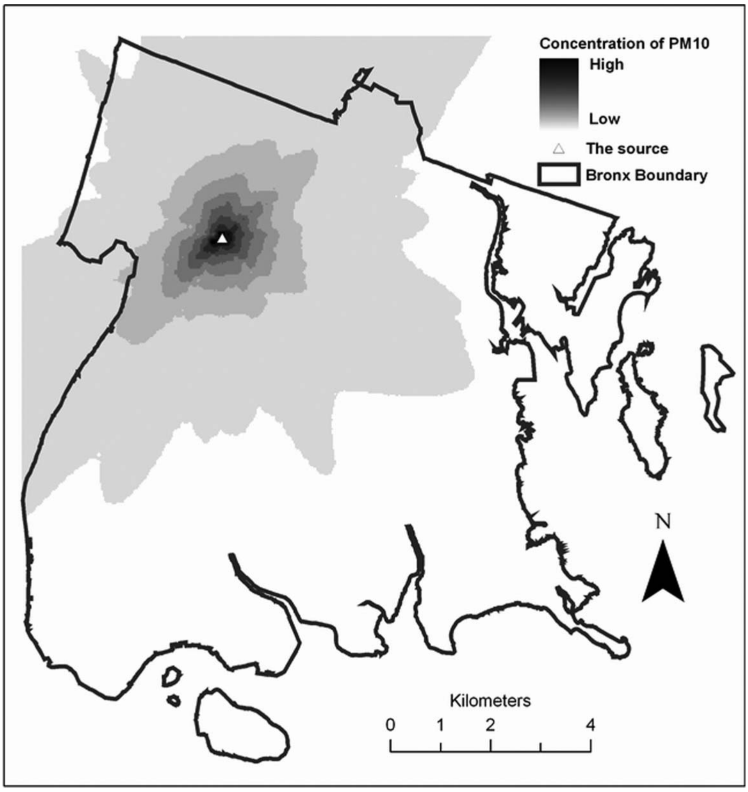

Figure 4. An example of a concentration surface for one pollution source created by using Kriging interpolation from AERMOD output.

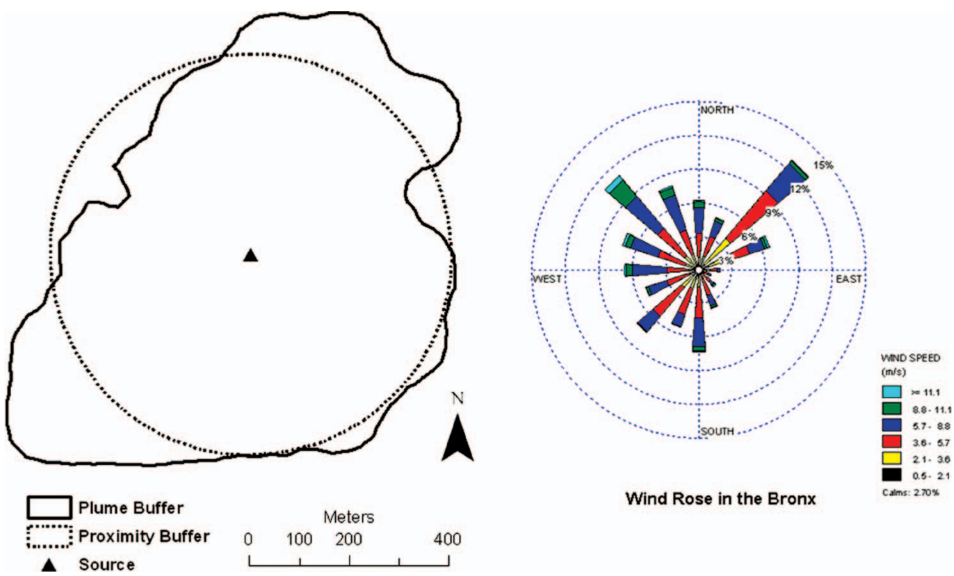

Figure 5. Comparison of plume buffer and proximity buffer for a source.

Table 4. Comparison of asthma rates obtained by plume and proximity buffers.

Geographical area	Population	Asthma hospitalization (5-yr. average)	Asthma rate (per 1000 per year)
Inside plume buffer	132,921	993	7.47
Outside plume buffer	1,185,142	7827	6.56
Inside proximity buffer	115,290	857	7.43
Outside proximity buffer	1,202,773	7963	6.58
All Bronx	1,318,063	8820	6.66

rates were associated with a higher potential exposure to local air pollution, rather than showing merely a correlation of asthma hospitalization rates and distance to pollution sources. Although the rates were very similar for plume and proximity buffers, there were important differences between the buffer types. Although both buffer types covered roughly the same areal extent per source, the plume buffer had an irregular shape, due to the air dispersion model results which used individual meteorological, topographical, and pollutant characteristics for each source. The plume buffers (containing the area with greater than 10% of the highest SII value) captured more population and asthma hospitalizations, in absolute numbers, than the proximity buffers (400 m fixed-distance buffer). This difference in captured population was not only due to the modeled air dispersion, but also because population density was not homogeneously distributed around each pollution source. In other words, the plume buffer analysis suggested that more people were potentially being impacted by local air pollution than was demonstrated by the proximity buffers.

However, the plume buffers we generated in this study still did not represent the actual exposure to ambient air pollution, since we calculated only the concentrations contributed by the 33 NEI stationary point sources, due to data limitations in ambient air monitoring source parameters. In order to get more definitive conclusions on the association between air pollution and asthma hospitalization rates, more pollution sources, including mobile sources, TRI facilities, and non-point stationary sources, would need to be included in the model.

Limitations and assumptions

Ecological studies utilizing complex models tend to contain many limitations and assumptions, some of which have already been noted. These limitations and assumptions exist in both data and methodology, and are described below.

Data limitations

Asthma hospitalization data, as with any point data that require geocoding in order to spatially locate events, are subject to the potential locational error associated with the georeferencing process (Cromley et al. 1997; Whitsel et al. 2004; Maantay 2007). When using discrete spatial data such as buffer polygons, positional accuracy of points assigned to areas inside or outside of these buffer zones can potentially have a great influence on the results of the analysis.

In addition to the issue of positional accuracy of case records, there are potential concerns with the available asthma hospitalization attribute (nonspatial) data.

The dataset used contained only cases of asthma hospitalization, and did not include emergency room, doctor, or clinic visits, nor did it include those with self-reported diagnoses of asthma. Only hospitalization data was available in a consistent and comprehensive way for asthma. Therefore, the dataset was not a proxy for asthma prevalence or incidence, but presumably reflected the most severe acute asthma events, since hospitalization was required. Admission data was inclusive of emergency room visits that resulted in hospital admissions, but did not include ER visits not resulting in admissions.

We used only residential location for the exposure analysis as this was the only available place-based variable in the asthma hospitalization dataset. Clearly, people are exposed to air pollutants not only at their residential address, but also at their workplace, school, and other locations, which could have an influence on exposure, and this was not reflected in this analysis.

Additionally, the causes of asthma are not totally understood and are extremely complex. There is a wide range of opinions among researchers about the main causes and the etiology of asthma, and even whether the diagnosis represents more than one disease (Infante-Rivard 1993; Peat et al. 1995; Delfino et al. 1996; Rosenstreich et al. 1997; Sears 1997; Claudio et al. 1999; Lau et al. 2000; Teague and Bayer 2001). In this study, we were trying to quantify the connection between asthma hospitalization (acute events) and air pollution exposure, rather than ascribe causality of the disease to these pollutants. The analysis was designed to examine the local effect of outdoor air pollution from selected stationary point sources, not taking into account other potential triggers or irritants (e.g. indoor air quality) or individual behavioral risk factors (e.g. smoking). Although this phase of the study did not examine socio-demographic characteristics of the affected population, we conducted a multiple regression analysis in Phase II of the study, and even after controlling for the potential confounders of race/ethnicity and poverty status, we found that there was still a significant correlation between proximity to air pollution sources and asthma hospitalization rates (Maantay et al. 2007).

There are also issues related to the temporal discrepancy between the asthma hospitalization data (1995–1999), and the meteorological data (1999), population data (decennial census, 2000), building data (2003 and 2005), and NEI (emissions) data (2002). The use of non-contemporaneous data was primarily due to lack of availability. The data sets were as proximate to 1999 as possible to match the final year of the asthma hospitalization data. Temporal agreement was not vital with respect to the tax-lot/building information since this did not normally change dramatically over such a short time period. As for the NEI emissions data, the 2002 data set was the closest year to the asthma hospitalization data for which the necessary source release parameters required by AERMOD were included. However, the total emissions in the Bronx, according to NEI data sets from 1999 and 2002, were relatively stable and consistent. The year 1999 for meteorological data was selected to best match with the hospitalization data, rather than match the meteorological data to the emissions data, which remained relatively constant.

The NEI data was the most readily available and consistent data source for major stationary source emissions, and had been used in many previous air pollution studies (Park et al. 2006; Phillips and Finkelstein 2006; Gbor et al. 2007; Kim and Stockwell 2007; Godowitch et al. 2008; Stone 2008). The emissions data are self-reported estimates by each facility's manager, rather than being monitored data, and give only annual emissions estimates for different air pollutants from each facility. Although it would be have been helpful to have access to more precise and complete data (since seasonal, monthly, daily, or even hourly variations occur in the emissions), this data is not required by regulatory agencies, and is, therefore, most often not measured or reported.

AERMOD output data is constrained by a similar temporal aggregation. The output is a measure of average annual pollutant concentrations, in order to match the temporal aggregation of our other data sets, rather than showing a snapshot of the air dispersion at any given time. The annual average concentrations do not allow for the detection of seasonal or sub-seasonal variations, but provide a general spatial pattern of the air dispersion.

Methodological limitations

As with many environmental models, AERMOD uses a number of inputs and parameters, most of which require some degree of generalization and averaging of data. Therefore, the extent and directionality of the air pollutant dispersion is generalized, both spatially and temporally.

Although AERMOD has been extensively tested and its output validated by the developers of the model (US EPA), we were not able to validate the model results empirically for our study. Without conducting stack monitoring of pollutants or monitoring ground-level air pollutant concentrations around each facility, there was no empirical way to confirm the results of AERMOD. Such monitoring is cost prohibitive and beyond the scope of this study. Although there are existing ambient air monitoring stations in the Bronx, it was not useful to validate the AERMOD output against their data due to the limited number, altitudinal location, and biased spatial distribution of these monitors. The existing monitoring stations are more useful for measuring ambient air quality around the sensors themselves rather than the spatial variation in pollutant concentrations originating from local sources. AERMOD only models the pollutants from the stack, and does not take into account background air quality or emissions from other sources.

The other main methodological limitation in this study was the use of buffers as a proxy for exposure. There are certain limitations to any buffer analysis. For example, the use of buffers as a proxy for exposure is essentially a binary model, which is a simplified reflection of reality, e.g. a case is characterized as being either "exposed" or "unexposed" based on its location *vis-a-vis* the buffer boundary. It should be noted that this constraint applies to any analysis using discrete boundaries, rather than a continuous surface. Both fixed distance and plume buffers are equally affected by this limitation.

Multiple buffers (e.g. concentric rings) could be created describing differing degrees of exposure, but the underlying limitation would still remain. Alternatively, continuous data could hypothetically yield more realistic results; however, it was not possible to create a valid continuous statistical surface of pollutant concentrations without modeling every major source in the Bronx region, which was beyond the scope of this analysis. It is important to stress that the case study presented in this analysis was intended to focus on health impacts from local source pollution rather than regional or ambient air quality.

We believe that even after taking into account the aforementioned limitations and assumptions, the results of this study are relevant, reliable, and valid.

Conclusions

This study loosely-couples AERMOD and ArcGIS through a set of new procedures including data preprocessing in ArcGIS, air dispersion modeling in AERMOD, and output post-processing in ArcGIS to simulate air dispersion from NEI stationary sources in the Bronx for five criteria pollutants (PM_{10}, $PM_{2.5}$, NO_x, CO, and SO_2). Based on the modeled concentrations, Source Impact Index values were calculated to represent the combined contribution of the five air pollutants from each source to the surrounding air environment, following the EPA method of calculating the Air Quality Index. Plume buffers were created from the SII values as proxies of human exposure to the pollution from the sources. Plume buffers modified the commonly-used proximity buffers by considering the realities of air dispersion. The associations between the asthma hospitalizations and distance to pollution sources were analyzed by comparing the plume and proximity buffers. The results showed that asthma hospitalization rates were higher inside of both plume and proximity buffers than those outside. Plume buffers also captured more people and asthma hospitalizations than the proximity buffers. These results suggest that higher asthma hospitalization rates are associated with higher exposure to local air pollution sources, and that more people may be exposed than previously calculated based on proximity buffer analysis.

The results of the loose-coupling of AERMOD and GIS show the advantages of air dispersion modeling and the creation of plume buffers over proximity analysis. The loose-coupling provides a feasible method for researchers to take advantage of both air dispersion modeling and GIS by avoiding the need for intensive programming and substantial GIS expertise.

In addition to the advantages to health researchers in gaining a better understanding of the spatiality of respiratory disease and the exposure extent of airborne pollutants, the results of the loose-coupling integrative method could have beneficial policy implications. The method we have outlined to integrate air dispersion modeling and GIS could be valuable to environmental protection, public health, and other agencies in conducting impact assessments, and analyzing likely ramifications of land use decisions. These assessments could then be used to inform policy decision-making in development proposals, re-zoning actions, transportation projects, environmental infrastructure construction and facility modifications, as well as be useful in determining community "fair share" burdens and equitable distribution and siting of noxious and beneficial land uses – the environmental "goods" and "bads". The loose-coupling method could have far-reaching influence on how environmental health justice considerations are taken into account in a more meaningful way.

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