# Risk and Exposure Assessment to Support the Review of the $NO_2$ Primary National Ambient Air Quality Standard: Second Draft

# Chapter 8

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## Disclaimer

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# 8. EXPOSURE ASSESSMENT AND HEALTH RISK CHARACTERIZATION

## 8.1 OVERVIEW

This section documents the methodology and data used in the inhalation exposure assessment and associated health risk characterization for $NO_2$ conducted in support of the current review of the $NO_2$ primary NAAQS. Two important components of the analysis include estimating temporally and spatially variable $NO_2$ concentrations and simulating human contact with these pollutant concentrations. Both air quality and exposure modeling approaches have been used to generate estimates of 1-hour $NO_2$ exposures within Atlanta, Georgia across a 3-year period (2001-2003). Exposure and potential health risk were characterized considering recent air quality conditions (*as is*), for air quality adjusted to just meet the current $NO_2$ standard (0.053 ppm annual average), and for just meeting several potential alternative standards (see chapter 5). The approaches used for assessing exposures in Atlanta are described below. Detailed input data and supporting discussion of the Atlanta case-study is provided in Appendix B-4, in addition to containing the methodology and results for the first exposure modeling case-study conducted in Philadelphia County as part of the 1st draft REA (EPA, 2008b). Briefly, the discussion that follows includes:

- Description of the inhalation exposure model and associated input data
- Evaluation of estimated $NO_2$ exposures
- Assessment of the quality and limitations of the input data for supporting the goals of the $NO_2$ NAAQS exposure and risk characterization.

## 8.2 OVERVIEW OF HUMAN EXPOSURE MODELING USING APEX

The EPA has developed the Air Pollutants Exposure Model (APEX) model for estimating human population exposure to criteria and air toxic pollutants. APEX serves as the human inhalation exposure model within the Total Risk Integrated Methodology (TRIM) framework (EPA 2006a; 2006b) and was recently used to estimate population exposures in 12 urban areas for the $O_3$ NAAQS review (EPA, 2007g; 2007h).

APEX is a probabilistic model designed to account for sources of variability that affect people's exposures. APEX simulates the movement of individuals through time and space and estimates their exposure to a given pollutant in indoor, outdoor, and in-vehicle microenvironments. The model stochastically generates a sample of simulated individuals using census-derived probability distributions for demographic characteristics. The population demographics are drawn from the year 2000 Census at the tract, block-group, or block level, and a national commuting database based on 2000 census data provides home-to-work commuting flows. Any number of simulated individuals can be modeled, and collectively they approximate a random sample of people residing in a particular study area.

Daily activity patterns for individuals in a study area, an input to APEX, are obtained from detailed diaries that are compiled in the Consolidated Human Activity Database (CHAD) (McCurdy et al., 2000; EPA, 2002). The diaries are used to construct a sequence of activity events for simulated individuals consistent with their demographic characteristics, day type, and season of the year, as defined by ambient temperature regimes (Graham and McCurdy, 2004). The time-location-activity diaries input to APEX contain information regarding an individuals' age, gender, race, employment status, occupation, day-of-week, daily maximum hourly average temperature, the location, start time, duration, and type of each activity performed. Much of this information is used to best match the activity diary with the generated personal profile, using age, gender, employment status, day of week, and temperature as first-order characteristics. The approach is designed to capture the important attributes contributing to an individuals' behavior, and of likely importance in this assessment (i.e., time spent outdoors) (Graham and McCurdy, 2004). Furthermore, these diary selection criteria give credence to the use of the variable data that comprise CHAD (e.g., data collected were from different seasons, different states of origin, etc.).

APEX has a flexible approach for modeling microenvironmental concentrations, where the user can define the microenvironments to be modeled and their characteristics. Typical indoor microenvironments include residences, schools, and offices. Outdoor microenvironments include for example near roadways, at bus stops, and playgrounds. Inside cars, trucks, and mass transit vehicles are microenvironments which are classified separately from indoors and outdoors. APEX probabilistically calculates the concentration in the microenvironment associated with each event in an individual's activity pattern and sums the event-specific exposures within each hour to obtain a continuous series of hourly exposures spanning the time period of interest. The estimated microenvironmental concentrations account for the contribution from ambient (outdoor) pollutant concentration and influential factors such as the penetration rate into indoor microenvironments, air exchange rates, decay/deposition rates, proximity to important outdoor sources, and indoor source emissions. Each of these influential factors are dependent on the microenvironment modeled, the available data to define each of the parameters, and the estimation method selected by the user. And, because the modeled individuals represent a random sample of the population of interest, the distribution of modeled individual exposures can be extrapolated to the larger population within the modeling domain.

The exposure modeling simulations can be summarized by five steps, each of which is detailed in the subsequent sections of this document. Briefly, the five steps are as follows.

1. **Characterize the study area**. APEX selects the census blocks within that study area – and thus identifies the potentially exposed population – based on user-defined criteria and availability of air quality and meteorological data for the area.
2. **Generate simulated individuals**. APEX stochastically generates a sample of hypothetical individuals based on the demographic data for the study area and estimates anthropometric and physiological parameters for the simulated individuals.
3. **Construct a sequence of activity events**. APEX constructs an exposure event sequence spanning the period of the simulation for each of the simulated individuals using the time-location-activity pattern data.
4. **Calculate hourly concentrations in microenvironments**. APEX users define microenvironments that people in the study area visit by assigning location codes in the activity pattern to the user-specified microenvironments. The model then calculates hourly pollutant concentrations in each of these microenvironments for the period of simulation, based on the user-provided microenvironment descriptions, the hourly air quality data, and for some of the indoor microenvironments, indoor sources of $NO_2$. Microenvironmental concentrations are calculated for each of the simulated individuals.
5. **Estimate exposures**. APEX estimates a concentration for each exposure event based on the microenvironment occupied during the event. These values can be averaged by clock hour to produce a sequence of hourly average exposures spanning the

specified exposure period. These hourly values may be further aggregated to produce daily, monthly, and annual average exposure concentrations.

## 8.3 CHARACTERIZATION OF STUDY AREA

### 8.3.1 Study Area Selection

The selection of the location used for this exposure analysis was based on the location of field and epidemiology studies, the availability of ambient monitoring and other input data, the desire to represent a range of geographic areas, population demographics, general climatology, and results of the ambient air quality characterization.

Atlanta, along with several other locations, was initially selected as a location of interest through statistical analysis of the ambient $NO_2$ air quality data (see section 7 and Appendix A). Briefly, criteria were established for selecting ambient monitoring sites containing high annual mean concentrations and/or exceedances of potential health effect benchmark concentrations. The 90$^{th}$ percentile served as the point of reference for the annual mean concentrations and, across all complete site-years for 2001-2006, this value was 23.5 ppb. Seventeen locations contained one or more site-years with an annual average concentration at or above the 90$^{th}$ percentile, of which Atlanta contained one site-year (26.6 ppb annual average). A 1-hour potential health effect benchmark level of 200 ppb was selected as the second criteria for location selection, and Atlanta had one measured concentration above this level. Based on the availability of health effects data associated with ambient concentrations (Tolbert et al., 2007), the availability of personal exposure data (Suh, 2008), and the analysis of the air quality data, Atlanta was selected as the second case-study location.

### 8.3.2 Study Area Description

The greater Atlanta metropolitan area covers the 13 counties within a radius of approximately 40 km about the Atlanta city center (33.65 °N 84.42 °W) in Fulton County. Due to the complexity of the air quality and exposure modeling to be performed in this exposure assessment, the study location (or modeling domain) was designated as the four counties directly surrounding the city of Atlanta (i.e., Cobb, DeKalb, Fulton, and Gwinnet Counties) (see Figure 8-1). These four counties comprise the urban center of the Atlanta MSA, and contain a large portion of the urbanized road systems in the area. This four county modeling domain contains

27,315 U.S. Census blocks with a combined population of 2,678,078 (2000 Census), comprising approximately 65% of the Atlanta MSA population.

### 8.3.3 Time Period of Analysis

Calendar years 2001 through 2003 were simulated to envelop the most recent year of emissions data available for the study location (i.e., 2002) and to include a total of 3 years of meteorological data to achieve a degree of stability in the dispersion and exposure model estimates.

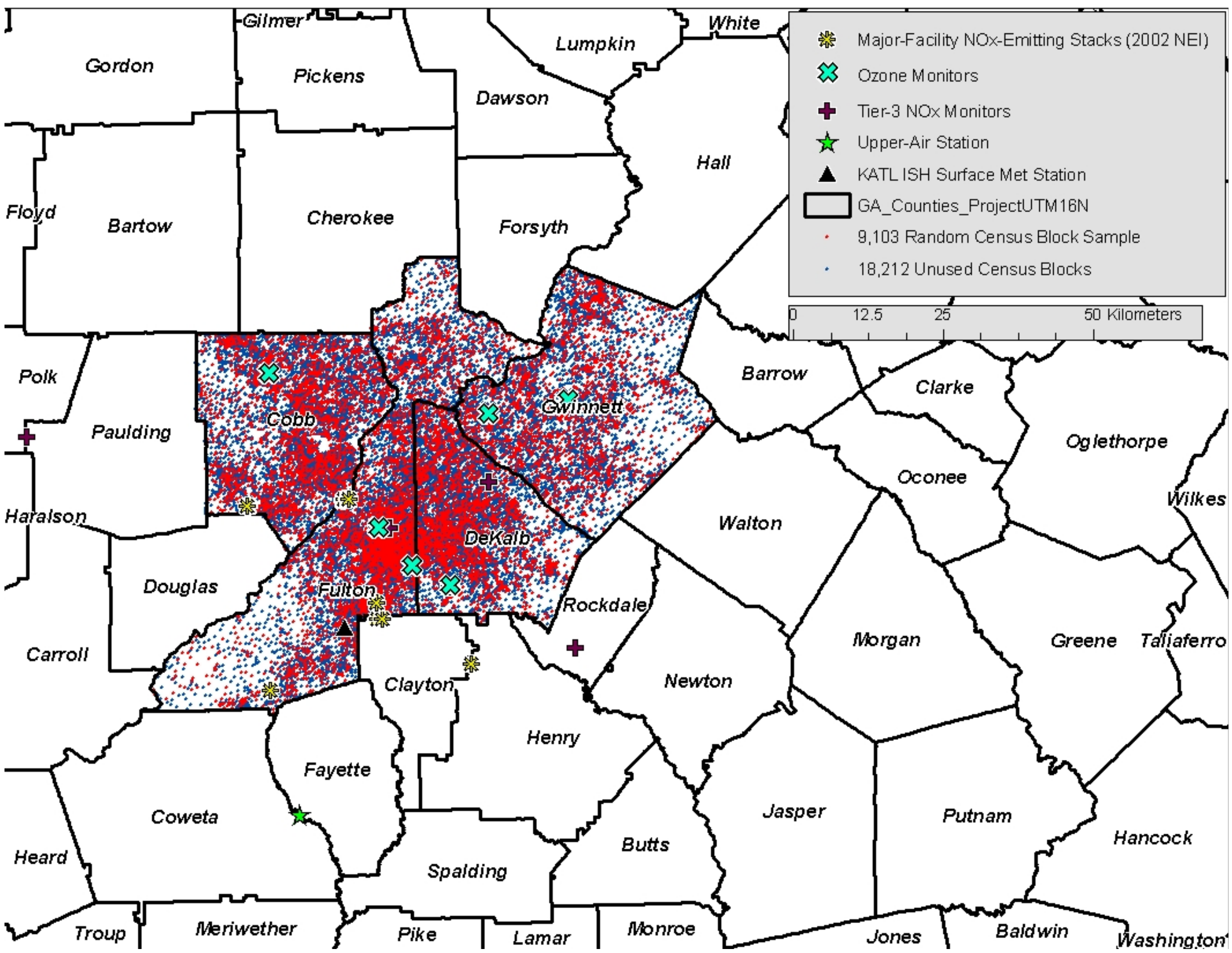


**Figure 8-1. Four county modeling domain used for Atlanta exposure assessment.**

### 8.3.4 Populations Analyzed

The exposure assessment included the total population residing in each modeled area and considered susceptible and vulnerable populations as identified in the ISA. These include population subgroups defined from either an exposure or health perspective. The population subgroups identified by the ISA (EPA, 2008b) that were included and that can be modeled in the exposure assessment include:

- Children (ages 5-18)
- Asthmatic children (ages 5-18)
- All persons (all ages)
- All Asthmatics (all ages)

In addition to these population subgroups, individuals anticipated to be exposed more frequently to $NO_2$ were assessed, including those commuting on roadways and persons residing near major roadways.

## 8.4 CHARACTERIZATION OF AMBIENT AIR QUALITY USING AERMOD

### 8.4.1 Overview

Air quality data used for input to APEX were generated using AERMOD, a steady-state, Gaussian plume model (EPA, 2004). The following steps were performed to estimate air concentrations using AERMOD.

1. **Collect and analyze general input parameters.** Meteorological data, processing methodologies, and information on surface characteristics and land use are used to determine pollutant dispersion characteristics, atmospheric stability, and mixing heights.
2. **Define sources and estimate emissions**. The emission sources modeled included, major stationary emission sources, on-road emissions that occur on

major and minor roadways, and emissions from Atlanta Hartsfield International Airport.[1]

3. **Define receptor locations**. Three sets of receptors were identified for the dispersion modeling, and included, ambient monitoring locations, census block centroids, and links along major roadways.
4. **Estimate concentrations at receptors**. Hourly concentrations were estimated for each year (2001-2003) of the simulation by combining the estimated concentration contributions from each of the emission sources to the defined receptors.

A brief description of input data and approaches used for estimating source emissions are described below. Additional details on the inputs and assumptions used in the dispersion modeling are provided Appendix B-4.

### 8.4.2 General Model Inputs

#### *8.4.2.1 Meteorological Inputs*

All meteorological data used for the AERMOD dispersion model simulations were processed with the AERMET meteorological preprocessor, version 06341. Raw meteorological data from the Southeast Aerosol Research and Characterization study (SEARCH) site in Atlanta were used as the primary source of meteorology for the AERMOD runs for the years 2001 through 2003. Raw hourly surface meteorological data for the 2001 to 2003 period were obtained from the Integrated Surface Hourly (ISH) Database,[2] primarily for use in modeling the emissions from the Atlanta Hartsfield International (KATL). Upper air data in the Forecast System Laboratory (FSL) format was downloaded from the FSL, (now Global Systems Division) website, http://www.fsl.noaa.gov/. Details regarding the data preparation and processing are given in Appendix B, Attachment 1.

#### *8.4.2.2 Surface Characteristics and Land Use Analysis*

In addition to the standard meteorological observations of wind, temperature, and cloud cover, AERMET analyzes three principal variables to help determine atmospheric stability and

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[1] Fugitive emissions from major point sources in the Atlanta area were not included as was done in the Philadelphia County case study, since the NEI shows all emissions to be accounted by stack totals.
[2] National Climatic Data Center (NCDC), http://www1.ncdc.noaa.gov/pub/data/techrpts/tr200101/tr2001-01.pdf

mixing heights: the Bowen ratio, surface albedo as a function of the solar angle, and surface roughness. A draft version of AERSURFACE (08256) was used to estimate land-use patterns and calculate these three variables as part of the AERMET processing, using the US Geological Survey (USGS) National Land Cover Data 2001 archives.[3] Details for the seasonal specification definitions, land-use sectors, and data processing are given in Appendix B, Attachment 1.

#### *8.4.2.4 Other AERMOD Input Specifications*

All emission sources in the Atlanta modeling domain were characterized as *urban*, using the 2000 census population of approximately 4.1 million people in the Atlanta MSA.[4] The AERMOD *toxics* enhancements were also employed to speed calculations from area sources. $NO_x$ chemistry was applied to all sources to determine $NO_2$ concentrations. For the roadway and airport emission sources the *Ozone Limiting Method* (OLM) (EPA, 2006c) was used, with plumes considered *grouped*. For all point source simulations, the *Plume Volume Molar Ratio Method* (PVMRM) was used to estimate the conversion of $NO_x$ to $NO_2$ (Hanrahan, 1999a, 1999b). The *equilibrium value* for the $NO_2$:$NO_x$ ratio was taken as 75%, the national average ambient background ratio.[5] The initial $NO_2$ fraction of $NO_x$ is anticipated to be about 10% or less (Finlayson-Pitts and Pitts, 2000; Yao et al., 2005), therefore a conservative value of 10% selected from the upper range of this estimate and used for all sources.

Hourly surface $O_3$ data for years 2001-2003 were obtained from five ambient monitors operating as part of EPA's Air Quality System (AQS)[6] and from one ambient monitor operating as part of the South Eastern Aerosol Research and Characterization (SEARCH) study.[7] Missing data were substituted based on seasonal and time of day characteristics, and hourly values were averaged across each of the $O_3$ monitors which were available for a particular hour. None of the AQS monitors had data available for November, December, January, and February, for these months only the SEARCH monitor data were used. The locations of these monitors are shown in Figure 8-1.

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[3] http://seamless.usgs.gov/
[4] http://www.census.gov/Press-Release/www/2001/sumfile1.html
[5] Appendix W to CFR 51, page 466. http://www.epa.gov/scram001/guidance/guide/appw_03.pdf.
[6] http://www.epa.gov/ttn/airs/airsaqs/detaildata/downloadaqsdata.htm
[7] Ambient data were obtained from the Jefferson Street ozone monitor, maintained by Atmospheric Research & Analysis, Inc. Available at http://www.atmospheric-research.com/studies/SEARCH/index.html.

### 8.4.3 Major Link On-Road Emission Estimates

Information on traffic data in the Atlanta area was obtained from the Atlanta Regional Commission (ARC) – the regional planning and intergovernmental coordination agency for the 10-county metropolitan area – via their most recent, baseline travel demand modeling (TDM) simulation for year 2005. Although considerable effort was expended to maintain consistency between the ARC approach to analysis of TDM data and that employed in this analysis, complete consistency was not possible due to the differing analysis objectives. The ARC creates county emission inventories. This study created spatially and temporally resolved emission strengths for dispersion modeling. Information about expected differences in traffic between the 2005 data year and 2001-2003 modeled years was not provided by ARC, nor was information about seasonal differences in MOBILE6.2 inputs. The approach used for estimating these major road emissions is discussed further below.

#### *8.4.3.1 Emission Sources and Locations*

The TDM simulation's data file outputs include a description of the fixed information for the highway network links and traffic descriptors for four time periods: morning, afternoon, evening, and nighttime. Each period's data includes free-flow speed, total vehicle count, total heavy duty truck count, total single occupancy vehicle count, and TDM-calculated congested speeds for the period. The description of the network consists of a series of nodes joining individual model links (i.e., roadway segments) to which the traffic volumes are assigned, and the characteristics of those links, such as endpoint location, number of lanes, link distance, and TDM-defined link daily capacity.

First, all links with annual average daily traffic (AADT) values greater than 15,000 vehicles per day (one-way) were classified as *major* within the four counties (Cobb, DeKalb, Fulton, and Gwinnett) and a part of a fifth county (Clayton), which contains a small portion of the beltway in the MSA. Then, link locations from the TDM were modified through a GIS analysis to represent the best known locations of the actual roadways, since there was not always a direct correlation between the two (see Appendix B-4.1.1). There were no hourly scaling factors provided for the ARC's TDM predictions, therefore the total period volume was spread uniformly amongst all hours contributing to that period (morning: 6AM-10AM, midday: 10AM-3PM, afternoon: 3PM-7PM, or nighttime: 7PM-6AM). A 5-hour rolling average was applied to the emission scaling factors to allow for a smoothing of the distribution. The heavy-duty vehicle (HDV) fraction for each hour of each period was obtained by dividing the total period heavy duty vehicle count by the total vehicle count, fixing the value as constant for all hours of the period, but allowing it to vary between periods and across links, according to the TDM parameterization. Because no information on seasonal variation was available, no seasonal variation was used in the simulations. The AADT and truck fraction from the ARC TDM used in the AERMOD simulations are shown in Tables 8-1 and 8-2, respectively.

**Table 8-1. Statistical summary of average annual daily traffic (AADT) volumes (one direction) for Atlanta AERMOD simulations.**

| Statistic | Road Type | CBD[1] | Fringe | Rural | Suburban | Urban |
|---|---|---|---|---|---|---|
| Count | Arterial | 229 | 180 | 14 | 1,299 | 1,221 |
| | Freeway | 109 | 94 | 2 | 616 | 616 |
| | Local | 41 | 60 | | 168 | 250 |
| Minimum AADT | Arterial | 15,015 | 15,019 | 16,603 | 15,002 | 15,017 |
| | Freeway | 15,049 | 16,745 | 23,569 | 15,111 | 15,025 |
| | Local | 15,442 | 15,052 | | 15,111 | 15,017 |
| Maximum AADT | Arterial | 51,820 | 49,853 | 23,433 | 64,487 | 46,824 |
| | Freeway | 150,047 | 109,204 | 24,028 | 144,434 | 155,083 |
| | Local | 110,425 | 98,420 | | 98,909 | 127,085 |
| Average AADT | Arterial | 24,814 | 21,732 | 19,016 | 21,383 | 22,434 |
| | Freeway | 73,598 | 56,741 | 23,799 | 59,164 | 64,744 |
| | Local | 25,737 | 26,536 | | 23,781 | 25,745 |

**Notes:**
[1] Central business district

**Table 8-2. Average heavy duty vehicle (HDV) fraction for Atlanta AERMOD simulations.**

| Functional Class | Time Period[1] | Region Type | | | | |
|---|---|---|---|---|---|---|
| | | CBD[2] | Fringe | Rural | Suburban | Urban |
| Arterial | Nighttime | 12% | 18% | 15% | 12% | 13% |
| | Morning | 14% | 19% | 18% | 15% | 15% |
| | Midday | 17% | 28% | 27% | 20% | 20% |
| | Afternoon | 10% | 16% | 15% | 12% | 12% |
| Freeway | Nighttime | 8% | 20% | 24% | 19% | 14% |
| | Morning | 9% | 20% | 26% | 19% | 15% |
| | Midday | 12% | 27% | 33% | 26% | 21% |
| | Afternoon | 7% | 16% | 21% | 15% | 12% |
| Local | Nighttime | 10% | 24% | | 18% | 15% |
| | Morning | 12% | 24% | | 19% | 16% |
| | Midday | 14% | 33% | | 25% | 21% |
| | Afternoon | 9% | 19% | | 15% | 12% |

**Notes:**
[1] morning: 6AM-10AM, midday: 10AM-3PM, afternoon: 3PM-7PM, or nighttime: 7PM-6AM
[2] Central business district

### *8.4.3.2 Emission Source Strength*

On-road mobile emission factors were derived from the MOBILE6.2 emissions model using ARC input files describing the 2002 vehicle registration distribution and corresponding to the 2008 $O_3$ season. To maintain consistency with the recent ARC simulations and current modeling parameters and maximize temporal resolution, the ARC's $O_3$ season input files were used as a basis for all MOBILE6.2 simulations, but were modified as follows. First, the 24-hour series of temperature and humidity values included in the ARC files were those derived as average values over peak $O_3$ days. To modify the focus from peak $O_3$ to average summer days, these values in the input files were modified by converting to average daily minimum and maximum temperature and corresponding specific humidity, determined by the same meteorological record used in the dispersion simulations. Also, winter and summer-specific fuels for the Atlanta region were used for all years, which differ only until the phase-in of Georgia Phase 2 gasoline in 2003, at which point winter and summer sulfur levels are identical. Finally, anti-tampering and inspection/maintenance programs, which were not included in the original ARC input files, were taken from MOBILE input files prepared by the State of Georgia for a previous project.

The simulations were executed to calculate average running $NO_x$ emission factors in grams per mile for a specific functional class (Freeway, Arterial, Local, or Ramp) and speed. Iterative MOBILE6.2 simulations were conducted to create tables of average Atlanta region emission factors resolved by speed (2.5 to 65 mph), functional class, season, and year (2001, 2002, or 2003) for each of eight combined MOBILE vehicle classes. The resulting tables were then consolidated into speed, functional class, and seasonal values for combined light- and heavy-duty vehicles. To create seasonal-hourly resolved emissions, spring and fall values were taken as the average of corresponding summer and winter values. See Appendix B-4 for an example of the calculated emission factors for Summer, 2001.

To determine the emission strengths for each link for each hour of the year, the Atlanta regional average MOBILE6.2 speed-resolved emissions factor tables were merged with the TDM link data, which had been processed to determine time-resolved speeds. The spatial-mean speed of each link at each time was calculated following the methodology of the Highway Capacity Manual.[8] Table 8-3 shows the resulting average speed for each functional class within each TDM region. The resulting emission factors were then coupled with the TDM-based activity estimates to calculate emissions from each of the major roadway links.

**Table 8-3. Average calculated speed by link type in Atlanta modeling domain.**

| Link Type | Average Speed (mph) | | | | |
|---|---|---|---|---|---|
| | CBD[1] | Fringe | Suburban | Urban | Rural |
| Arterial | 22 | 37 | 40 | 30 | 51 |
| Freeway | 54 | 62 | 60 | 57 | 64 |
| Local | 26 | 40 | 40 | 34 | N/A |

Notes:
[1] Central Business District

*8.4.3.3 Other Emission Parameters*

Each roadway link is characterized as a rectangular area source with the width given by the number of lanes and an assumed universal lane width of 12 ft (3.66 m). The length and orientation of each link is determined as the distance and angle between end nodes from the

[8] As defined in Chapter 9 of Recommended Procedure for Long-Range Transporation Planning and Sketch Planning, NCHRP Report 387, National Academy Press, 1997. 151 pp., ISBN No: 0-309-060-58-3.

adjusted TDM locations. In cases where the distance is such that the aspect ratio is greater than 100:1, the links were disaggregated into sequential links, each with a ratio less than that threshold. There were 737 links that exceeded this ratio and were converted to 1,776 segmented sources. Thus, the total number of area sources included in the dispersion simulations is 5,570. Note that there are some road segments whose length was zero after GIS adjustment of node location. This is assumed to be compensated by adjacent links whose length will have been expanded by a corresponding amount. Table 8-4 shows the distribution of on-road area source sizes.

**Table 8-4. On-road area source sizes**.

| Statistic | Number of Lanes | Segment Width (m) | Segment Length (m) |
|---|---|---|---|
| Minimum | 1 | 3.7 | 0.0 |
| Median | 2 | 7.3 | 352.8 |
| Mean | 2.7 | 9.9 | 426.3 |
| 1-$\sigma$ Deviation | 1.2 | 4.5 | 330.0 |
| Maximum | 8 | 29.3 | 2218.1 |

Resulting daily emission estimates were temporally allocated to hour of the day and season using MOBILE6.2 emission factors, coupled with calculated hourly speeds from the post-processed TDM and allocated into SEASHR emission profiles for the AERMOD dispersion model. That is, 96 emissions factors are attributed to each roadway link to describe the emission strengths for 24 hours of each day of each of four seasons and written to the AERMOD input control file.

For light duty vehicles (LDV) it was assumed that the initial vertical extent of the plume is about 1.7 times the average vehicle height, or about 2.6 meters for an average vehicle height of about 1.53 meters (5 feet), to account for the effects of vehicle-induced turbulence among other factors. The source release height is based on the midpoint of the initial vertical extent, or about 1.3 meters. The initial vertical dispersion coefficient (sigma-$Z_o$) was based on the initial vertical extent divided by 2.15, or 1.2 meters.

For the heavy duty vehicles (HDV) as with LDVs, the initial vertical extent of the plume was assumed 1.7 times the average vehicle height, or about 6.8 meters for an average vehicle height of about 4.0 meters. Similarly, source release heights were based on the midpoint of the initial vertical extent, or 3.4 meters. The initial sigma-Zo also based on the initial vertical extent divided by 2.15, was 3.2 meters.

For effective source parameters representing a mix of LDV and HDV for a particular major roadway link, the source release height and initial sigma-Zo were then assigned using an emissions-weighted average based on the vehicle mix for that roadway link.

The total $NO_x$ emissions on the major roadways links were estimated to be 88,438 tons per year (tpy) or approximately 70% of the total on-road emissions.

### 8.4.4 Minor Link On-road Emission Estimates

On-road mobile emissions that do not occur on major roadway links were assigned to US Census tracts and simulated as area sources represented by the tract polygons. There are 478 census tract area sources across the 4-county Atlanta modeling domain, and a small part of Clayton County (Figure 8-2). Emission magnitudes and temporal profiles were derived with the same procedure as for the major roadway links, however individual link values were not stored. Instead, each link was assigned to its respective tract and the combined emission total across

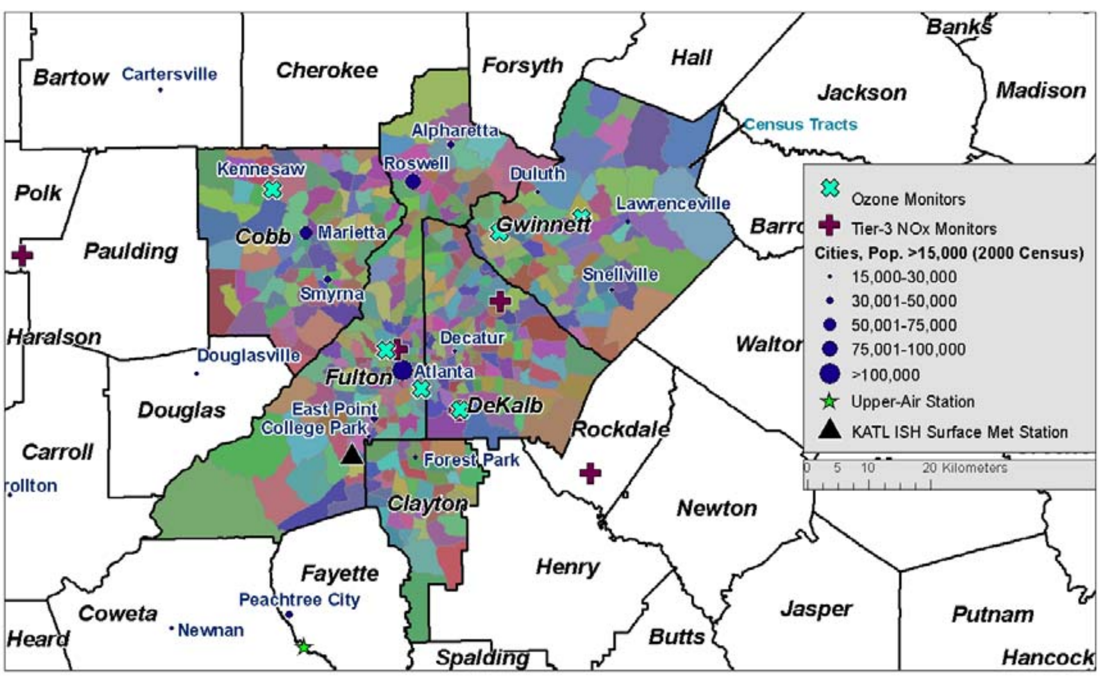


**Figure 8-2. The 478 U.S. Census tracts representing area sources for on-road mobile emissions that do not occur on major roadway links.**

links for a specific season and hour were determined for each tract. The resulting total seasonal-hourly emissions profile for each tract area source was then used in AERMOD. Estimated $NO_x$ emissions on the minor roadway links was 38,288 tpy (Table 8-5).

**Table 8-5. On-road emissions from major and minor links in Atlanta, 2002.**

| County | | Total Emissions (tpy) | | |
|---|---|---|---|---|
| FIPS | Name | Minor Link | Major Link | % Minor |
| 13063 | Clayton | 1,693 | 6,185 | 21% |
| 13067 | Cobb | 8,329 | 15,816 | 34% |
| 13089 | DeKalb | 7,134 | 19,871 | 26% |
| 13121 | Fulton | 12,047 | 30,999 | 28% |
| 13135 | Gwinnett | 8,835 | 15,568 | 36% |
| | **Total** | **38,039** | **88,438** | **30%** |

### 8.4.5 Adjustment of On-road Mobile Source Strengths to 2002 NEI Vehicle Emissions

As noted above, the TDM data received from ARC specified traffic count projections for 2005 instead of the 2001-2003 target years for this analysis. All other model inputs were estimated for the target years, e.g., on-road mobile source emission factors, point source emissions (see section 8.4.6 below), airport emissions (see section 8.4.7 below), and meteorological data. Therefore, to maintain consistency, the on-road emission strengths were adjusted to match 2002 totals for the 4-county modeling domain from the NEI.

Table 8-6 shows the comparisons of the on-road mobile source emissions estimated for 2002 as described above (i.e., 2005 traffic counts and 2002 emission factors) with the NEI estimates for 2002. Note that the differences in these estimates may be the result of differences in other factors in addition to the target year traffic counts, such as fleet mix and heavy-duty vehicle fractions. Based on this comparison an adjustment factor of 0.78 was uniformly applied to all on-road mobile source emission strengths in the Atlanta modeling domain, for both major and minor links.

**Table 8-6. On-road vehicle emission strengths by county for Atlanta modeling domain: modeled vs NEI 2002.**

| County | Modeled major link $NO_x$ emissions (tpy) | Modeled minor link $NO_x$ emissions (tpy) | Total modeled on-road vehicle $NO_x$ emissions (tpy) | NEI on-road vehicle $NO_x$ emissions for 2002 (tpy) | Ratio of NEI-2002-to-modeled $NO_x$ emissions |
|---|---|---|---|---|---|
| Cobb | 15,816 | 8,329 | 24,145 | 18,754 | 0.78 |
| DeKalb | 19,871 | 7,134 | 27,006 | 21,715 | 0.80 |
| Fulton | 30,999 | 12,047 | 43,046 | 33,886 | 0.79 |
| Gwinett | 15,568 | 8,835 | 24,403 | 18,080 | 0.74 |
| **TOTAL** | 82,254 | 36,346 | 118,599 | 92,434 | **0.78** |

### 8.4.5 Stationary Sources Emissions Preparation

Data for the parameterization of major point sources in Atlanta comes primarily from three sources: the 2002 National Emissions Inventory (NEI; US EPA, 2007e), Clean Air Markets Division (CAMD) Unit Level Emissions Database (US EPA, 2007f), and temporal emission profile information contained in the EMS-HAP (version 3.0) emissions model.[9] The NEI database contains stack locations, emissions release parameters (i.e., height, diameter, exit temperature, exit velocity), and annual emissions for $NO_x$-emitting facilities. The CAMD database contains information on hourly $NO_x$ emission rates for units in the US, where the units are the boilers or equivalent, each of which can have multiple stacks.

First, major stationary sources were selected from the NEI where stacks within facilities contain at least 100 tpy total $NO_x$ emissions and are located either within the 4-county modeling domain or within 10 km of the modeling domain. Seven $NO_x$-emitting facilities met these criteria (Figure 8-3). Stacks within the facilities that were listed separately in the NEI were combined for modeling purposes if they had identical stack physical parameters and were co-located within about 10 m. This resulted in 28 combined stacks (stack parameters are in Appendix B-4) and account for 16% of the of $NO_x$ point sources and 51% of the total $NO_x$ point source emissions in this buffered four county Atlanta area.

The CAMD database was then queried for facilities that matched the facilities identified from the NEI database using the facility name, the Office of Regulatory Information Systems (ORIS) identification code, and facility total emissions. Only one of the 7 major facilities

[9] http://www.epa.gov/ttn/chief/emch/projection/emshap30.html

identified was found in the CAMD data base: the Georgia Power Company McDonough Steam-Generating Plant. The CAMD hourly emissions profiles for these two units are summed together and then, after appropriate scaling, used to represent 2 major-facility combined stacks.

For the remaining 26 major-facility combined stacks, hourly $NO_x$ emissions profiles were created based on the hourly profile typical of that stack's SCC, the season, and the day of week. These SCC-based temporal profiles are year-independent, and were developed for the EPA's EMS-HAP model,[10] described in the EMS-HAP model Version 2 User's Guide, Section D-7.[11] As with CAMD hourly emissions, these SCC-based emission profiles are scaled such that the annual total emissions are equal to those of NEI 2002.

### 8.4.6 Airport Emissions Preparation

The Atlanta-Hartsfield International Airport emissions were assigned to a polygon that defined an area source for simulation. The perimeter dimensions of the Atlanta-Hartsfield International Airport were determined by GIS analysis of aerial photograph. As with some point source emissions, the annual $NO_x$ emission totals were extracted from the NEI and the temporal profiles from the EPA's EMS-HAP model. These seasonal, SCC-based emissions were scaled such that the annual total emissions are equal to those of NEI 2002: 5,761 tpy, with about 90% coming from commercial aircraft (see Figure 8-1 for airport location, Appendix B-4 for depiction of area source polygon).

The initial vertical extent of the plume for aircraft emissions was estimated as 10 m to account for typical emission heights and initial dilution parameters. A source release height of 5 m was selected based on the midpoint of the initial vertical extent and the initial vertical dispersion coefficient was estimated using the initial vertical extent divided by 2.15, or 4.6 meters. For cargo-handling equipment a release height of 3.15 m was assumed, which is the average for cargo-handling equipment from a study by the California Air Resources Board (CARB 2006). The initial vertical dispersion coefficient was estimated as the release height divided by 2.15, or 1.47 m. For effective source parameters representing a mix of aircraft and cargo-handling equipment, the source release height and initial sigma-Zo were estimated using an emissions-weighted average with 92% of emissions contributed by aircraft. The aggregate value for release height was 4.85 m with a sigma-zi of 4.22 m.

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[10] http://www.epa.gov/scram001/dispersion_related.htm#ems-hap
[11] http://www.epa.gov/scram001/userg/other/emshapv2ug.pdf

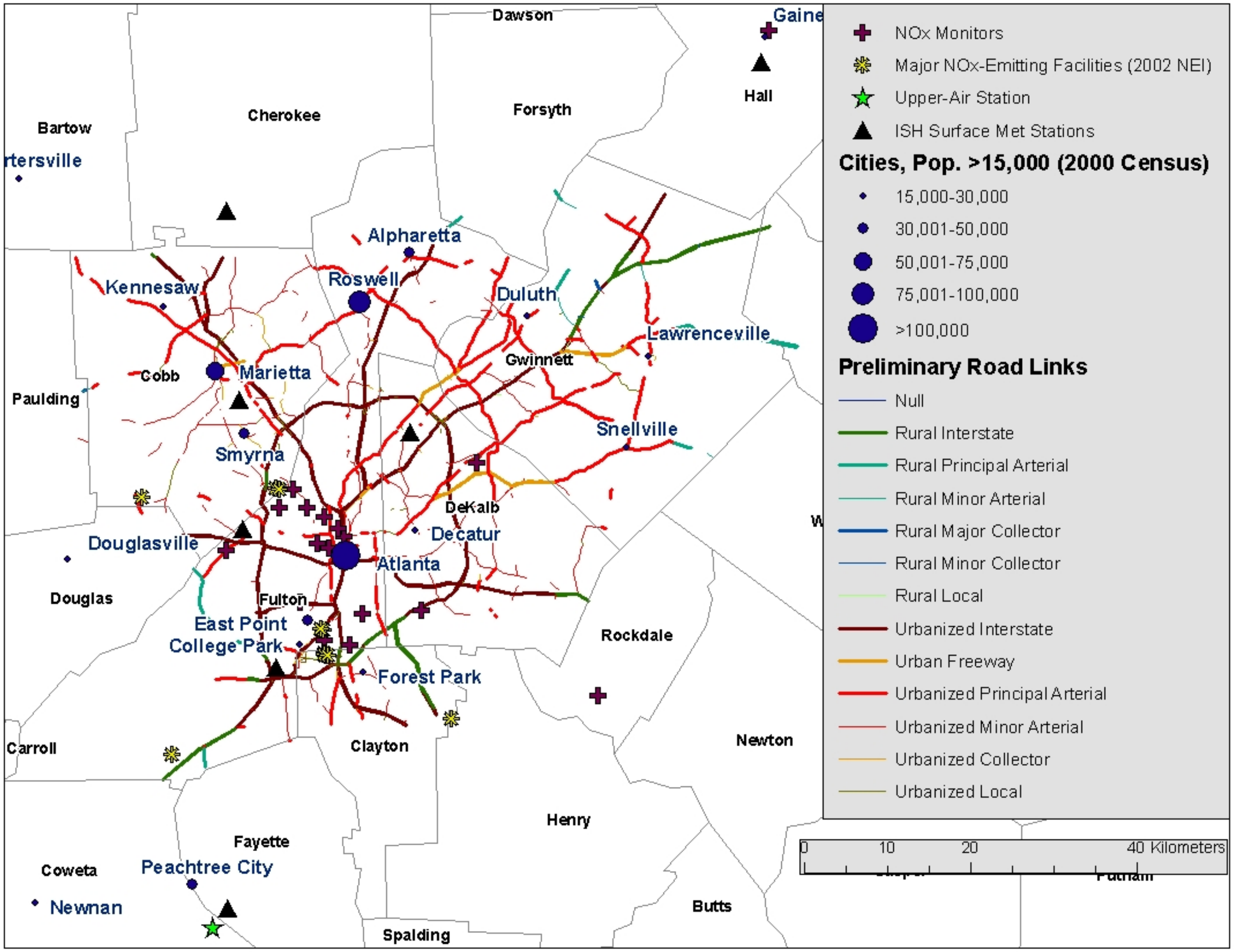


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**Figure 8-3. Location of major roadway links and major stationary emission sources in Atlanta modeling domain.**

### 8.4.7 Receptor Locations

Three sets of receptors were chosen to represent the locations of interest. The first set was selected to represent the locations of the residential population of the modeling domain. These receptors were the 27,315 US Census block centroids. In an effort to make the Atlanta case-study more time efficient, a statistical analysis was performed on the Philadelphia exposure assessment results reported in March 2008 (see Appendix B, section 3) to determine the degree of uncertainty introduced by modeling a subset of the block receptors only. The findings of that analysis indicated that the use of a random selection of 1/3 of the block centroids would provide estimates of exposure to exceedances of 200 ppb that were within 4% (90% confidence bounds = 0.3% - 10%) of the estimates obtained based on using all the block receptors. It was judged that this uncertainty was minimal when compared to other uncertainties in the analysis, and therefore, a random selection of 9,103 (1/3) of the block centroids was used for this analysis. These 9,103 Census block receptors are shown along with the other 18,212 block centroids are shown in Figure 8-3. For modeling efficiency, each receptor was assigned a height of 0.0 ft (0.0 m). The effect of this in comparison with a standard breathing height of 1.8 m is negligible.

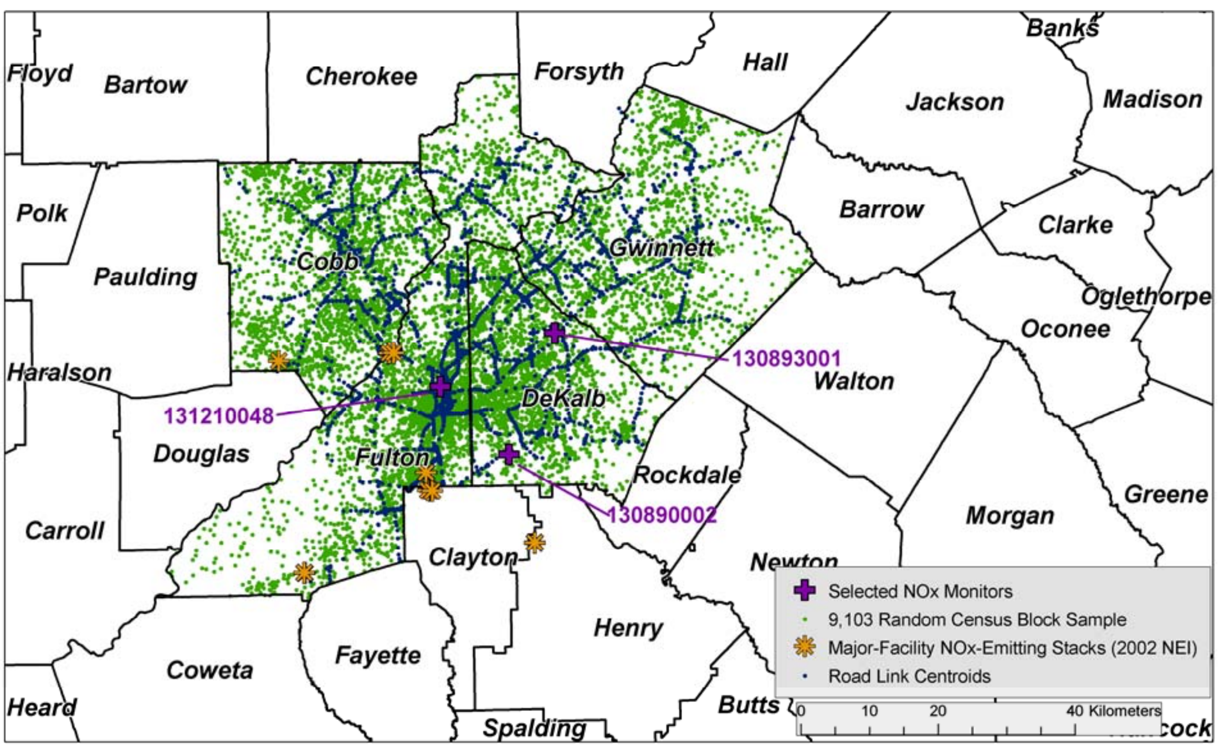


**Figure 8-4. Location of modeled receptors in Atlanta modeling domain.**

The second set of receptors was chosen to represent the on-road microenvironment (Figure 8-4). For this set, one receptor was placed at the center of each of the 5,570 sources. The distribution of distances of the on-road and the block centroid receptors was estimated to determine the distance relationship between the on-road emissions and population-based receptors. Approximately 1% of the blocks are within 50 m of a major roadway link and 26% within 400 m, with a geometric mean of the distribution between 750 m and 800 m (a detailed distribution is provided in Appendix B-4).

The third set of receptors included the locations of the available ambient $NO_x/NO_2$ monitors. These receptors were defined for use in evaluating the dispersion model performance. When considering the four Atlanta counties and period of analysis, there were three monitors within the modeling domain containing valid ambient $NO_2$ monitoring concentrations (Figure 8-4).

### 8.4.8 Modeled Air Quality Evaluation

#### *8.4.8.1 Comparison of Hourly Cumulative Density Functions*

The hourly $NO_2$ concentrations estimated from each of the four source categories were combined at each receptor. These concentration predictions were then compared with measured concentrations at ambient $NO_2$ monitors. Rather than compare concentrations just at the single modeled receptor point to the ambient monitor concentrations, a distribution of concentrations was developed for the predicted concentrations for all receptors within a 4 km distance of the monitors, not including receptors within 100 m of a major road. Further, instead of a comparison of central tendency values alone for the number of receptors modeled (mean or median), the complete modeled and measurement concentration distributions were used for comparison.

As an initial comparison of modeled versus measured air quality, all modeled receptors within 4 km of each ambient monitor location, excluding those receptors on roadways or within 100 m of a major roadway, were used to generate a prediction envelope.[12] This envelope was constructed based on selected percentiles from the modeled concentration distribution at each receptor for comparison to the ambient monitor concentration distribution. The 2.5$^{th}$ and 97.5$^{th}$ percentiles from all monitor distribution percentiles[13] were selected to create the lower and upper

[12] 500 m to 4 km is the area of representation of a neighborhood-scale monitor, according to EPA guidance.

[13] As an example, suppose there are 1000 receptors surrounding a monitor, each receptor containing 8,760 hourly values used to create a concentration distribution. Then say the 73$^{rd}$ percentile concentration prediction is to be estimated for each receptor. The lower bound of the 73$^{rd}$ percentile of the modeled receptors would represented by

bounds of the envelope, while the 50th percentile concentrations were combined to create a distribution representing the central tendency (Figure 8-5). The distribution of the modeled values estimated for the monitor receptor is also presented, along with the complete hourly concentration distribution measured at each ambient monitor.

The hourly concentration distributions modeled at receptors within 4 km of each of the ambient monitor locations provide a reasonable representation of the measured ambient $NO_2$ concentrations. The lower and upper bounds of the predicted concentration distributions surround the measured ambient concentration distribution at many of the percentiles. The actual modeled monitor receptor concentration distributions were generally above that of the corresponding measured concentrations, resulting in overestimation at some of the upper percentiles by about 20-50%. At one monitoring location however, the overestimate was generally less than 10 ppb, or between 10-20% of that measured. When considering the lowest potential health effect benchmark levels, the modeled monitor receptor contained 22, 2, and 11 predicted values above 100 ppb 1-hour, compared with 0, 0, and 3 of the measured values at monitors 130890002, 130893001, and 131210048, respectively. There were only two predicted exceedances of 150 ppb 1-hour recorded at one monitor (ID 130890002), while none of the modeled monitors had estimated $NO_2$ concentrations above 200 ppb 1-hour.

#### *8.4.8.2 Comparison of annual average diurnal concentration profiles*

A second comparison considered the diurnal variation in $NO_2$ concentrations. First each receptor was averaged during each hour of the day within the modeled year (e.g., n=365 values for hour 1), to obtain the annual average $NO_2$ concentration for each hour. Then a prediction envelope was constructed similar to that described above from modeled receptors located within 4 km of each ambient monitor. These modeled distributions, along with that of each ambient monitor hourly average concentration are illustrated in Figure 8-6.

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the 2.5th percentile of all the calculated 73rd percentile concentration predictions, i.e., the 25th highest 73rd percentile concentration prediction across the 1000 73rd percentile values generated from all of the receptors. Note that, at any given percentile along either of the envelope bounds as well as at the central tendency distribution (the receptor 50th percentile), the concentration from a different receptor may be used.

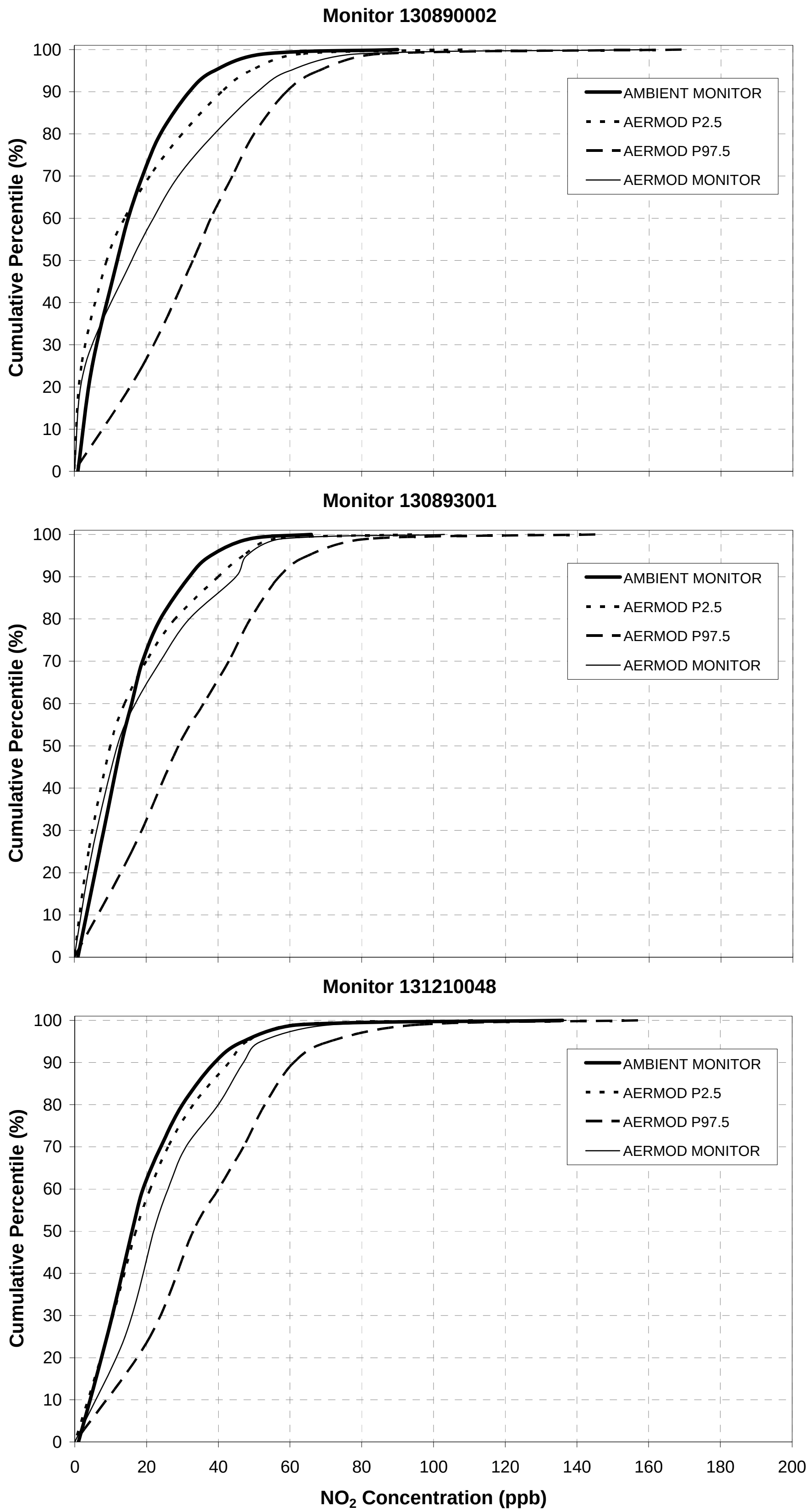



**Figure 8-5. Comparison of measured ambient monitor $NO_2$ concentration distribution with the modeled monitor receptor and receptors within 4 km of the monitors at three locations in Atlanta for Year 2002.**

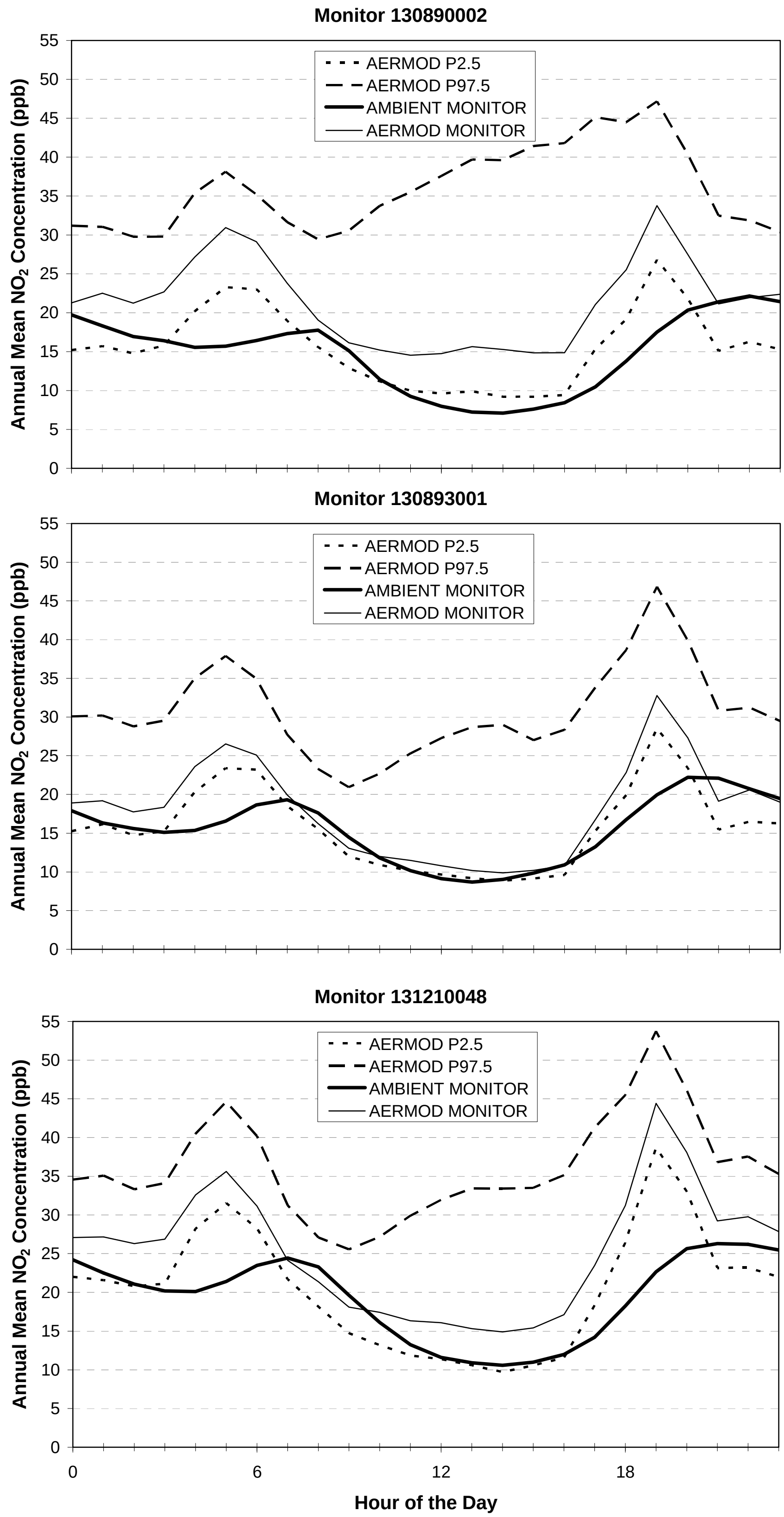



**Figure 8-6. Comparison of measured ambient monitor $NO_2$ concentration diurnal profile with the modeled monitor receptor and receptors within 4 km of the monitors at three locations in Atlanta for Year 2002.**

When comparing the modeled predicted and ambient measured diurnal profiles, there was general agreement between the patterns and many hours of the day where the observed values fell within the model prediction envelope. However, $NO_2$ concentrations are overestimated at certain times of the day, generally between the hours of 4-6AM and 5-8PM. The overestimation is not entirely unexpected given the results of the distribution of hourly concentrations illustrated in Figure 8-5. Given that the air quality concentration estimates are generally conservative from a health protection perspective, and that the values at the upper tails of the hourly distribution are not unusual in comparison with the other portions of the concentration distribution, it was determined that adjustment of the modeled air quality based on the three monitors was not necessary.

#### *8.4.8.3 Comparison of estimated on-road $NO_2$ concentrations*

The two independent approaches used to estimate on-road $NO_2$ concentrations, one using ambient monitor data combined with an on-road simulation factor (section 7) and the other using the AERMOD dispersion model, were compared to one another. There are no on-road $NO_2$ concentration measurements in Atlanta for the modeled data to be compared with, although it should be noted that the data used to estimate the simulation factors and applied to the monitor data were measurement based.

First a comparison can be made between the modification factors used for estimating on-road concentrations in the air quality analysis and similar factors that can be generated using AERMOD estimated concentrations for year 2002. As described above in section 7, an empirical distribution of on-road simulation factors was derived from on-road and near-road $NO_2$ concentration measurements published in the extant literature. The derived empirical distribution was separated into two components, one for application to summertime ambient concentrations, and the second for all other seasons. The two empirical distributions are presented in Figure 8-7, and represent the factors that are multiplied by the ambient monitor concentration (i.e., at monitors ≥ 100 m from a major road) and used to estimate the on-road concentration in the air quality characterization. The one-hour $NO_2$ concentrations estimated at AERMOD receptors ≥ 100 m from a major road were compared with the concentrations estimated at their closest on-road receptor to generate a similar ratio (i.e., on-road/non-road $NO_2$ concentrations). These AERMOD generated ratios were also stratified into two seasonal categories, one containing the summer ratios (June, July, and August) and the other for all other times of the year. The AERMOD on-road factor distributions in semi-empirical form are also presented in Figure 8-7. The values for each of the method and season distributions are provided in Appendix B-4.

Both the modeled and measurement derived distributions have the same seasonal pattern, that is the summer ratios are consistently greater than the non-summer ratios throughout the entire distribution. There are small differences when comparing the two approaches at the lowest distribution percentiles, with the AERMOD ratios consistently below that of the empirically derived factors. This is likely due to the differences in the population of samples used to generate each type of distribution. The measurement study-derived distribution used data from on-road concentration measurements and from monitoring sites located at a distance from the road, sites that by design of the algorithm and the factor selection criteria are likely not under the influence of non-road $NO_2$ emission sources. Thus, the measurement study derived ratios never fall below one, there are no on-road concentrations less than any corresponding non-road influenced concentrations. This was, by design, a reasonable and conservative assumption for estimating the on-road concentrations for the air quality characterization. The AERMOD receptors however, include all types of emission sources such that there are possibilities for concentrations at non-road receptors that are greater than particular on-road receptors, likely a more realistic depiction of the actual relationship between on-road and non-road receptors.

There are some similarities that follow when comparing each of the AERMOD with the measurement study derived distributions the lower to mid percentiles. Overlap of the two different approaches occurs at about the $30^{th}$ percentile and continues through the $50^{th}$ percentile. The AERMOD predicted ratio distributions extend beyond the range of values offered by the measurement study derived ratios at the mid to upper percentiles. This could indicate that the AERMOD approach is better accounting for locally high $NO_2$ concentrations than those reported by the limited measurement studies.

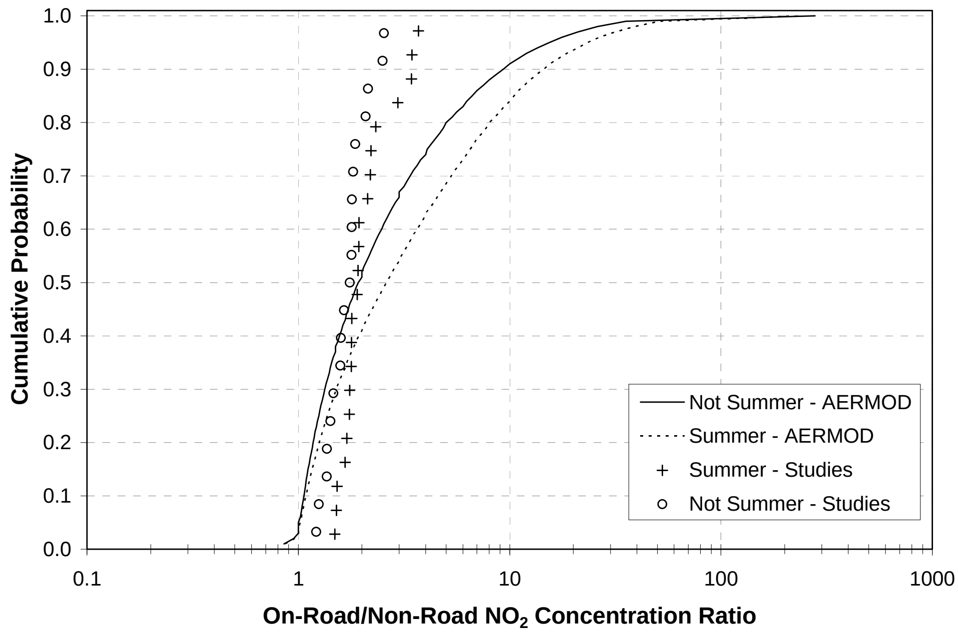



**Figure 8-7. Comparison of on-road/non-road ratios developed from AERMOD concentration estimates for year 2002 and those derived from data reported in published $NO_2$ measurement studies.**

A second comparison was conducted using the hourly on-road $NO_2$ concentrations estimated by AERMOD for 3,259 on-road receptors in Atlanta for the years 2001-2003. The 24 hourly values modeled for each day at each receptor were rounded to the nearest 1 ppb. The second set of estimated on-road $NO_2$ concentrations was generated as part of the Air Quality Characterization by applying randomly selected on-road factors to the ambient monitor concentrations in the Atlanta MSA, using the same three ambient monrtors which were all lcocated > 100 m from a major road. Table 8-7 compares the summary statistics of the hourly concentrations and the number of estimated exceedances of three potential health effect benchmark levels (i.e., 100, 150, and 200 ppb) using the two different approaches to estimate on-road concentrations. The AERMOD predicted and ambient monitor simulated concentration distributions have very similar variances, although the AERMOD estimated concentraions are about 40% greater at the mean and about 15 ppb higher at each of the percentiles (save the max). The AERMOD on-road receptors also consistently had a greater number of exceedances of potential health effect benchmark levels than that estimated using the on-road monitor simulation. For example, the AERMOD receptors had an average of 241 exceedances of 100 ppb per site-year while the simulated on-road monitors had an average of 169 exceedances per year, a difference of about 40%. This difference between the two approaches was prevalent throughout each of the percentiles and when considering each of the 1-hour concentration levels. The differences could be due to the greater number of receptors modeled by AERMOD (n=3,259) compared with the on-road monitor simulation (n=3) and that the AERMOD generated on-road receptors could include locations with greater influence by roadway emissions that are not captured by the simplified approach conducted in the Air Quality Characterization. Based on the results of these comparisons and the accounting for much of the expected emissions in the modeling domain, it was determined that adjustment of the modeled concentrations to the ambient monitors was not necessary, as was done for the Philadelphia County case-study used in the 1st draft REA (results summarized in Appendix B-3).

**Table 8-7. Summary statistics of on-road hourly $NO_2$ concentrations (ppb) and the numbers of hourly concentrations above 100, 150, and 200 ppb in a year using both the AERMOD and the on-road ambient monitor simulation approaches in Atlanta.**

| Statistic | On-Road Hourly $NO_2$ (ppb) | | Number of hours >100 ppb | | Number of hours >150 ppb | | Number of hours >200 ppb | |
|---|---|---|---|---|---|---|---|---|
| | AERMOD | AQ Monitors | AERMOD | AQ Monitors | AERMOD | AQ Monitors | AERMOD | AQ Monitors |
| N | 28,548,840 | 6,622,300 | 3,259 | 800 | 3,259 | 800 | 3,259 | 800 |
| Mean | 43.0 | 31.3 | 241 | 169 | 28 | 20 | 5 | 3 |
| Std | 25.1 | 25.4 | 307 | 227 | 51 | 43 | 14 | 7 |
| Var | 630.8 | 646.3 | 94,102 | 51,427 | 2,577 | 1,856 | 190 | 54 |
| p0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| p5 | 9 | 3 | 2 | 2 | 0 | 0 | 0 | 0 |
| p10 | 15 | 6 | 4 | 8 | 0 | 0 | 0 | 0 |
| p15 | 19 | 9 | 7 | 11 | 0 | 0 | 0 | 0 |
| p20 | 23 | 11 | 11 | 16 | 0 | 0 | 0 | 0 |
| p25 | 26 | 13 | 16 | 23 | 0 | 0 | 0 | 0 |
| p30 | 29 | 15 | 23 | 33 | 0 | 0 | 0 | 0 |
| p35 | 32 | 17 | 30 | 42 | 0 | 1 | 0 | 0 |
| p40 | 34 | 20 | 41 | 55 | 0 | 1 | 0 | 0 |
| p45 | 37 | 22 | 56 | 67 | 1 | 3 | 0 | 0 |
| p50 | 40 | 25 | 79 | 87 | 1 | 3 | 0 | 0 |
| p55 | 44 | 28 | 119 | 111 | 3 | 5 | 0 | 0 |
| p60 | 46 | 31 | 185 | 132 | 6 | 8 | 0 | 1 |
| p65 | 49 | 35 | 253 | 160 | 12 | 9 | 1 | 1 |
| p70 | 52 | 38 | 317 | 184 | 22 | 13 | 2 | 1 |
| p75 | 56 | 43 | 399 | 220 | 37 | 21 | 4 | 2 |
| p80 | 60 | 49 | 485 | 280 | 50 | 26 | 7 | 3 |
| p85 | 66 | 56 | 584 | 353 | 71 | 36 | 11 | 3 |
| p90 | 74 | 65 | 706 | 426 | 96 | 53 | 18 | 9 |
| p95 | 88 | 81 | 879 | 649 | 132 | 110 | 31 | 17 |
| p100 | 556 | 437 | 1,929 | 1,595 | 542 | 373 | 181 | 55 |

## 8.5 SIMULATED POPULATION

One of the important population subgroups for the exposure assessment is asthmatics. Evaluating exposures for this population requires an estimation of both adult and children asthma prevalence rates. The proportion of the population of children characterized as being asthmatic was estimated by statistics on asthma prevalence rates recently used in the NAAQS review for $O_3$ (US EPA, 2007g; 2007h). Specifically, the analysis generated age and gender specific asthma prevalence rates for children ages 0-17 using data provided in the National Health Interview Survey (NHIS) for 2003 (CDC, 2007). Adult asthma prevalence rates for Atlanta were derived from the Behavioral Risk Factor Surveillance System (BRFSS) survey information for years 2004 – 2005 (Blackwell and Kanny, 2007). Table 8-8 provides a summary of the prevalence rates used in the exposure analysis by age and gender. Additional information on the variability in these prevalence rates is given in Appendix B-4.

**Table 8-8. Asthma prevalence rates by age and gender used for Atlanta.**

| Region (Study Area) | Age[1] | Asthma Prevalence[2] | |
|---|---|---|---|
| | | Female | Male |
| Atlanta (South) | 0 | 0.034 | 0.041 |
| | 1 | 0.052 | 0.070 |
| | 2 | 0.071 | 0.102 |
| | 3 | 0.088 | 0.129 |
| | 4 | 0.099 | 0.144 |
| | 5 | 0.119 | 0.165 |
| | 6 | 0.122 | 0.164 |
| | 7 | 0.112 | 0.133 |
| | 8 | 0.093 | 0.138 |
| | 9 | 0.091 | 0.168 |
| | 10 | 0.108 | 0.178 |
| | 11 | 0.132 | 0.162 |
| | 12 | 0.123 | 0.145 |
| | 13 | 0.097 | 0.143 |
| | 14 | 0.095 | 0.153 |
| | 15 | 0.100 | 0.151 |
| | 16 | 0.115 | 0.140 |
| | 17 | 0.145 | 0.122 |
| | >17 | 0.083 | 0.050 |

| Region (Study Area) | Age[1] | Asthma Prevalence[2] | |
|---|---|---|---|
| | | Female | Male |

**Notes:**
[1] Ages 0-17 from the National Health Interview Survey (NHIS) for 2003 (CDC, 2007), ages >17 from the Behavioral Risk Factor Surveillance System (BRFSS) survey information (Blackwell and Kanny, 2007)
[2] Asthma prevalence is given as fraction of the population. Multiply by 100 to obtain the percent.

The total population simulated for Atlanta was approximately 2.68 million persons, of which there was a total simulated population of about 212,000 asthmatics. The model simulated approximately 500,000 children, of which there were about 64,000 asthmatics.

## 8.6 CONSTRUCTION OF LONGITUDINAL ACTIVITY SEQUENCES

Exposure models use human activity pattern data to predict and estimate exposure to pollutants. Different human activities, such as spending time outdoors, indoors, or driving, will result in varying pollutant exposure concentrations. To accurately model individuals and their exposure to pollutants, it is critical to understand their daily activities. EPA's Consolidated Human Activity Database (CHAD) provides data for where people spend time and the activities performed. Typical time-activity pattern data available for inhalation exposure modeling consist of a sequence of location/activity combinations spanning 24-hours, with 1 to 3 diary-days for any single study individual.

The exposure assessment performed here requires information on activity patterns over a full year. Long-term multi-day activity patterns were estimated from single days by combining the daily records using an algorithm that represents the day-to-day correlation of activities for individuals. The algorithm first uses cluster analysis to divide the daily activity pattern records into groups that are similar, and then select a single daily record from each group. This limited number of daily patterns is then used to construct a long-term sequence for a simulated individual, based on empirically-derived transition probabilities. This approach is intermediate between an assumption of no day-to-day correlation (i.e., re-selection of diaries for each time period) and perfect correlation (i.e., selection of a single daily record to represent all days). Details regarding the algorithm and supporting evaluations are provided in Appendix B-4, Attachments 2 and 3.

## 8.7 CALCULATING MICROENVIRONMENTAL CONCENTRATIONS

Probabilistic algorithms are used to estimate the pollutant concentration associated with each exposure event. The estimated pollutant concentrations account for temporal and spatial variability in ambient (outdoor) pollutant concentration and factors affecting indoor microenvironment, such as a penetration, air exchange rate, and pollutant decay or deposition rate. APEX calculates air concentrations in the various microenvironments visited by the simulated person by using the ambient air data estimated for the relevant blocks/receptors, the user-specified algorithm, and input parameters specific to each microenvironment. The method used by APEX to estimate the microenvironmental concentration depends on the microenvironment, the data available for input to the algorithm, and the estimation method selected by the user. The current version of APEX calculates hourly concentrations in all the microenvironments at each hour of the simulation for each of the simulated individuals using one of two methods: by mass balance or a transfer factors method. Details regarding the algorithms used for estimating specific microenvironments and associated input data derivations are provided in Appendix B.

Briefly, the mass balance method simulates an enclosed microenvironment as a well-mixed volume in which the air concentration is spatially uniform at any specific time. The concentration of an air pollutant in such a microenvironment is estimated using the following processes:

- Inflow of air into the microenvironment
- Outflow of air from the microenvironment
- Removal of a pollutant from the microenvironment due to deposition, filtration, and chemical degradation
- Emissions from sources of a pollutant inside the microenvironment.

A transfer factors approach is simpler than the mass balance model, however, most parameters are derived from distributions rather than single values to account for observed variability. It does not calculate concentration in a microenvironment from the concentration in the previous hour as is done by the mass balance method, and contains only two parameters. A proximity factor is used to account for proximity of the microenvironment to sources or sinks of pollution, or other systematic differences between concentrations just outside the microenvironment and the ambient concentrations (at the measurements site or modeled receptor). The second parameter, a penetration factor, quantifies the amount of outdoor pollutant penetrates into the microenvironment.

### 8.7.1 Microenvironments Modeled

In APEX, microenvironments represent the exposure locations for simulated individuals. For exposures to be estimated accurately, it is important to have realistic microenvironments that match closely to the locations where actual people spend time on a daily basis. As discussed above, the two methods available in APEX for calculating pollutant levels within microenvironments were mass balance or a transfer factors approach. Table 8-9 lists the microenvironments used in this study, the calculation method used, and the type of parameters needed to calculate the microenvironment concentrations.

**Table 8-9. List of microenvironments modeled and calculation methods used.**

| Microenvironment | Calculation Method | Parameter Types used [1] |
|---|---|---|
| Indoors – Residence | Mass balance | AER and DE |
| Indoors – Bars and restaurants | Mass balance | AER and DE |
| Indoors – Schools | Mass balance | AER and DE |
| Indoors – Day-care centers | Mass balance | AER and DE |
| Indoors – Office | Mass balance | AER and DE |
| Indoors – Shopping | Mass balance | AER and DE |
| Indoors – Other | Mass balance | AER and DE |
| Outdoors – Near road | Factors | PR |
| Outdoors – Public garage - parking lot | Factors | PR |
| Outdoors – Other | Factors | None |
| In-vehicle – Cars and Trucks | Factors | PE and PR |
| In-vehicle - Mass Transit (bus, subway, train) | Factors | PE and PR |
| [1] AER=air exchange rate, DE=decay-deposition rate, PR=proximity factor, PE=penetration factor | | |

### 8.7.2 Microenvironment Descriptions

#### *8.7.2.1 Microenvironment 1: Indoor-Residence*

The Indoors-Residence microenvironment uses several variables that affect $NO_2$ exposure: whether or not air conditioning is present, the average outdoor temperature, the $NO_2$ removal rate, and an indoor concentration source.

Air conditioning (A/C) status of an individual's residential microenvironment was simulated randomly using the probability that a residence has an air conditioner. For the Atlanta modeling domain an air-conditioning prevalence of 97.0 % was used (AHS, 2004). Air exchange rate (AER) data for the indoor residential microenvironment were obtained from EPA (2007g). Briefly, AER data were reviewed, compiled, and evaluated from the extant literature to generate location-specific AER distributions categorized by influential factors, namely temperature and presence of A/C. In general, lognormal distributions provided the best fit, and are defined by a geometric mean (GM) and standard deviation (GSD). Because no fitted distribution was available specifically for Atlanta, distributions were selected from other locations thought to have similar characteristics, qualitatively considering factors that might influence AERs including the age composition of housing stock, construction methods, and other meteorological variables not explicitly treated in the analysis, such as humidity and wind speed patterns. To avoid unusually extreme simulated AER values, bounds of 0.1 and 10 were selected for minimum and maximum AER, respectively. Table 8-10 summarizes the distributions used by A/C prevalence and temperature categories.

**Table 8-10. Geometric means (GM) and standard deviations (GSD) for air exchange rates by A/C type, and temperature range used for Atlanta exposure assessment.**

| A/C Type | Temp (ºC) | N | GM | GSD |
|---|---|---|---|---|
| No A/C[1] | <=10 | 61 | 0.9258 | 2.0836 |
| | 10-20 | 87 | 0.7333 | 2.3299 |
| | >20 | 44 | 1.3782 | 2.2757 |
| Central or Room A/C[2] | <=10 | 157 | 0.9617 | 1.8094 |
| | 10-20 | 320 | 0.5624 | 1.9058 |
| | 20-25 | 196 | 0.3970 | 1.8887 |
| | >25 | 145 | 0.3803 | 1.7092 |

**Notes:**
[1] Distribution derived from Research Triangle Park study. See EPA (2007g).
[2] Distribution derived from non-California cities. See EPA (2007g).

The same $NO_2$ removal rate distribution was used for all indoor microenvironments that use the mass balance method. This removal rate is based on data provided by Spicer et al. (1993) and was approximated with a uniform distribution, U{1.02, 1.45 $h^{-1}$} based on the six reported values.

An indoor emission source term was included in the APEX simulations to estimate $NO_2$ exposure to gas cooking (hereafter referred to as "indoor sources"). Three types of data were used generate this emission factor: (1) the fraction of households in the Atlanta MSA that use gas for cooking fuel, (2) the range of contributions to indoor $NO_2$ concentrations that occur from cooking with gas, and (3) the diurnal pattern of cooking in households.

The fraction of households in Atlanta that use gas cooking fuel (i.e., 39%) was obtained from AHS (2004). Data used for estimating the contribution to indoor $NO_2$ concentrations that occur during cooking with gas fuel were derived from a study sponsored by the California Air Resources Board (CARB, 2001). A uniform distribution of concentration contributions for input to APEX was estimated as U{4, 188 ppb}. An analysis by Johnson et al (1999) of survey data on gas stove usage collected by Koontz et al (1992) showed an average number of meals prepared each day with a gas stove of 1.4. The diurnal allocation of these cooking events was estimated using food preparation time obtained from CHAD diaries was stratified by hour of the day and normalized to the expected value of daily food preparation events to 1.4 (Table 8-11).

**Table 8-11. Probability of gas stove cooking by hour of the day.**

| Hour of the Day | Probability of Cooking (%)[1] |
|---|---|
| 0 | 0 |
| 1 | 0 |
| 2 | 0 |
| 3 | 0 |
| 4 | 0 |
| 5 | 5 |
| 6 | 10 |
| 7 | 10 |
| 8 | 10 |
| 9 | 5 |
| 10 | 5 |
| 11 | 5 |
| 12 | 10 |
| 13 | 5 |
| 14 | 5 |
| 15 | 5 |
| 16 | 15 |

| Hour of the Day | Probability of Cooking (%)[1] |
|---|---|
| 17 | 20 |
| 18 | 15 |
| 19 | 10 |
| 20 | 5 |
| 21 | 5 |
| 22 | 0 |
| 23 | 0 |

**Notes:**
[1] Values rounded to the nearest 5%. Data sum to 145% due to rounding convention and the scaling to represent 1.4 cooking events/day.

#### *8.7.2.2 Microenvironments 2-7: All other indoor microenvironments*

The remaining five indoor microenvironments, which represent Bars and Restaurants, Schools, Day Care Centers, Office, Shopping, and Other environments, were all modeled using the same data and functions. An air exchange rate distribution (GM = 1.109, GSD = 3.015, Min = 0.07, Max = 13.8) was based on an indoor air quality study (Persily et al, 2005; see US EPA, 2007g for details in derivation). The removal rate is the same uniform distribution used in the Indoor-Residence microenvironment. The Bars and Restaurants microenvironment included an estimated contribution from indoor sources as was described for the Indoor-Residence, only there was an assumed 100% prevalence rate and the cooking with a gas appliance and it occurred at any hour of the day.

#### *8.7.2.3 Microenvironments 8 and 9: Outdoor Microenvironments*

Two outdoor microenvironments, the Near Road and Public Garage/Parking Lot, used the transfer factors method to calculate pollutant exposure. Penetration factors are not applicable to outdoor environments (effectively, PEN=1). The distribution for proximity factors were developed from the dispersion model estimated concentrations, using the relationship between on-road to receptor estimated concentrations.

#### *8.7.2.4 Microenvironment 10: Outdoors-General*

The general outdoor environment concentrations are well represented by the modeled concentrations. Therefore, both the penetration factor and proximity factor for this microenvironment were set to 1.

#### *8.7.2.5 Microenvironments 11 and 12: In Vehicle- Cars and Trucks, and Mass Transit*

Penetration factors were developed from data provided in Chan and Chung (2003). Since major roads were the focus of this assessment, reported indoor/outdoor ratios for highway and urban streets were used here. Mean values range from about 0.6 to just over 1.0, with higher values associated with increased ventilation (i.e., window open). A uniform distribution U{0.6, 1.0} was selected for the penetration factor for Inside-Cars/Trucks due to the limited data available to describe a more formal distribution and the lack of data available to reasonably assign potentially influential characteristics such as use of vehicle ventilation systems for each location. Mass transit systems, due to the frequent opening and closing of doors, was assigned a point estimate of 1.0 based on the reported mean values for open windows ranging from 0.96 and 1.0. Proximity factors were developed from the dispersion model estimated concentrations, using the relationship between the on-road to receptor estimated concentrations.

## 8.8 EXPOSURE MEASURES AND HEALTH RISK CHARACTERIZATION

APEX calculates the time series of exposure concentrations that a simulated individual experiences during the simulation period. APEX determines the exposure using hourly ambient air concentrations, calculated concentrations in each microenvironment based on these ambient air concentrations (and indoor sources if present), and the minutes spent in a sequence of microenvironments visited according to the composite diary. The hourly exposure concentration at any clock hour during the simulation period is determined using the following equation:

$$C_i = \frac{\sum_{j=1}^{N} C_{ME(j)}^{hourlymean} \quad t_{(j)}}{T}$$

where,

| | | |
|---|---|---|
| $C_i$ | = | Hourly exposure concentration at clock hour *i* of the simulation period (ppm) |
| $N$ | = | Number of events (i.e., microenvironments visited) in clock hour *i* of the simulation period. |
| $C_{ME(j)}^{hourlymean}$ | = | Hourly mean concentration in microenvironment *j* (ppm) |
| $t_{(j)}$ | = | Time spent in microenvironment *j* (minutes) |

*T* = 60 minutes

From the hourly exposures, APEX calculates time series of 1-hour average exposure concentrations that a simulated individual would experience during the simulation period. APEX then statistically summarizes and tabulates the hourly (or daily, annual average) exposures. In this analysis, the exposure indicator is 1-hr exposures above selected health effect benchmark levels. From this, APEX can calculate two general types of exposure estimates: counts of the estimated number of people exposed at or above a specified $NO_2$ concentration level and the number of times per year that they are so exposed; the latter metric is in terms of person-occurrences or person-days. The former highlights the number of individuals exposed at least *one or more* times per modeling period to the potential health effect benchmark level of interest. APEX can also report counts of individuals with multiple exposures. This person-occurrences measure estimates the number of times per season that individuals are exposed to the exposure indicator of interest and then accumulates these estimates for the entire population residing in an area.

APEX tabulates and displays the two measures for exposures above levels ranging from 100 to 300 ppb by 50 ppb increments for 1-hour average exposures. These results are tabulated for the population and subpopulations of interest.

### 8.8.1 Adjustment for Just Meeting the Current and Alternative Standards

We used a different approach to simulate just meeting the current and alternative standards than was used in the Air Quality Characterization (Appendix A). In this case, instead of adjusting upward[14] the air quality concentrations, to reduce computer processing time, we adjusted the health effect benchmark levels by the same factors described for each specific location and simulated year (Table 8-12). Since it is a proportional adjustment, the end effect of adjusting concentrations upwards versus adjusting benchmark levels downward within the model is the same. The same follows for where as is concentrations were in excess of an alternative standard level (e.g., 50 ppb for the 98$^{th}$ percentile averaged over three years), only the associated benchmarks are adjusted upwards (i.e., a higher threshold simulating lower exposures).

[14] To evaluate the current and most of the alternative standards proposed, ambient concentrations were lower than air quality that would just meet the standards.

**Table 8-12. Adjusted potential health effect benchmark levels used by APEX to simulate just meeting the current standard and various alternative standards considered.**

| Model Scenario | Averaging Time | Conc (ppb) | Conditions | Potential health effect benchmark level (ppb) | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | 100 | 150 | 200 | 250 | 300 |
| As-is | | | | 100 | 150 | 200 | 250 | 300 |
| Current Standard | Annual | 53 | Year 2001 | 44 | 66 | 88 | 110 | 132 |
| | | | Year 2002 | 37 | 55 | 73 | 91 | 110 |
| | | | Year 2003 | 31 | 46 | 62 | 77 | 93 |
| Alternative Standards | 1 hour | 50 | $98^{th}$ %ile | 163 | nd | 327 | nd | 490 |
| | | | $99^{th}$ %ile | 177 | nd | 355 | nd | 532 |
| | | 100 | $98^{th}$ %ile | 82 | nd | 163 | nd | 245 |
| | | | $99^{th}$ %ile | 89 | nd | 177 | nd | 266 |
| | | 150 | $98^{th}$ %ile | 54 | nd | 109 | nd | 163 |
| | | | $99^{th}$ %ile | 59 | nd | 118 | nd | 177 |
| | | 200 | $98^{th}$ %ile | 41 | nd | 82 | nd | 123 |
| | | | $99^{th}$ %ile | 44 | nd | 89 | nd | 133 |

**Notes:**
[nd] not done due to model constraints on number of levels possible in one model simulation.

When modeling indoor sources, the indoor concentration contributions needed to be scaled by the similar proportions. This additional scaling was necessary so as not to affect the impact of the estimated indoor concentrations while adjusting the benchmark levels. To clarify how this was done, exposure concentrations an individual experiences are first defined as the sum of the contribution from ambient concentrations and from indoor sources (if present) and this concentration can be either above or below a selected concentration level of interest:

$$C_{esposure} = aC_{ambient} + bC_{indoor} > C_{threshold}$$

where,

$C_{exposure}$ = individual exposure concentration (ppm)

$a$ = proportion of exposure concentration from ambient (unitless fraction)

$C_{ambient}$ = ambient concentration in the absence of indoor sources

$b$ = proportion of exposure concentration from indoor (unitless fraction, equivalent to 1-a)

$C_{indoor}$ = indoor source concentration contribution (ppm)

$C_{threshold}$ = an exposure concentration of interest (ppm)

It follows that if we are interested in adjusting the ambient concentrations upwards by some proportional factor *f* (a unitless number), this can be described with the following:

$$fa\,C_{ambient} + bC_{indoor} > C_{threshold}$$

This is equivalent to

$$aC_{ambient} + b(C_{indoor} \ / \ f) > (C_{threshold} \ / \ f)$$

Therefore, if the potential health effect benchmark level and the indoor concentrations are both proportionally scaled downward by the same adjustment factor, the contribution of both sources of exposure (i.e., ambient and indoor) are maintained and the same number of estimated exceedances would be obtained as if the ambient concentration were proportionally adjusted upwards by factor *f*.

# 8.9 EXPOSURE MODELING AND HEALTH RISK CHARACTERIZATION RESULTS

### 8.9.1 Overview

The results of the exposure and risk characterization are presented here for the four county modeling domain in Atlanta. Several exposure scenarios were considered for the exposure assessment including an analysis of three averaging times for $NO_2$ concentrations (annual, 24-hour, and 1-hour), an analysis of the contribution to $NO_2$ exposures of both indoor and outdoor sources, and an analysis of $NO_2$ exposures assuming air quality that just meets the current annual and several alternative 1-hour daily maximum standards. The year 2002 served as the base year for all scenarios, while 2001 and 2003 were only evaluated for a limited number of scenarios. Exposures were simulated for four population groups; all persons, all children (ages 5-17), all asthmatics, and asthmatic children (ages 5-17).

The exposure results that are summarized below focus on asthmatics. Key results are presented in the next three subsections, with complete results for each of these two population subgroups provided in Appendix B-4. In addition, due to limitations in the data summaries output from the current version of APEX, certain exposure data could only be output for the entire population modeled (i.e., all persons - includes asthmatics and healthy persons of all ages) rather than the particular subpopulation. The summary exposure results for the entire population (e.g., annual average exposure concentrations, time spent in microenvironments at or above a potential health effect benchmark level) is assumed representative of the asthmatic population in the modeling results because the asthmatic population does not have its microenvironmental concentrations and activities estimated any differently from those of the total population. The assumption of modeling asthmatics similarly to healthy individuals (i.e., using the same time-location-activity profiles) is supported by the findings of van Gent et al. (2007), at least when considering children 7-10 years in age. These researchers used three different activity-level measurement techniques; an accelerometer recording 1-minute time intervals, a written diary considering 15-minute time blocks, and a categorical scale of activity level. Based on analysis of 5-days of monitoring, van Gent et al. (2007) showed no difference in the activity data collection methods used as well as no difference between asthmatic children and healthy children when comparing their activity levels.

### 8.9.2 Annual Average Exposure Concentrations (as is)

Figure 8-8 illustrates the annual average exposure concentrations for the total simulated population (i.e., both asthmatics and healthy individual of all ages), considering the modeled year 2002 air quality (as is) and both with and without indoor sources. Also plotted on this figure is the distribution of the annual average $NO_2$ concentrations predicted by AERMOD separated into two broad receptor categories. As a point of reference, the measured annual average concentration for the three ambient monitors in the Atlanta modeling domain ranged from 15 ppb to 19 ppb in year 2002. About half of the AERMOD predicted annual average $NO_2$ concentrations for the non-road receptors were below the range of the ambient monitoring concentrations, with most containing less than 30 ppb, although about 5% of these receptors contained concentrations above this level. It should be noted that the non-road receptors included here could contain a number of block centroids located near a major road. Consistent with what was observed in the air quality characterization data for on-road concentration estimates, the AERMOD long-term average concentrations predicted at the roadway links are about twice that of the estimated concentrations at non-road receptors.

The hourly $NO_2$ concentrations output from AERMOD were input into the exposure model, providing a wide range of estimated exposures calculated by APEX (Figure 8-8). All persons were estimated to experience exposures below an annual average exposure of 53 ppb, even when considering indoor source concentration contributions. The estimated annual average exposures were below that of both the modeled receptors and the measured air quality. For example, the median annual average exposure was about 6 ppb less than the modeled median non-road receptor concentration when the exposure estimation included indoor sources, and about 9 ppb less when annual average exposures were estimated without the indoor sources. In the absence of indoor source contributions, personal exposure concentrations for most of the simulated individuals are estimated to be about 40 to 70 percent that of the local ambient or outdoor concentration. This estimate is consistent with studies reporting such a relationship based on measurements of personal exposure and ambient concentrations that ranges from around 0.3 to 0.6 (Table AX3.5-1b, ISA ANNEX).

In comparing the estimated exposures with and without indoor sources, indoor sources were estimated to contribute between 1 and 4 ppb to the total annual average exposures. This would correspond to indoor sources contributing approximately 1/3 of the annual average exposures for persons using gas cooking appliances. Again, while Figure 8-8 summarizes the entire population, the data are representative of what would be observed for the population of asthmatics or asthmatic children.

Year-to year-variation was evaluated by comparing the estimated annual average exposure distributions for each year simulated. Each simulated year of data was very similar, with estimated median annual average exposures at about 10 ppb and 95% of the simulated individuals' annual average exposures within 5.9 and 15.8 ppb (Figure 8-9).

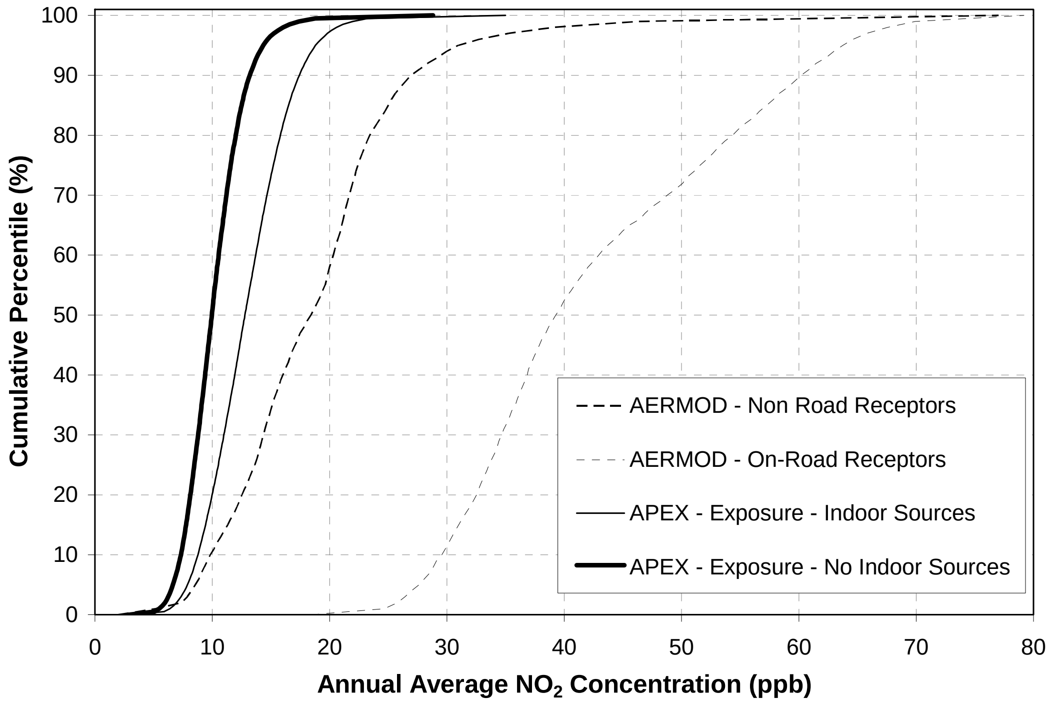



**Figure 8-8. Comparison of annual average AERMOD predicted $NO_2$ concentrations (on-road and non-road receptors) and APEX modeled $NO_2$ exposures (with and without modeled indoor sources) in Atlanta modeling domain for year 2002.**

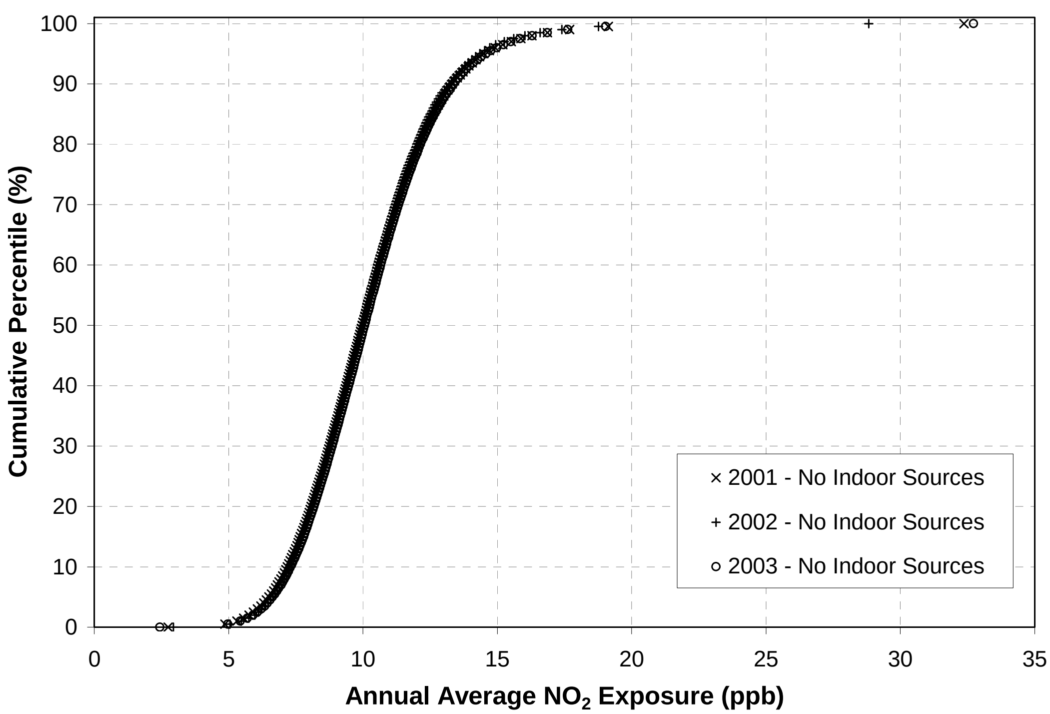



**Figure 8-9. Comparison of estimated annual average $NO_2$ exposures for Years 2001-2003 in Atlanta modeling domain without modeled indoor sources.**

### 8.9.3 Daily Average Exposures (as is)

As mentioned earlier, APEX is capable of providing exposure results across a variety of averaging times, including 24-hour average exposures. This averaging time serves as a good point of comparison with the personal exposures reported in the published literature. As mentioned above regarding APEX default results, the daily mean exposures were estimated for the total simulated population. In this simulation, each person has 365 daily mean personal exposures, thus each individual experiences a daily average concentration distribution (i.e., each person has a median daily average exposure, a 99$^{th}$ percentile daily average exposure, etc.). These modeled exposures were compared with personal $NO_2$ measurement data obtained from Suh (2008) for the participants of an Atlanta epidemiological study conducted by Wheeler et al. (2006). The personal exposure measurements were collected across two seasons (Fall and Spring)[15] and considered cooking fuel (gas or electric cooking) as an influential variable for personal exposures. A total of 30 individuals participated in the study, of which 13 subjects contained personal exposure data for both seasons, with no persons having used both cooking fuels. An average of 6 daily average personal exposure measurements was available for each individual when stratified by season and cooking fuel (minimum number of days = 3, max = 7). Because there were few personal exposure measurements, an exposure distribution was constructed from each individual, simply using their minimum, median, and maximum daily mean exposures and are summarized in Figure 8-9. In comparing the median personal daily mean exposures using the two stratification variables, two trends can be noted. First, the use of gas as a cooking fuel increased daily median personal exposures by about 3 to 10 ppb in both seasons. Second, seasonal differences were also present, with personal daily average exposures higher during the spring by about 1 to 3 ppb when comparing the individual median values for the persons employing gas or electric cooking. While these general trends are noted, it should be added that the maximum daily average exposures were highest in the Spring and similar for both of the cooking fuel categories.

Daily mean exposures estimated using APEX were also evaluated in a similar manner, by stratifying the results based on the same seasons and whether or not indoor sources were included in the model simulation. The specific period from 1999-2000 was not modeled by

[15] Fall was designated here for sample collection dates reported in the months of September, October, and November 1999; Spring was designated where sample collection dates were reported in the months of April and May 2000.

APEX although this period was included in the personal exposure measurement study. The APEX simulation results for year 2002 were selected for comparison with the exposure measurements obtained from Suh (2008). A distribution of each person's estimated daily exposure was constructed, using the median daily mean exposure to represent the central tendency and a 95 % prediction interval to represent the lower and upper bounds of exposure (i.e., the 2.5$^{th}$ and the 97.5$^{th}$ percentiles). The results of this analysis, stratified by season and by inclusion of indoor sources, are presented in Figure 8-10.

The distributions of median daily mean exposures are comparable to one another, although the Fall season was about 1 ppb higher than the Spring exposures. The range of estimated daily mean exposures, given by the 95% prediction interval, was also similar across the season categories. In comparing the simulations where indoor sources were modeled to the simulations conducted without indoor source contributions, the estimated exposures were between 1 to 4 ppb greater for the indoor source simulations. It should be noted that the indoor source exposure distributions include exposures for all of the simulated individuals, some of which do not have gas cooking occurring at home. The APEX simulated daily mean exposures are similar to the measured personal exposures (Figure 8-10) when considering the values and range of the median concentrations as well as the values and range of the bounding percentiles.

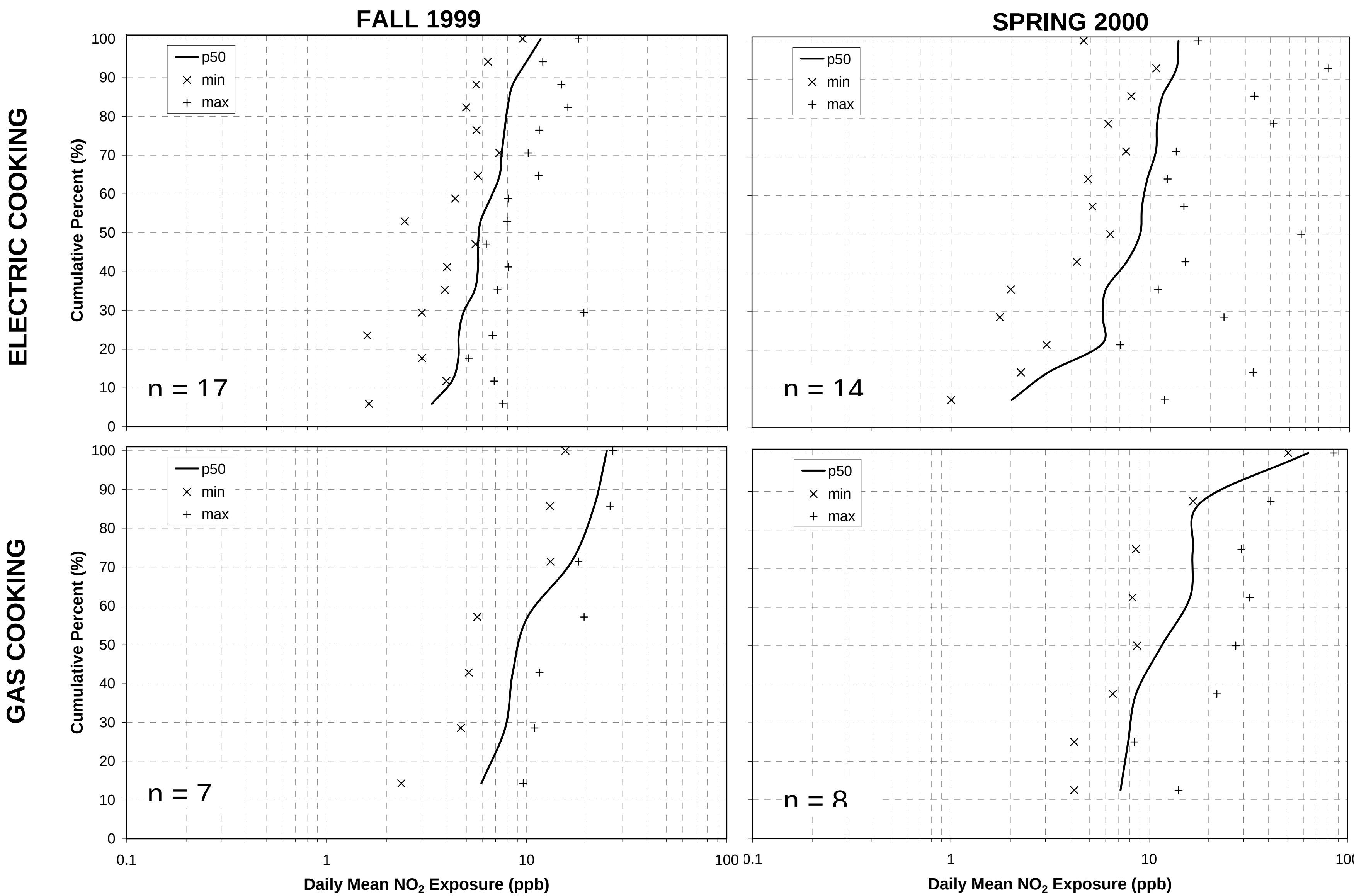



**Figure 8-10. Distribution of measured daily average personal $NO_2$ exposures for individuals in Atlanta, stratified by two seasons (Fall or Spring) and cooking fuel (gas or electric). Minimum (min), median (p50), and maximum (max) were obtained from each individual's multi-day exposure measurements. The figure generated here was based on personal exposure measurements obtained from Suh (2008).**

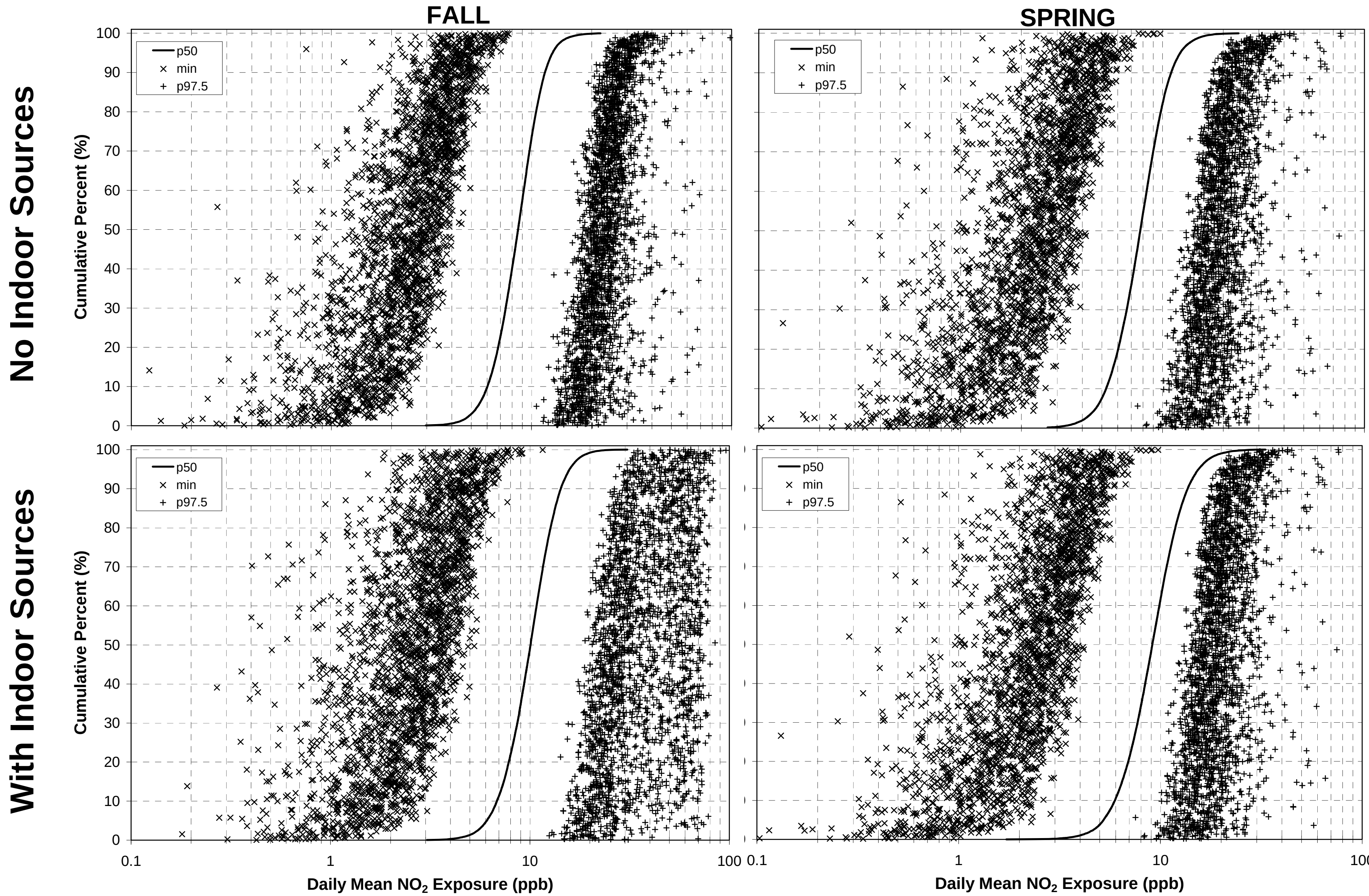



**Figure 8-11. Distribution of estimated daily average $NO_2$ exposures for individuals in Atlanta, stratified by two seasons (Fall or Spring) and with and without indoor sources, for Year 2002 APEX simulation. Lower bound (2.5th percentile, p2.5), median (p50), and upper bound (97.5th percentile, p97.5) were calculated from each simulated persons 365 days of exposure. A random sample of 5% of persons (about 2,500 individuals) is presented in each figure to limit the density of the graphs.**

### 8.9.4 One-Hour Exposures

#### *8.9.4.1 Overview*

Because the focus of the exposure and risk characterization is on short-term 1-hour daily maximum exposures, analyses were performed using the APEX estimated 1-hour exposure concentrations. The number of exposures above the selected potential health effect benchmark levels (i.e., 100, 150, 200, 250, and 300 ppb, 1-hour average) were estimated. An exceedance was recorded when the maximum exposure concentration estimated for the individual was above the selected benchmark level in a day. Estimates of repeated exposures are also recorded, that is where 1-hour exposure concentrations were above a selected benchmark level in a day added together across multiple days (therefore, the maximum number of multiple exceedances per individual is 365). Persons of interest in this exposure analysis are those with particular susceptibility to $NO_2$ exposure, namely individuals with asthma. The potential health effect benchmark levels used are appropriate for characterizing the potential risk of adverse health effects for asthmatics. The majority of the results presented in this section are for the entire (i.e., all ages) simulated asthmatic population because the pattern of exposure results for asthmatic children were very similar. However, the exposure analysis was also performed for the total population to assess numbers of persons exposed to these levels and to provide additional information relevant to the asthmatic population (such as time spent in particular microenvironments). The 1-hour exposure results are presented separately for three scenarios, (1) considering the exposures associated with as is air quality, (2) simulating exposures with air quality that would just meet the current annual average standard, and (3) simulating exposures associated with air quality that would just meet alternative 1-hour daily maximum standards. In addition, the presence (or not) of indoor sources was also considered within each of these three scenarios.

#### *8.9.4.2 Estimated Number of 1-hour Exposures Above Selected Levels (as is)*

The results presented in this section were generated from the modeled air quality as input to APEX without any adjustment to the air concentrations or the potential health effect benchmark levels. Figure 8-12 summarizes the estimated number of asthmatics exposed at each of the potential health effect benchmark levels using the modeled air quality for each year, without any contribution from indoor sources. As observed with the annual average exposure concentrations, there is great similarity in the estimated numbers of exceedances for each of the three years modeled. Year-to-year variability in the number of asthmatics exposed as indicated by a coefficient of variation (COV=mean/standard deviation) was at most 3.3%, calculated for the 300 ppb benchmark level. All persons (i.e., just over 212,000) were estimated to be exposed at least one time to a 1-hour daily maximum concentration of 100 ppb in a year. The number of asthmatics exposed to greater concentrations (e.g., 200 or 300 ppb) drops only slightly and is estimated to be somewhere between 117,000 – 196,000 depending on the 1-hour concentration level and year of air quality simulated. Similar patterns across the benchmark levels were observed for simulated asthmatic children, albeit with lower total numbers of asthmatic children with exposures at or above the potential health effect benchmark levels.

The results for all asthmatics and asthmatic children were similar in terms of the proportion of the population exposed and the year-to year variability in numbers of exceedances. For example, nearly 61,000 asthmatic children were estimated to be exposed one time to a 1-hour daily maximum $NO_2$ concentration of at least 200 ppb for year 2002, comprising about 95% of that subpopulation (Figure 8-13). The number of children with at least one exceedance of 300 ppb was less, estimated to be about 41,000 using the 2002 air quality, or about 64% of all asthmatic children. As a comparison, the percent of all asthmatics experiencing exposures at or above 200 and 300 ppb was 92% and 59%, respectively. The year-to-year variability in the number of asthmatic children exposed at or above the selected benchmark levels was also small, although slightly higher than that estimated for the total asthmatics. The highest COV for asthmatic children was also observed for exceedances of the 300 ppb benchmark (COV = 4.9%)

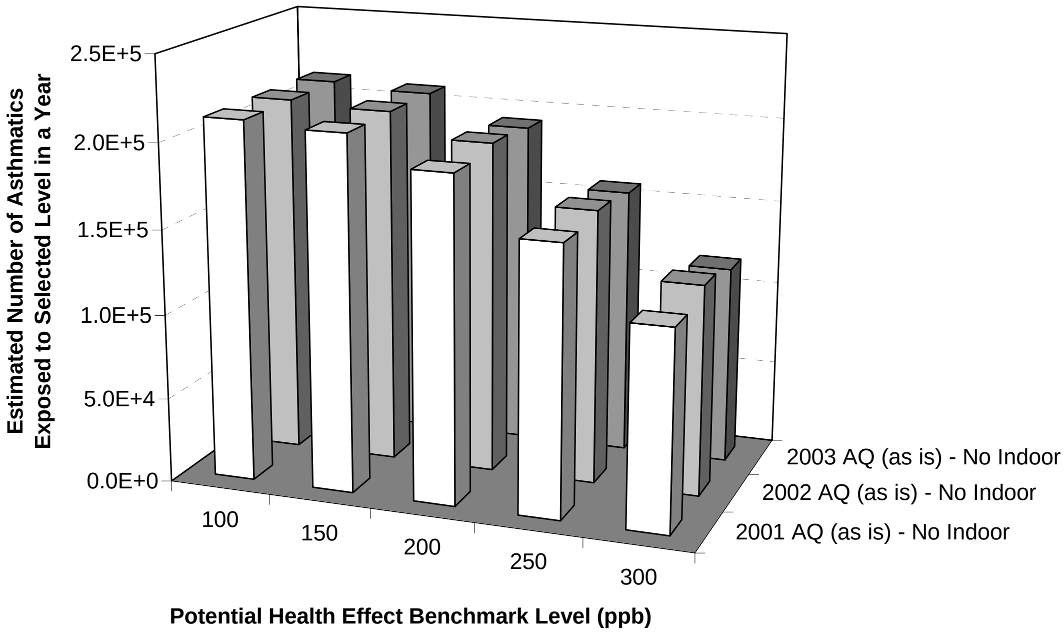



**Figure 8-12. Estimated number of all simulated asthmatics in the Atlanta model domain with at least one $NO_2$ exposure at or above the potential health effect benchmark levels, using modeled 2001-2003 air quality (as is), without indoor sources.**

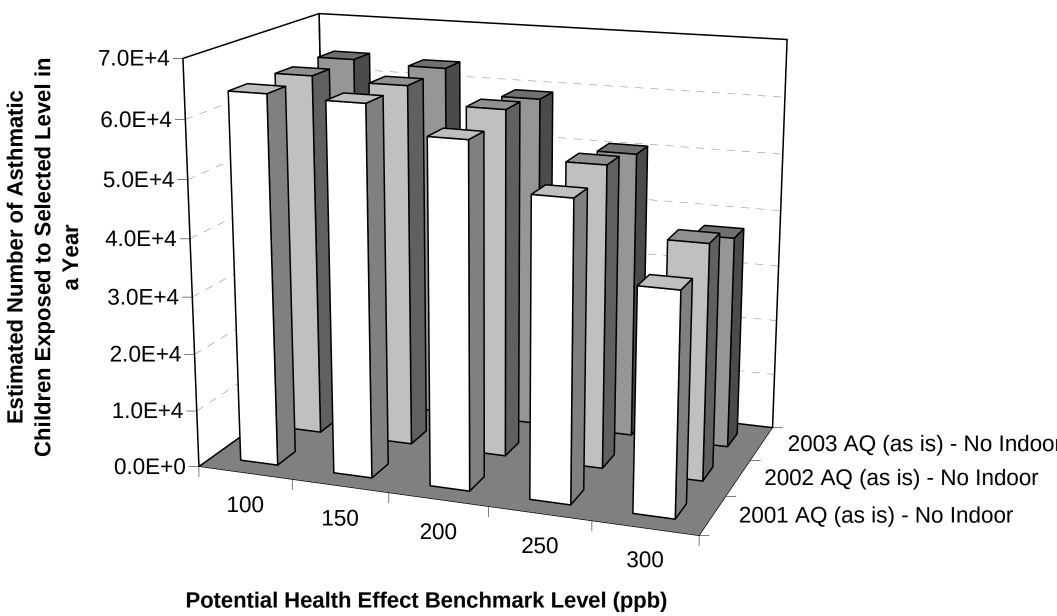



**Figure 8-13. Estimated number of simulated asthmatic children in the Atlanta model domain with at least one $NO_2$ exposure at or above the potential health effect benchmark levels, using modeled 2001-2003 air quality (as is), without modeled indoor sources.**

Additional exposure estimates were generated using the modeled 2002 air quality (as is). Those estimates include an evaluation of the contribution of indoor sources. APEX allows for the same persons to be simulated (i.e., demographics of the population were conserved), as well as using the same individual time-location-activity profiles generated for each person. Figure 8-14 illustrates the estimated number of asthmatics experiencing exposures above the potential health effect benchmarks, both with indoor sources and without indoor sources included in the model runs. The number of asthmatics at or above the selected benchmark levels at least one time in a year is very similar when including indoor source concentration contributions (i.e., gas cooking) compared to the number of persons whose exposure estimates did not include indoor sources. The reduction in numbers of asthmatics exposed at least once at or above any potential health effect benchmark level ranged from 0 to around 5,000 when indoor source contributions were excluded.

The number of person-days of exposure at or above a given potential benchmark levels gives a different perspective on the contribution of indoor sources. Figure 8-15 illustrates the total number of days where the particular concentration level was exceeded, representing the sum of all multiple exposures (in contrast to focusing on persons as was done for example in Figure 8-12) for the simulated population in a given year. Since most individuals were exposed at least one time at many of the 1-hour levels, it was difficult to discern the effect that indoor sources had on the estimated exposures. Now it can be seen that the indoor source contribution increases not just the number of persons exposed, but more importantly how many times they would be exposed per year above the selected benchmark level. It appears that on average, there is an increase in the number of person-days by about a factor of 2.1 and 1.8 for the 100 and 150 ppb 1-hour concentration levels, respectively, while the higher benchmark levels are largely unaffected by the presence of indoor sources.

An evaluation of the time spent in the 12 microenvironments was performed to estimate where simulated individuals are exposed to concentrations above the potential health effect benchmark levels. Currently, the output generated by APEX is limited to compiling the microenvironmental time for the total population (includes both asthmatic individuals and healthy persons) and the summaries provide the total time spent above the selected potential health effect benchmark levels. As mentioned above, the data still provide a reasonable approximation for each of the population subgroups (e.g., asthmatics or asthmatic children) because their microenvironmental concentrations and activities are not estimated any differently from those of the total population simulated by APEX.

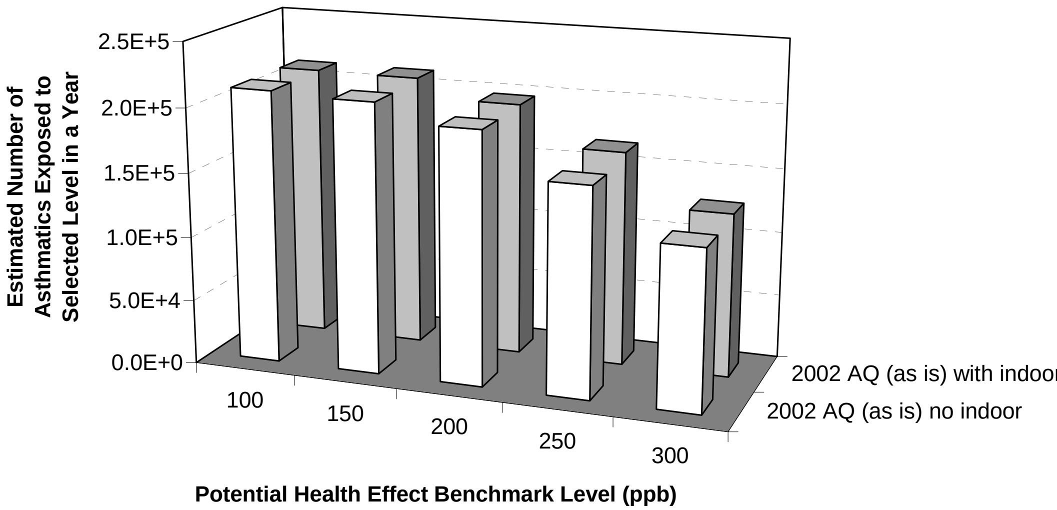



**Figure 8-14. Estimated number of all simulated asthmatics in the Atlanta model domain with at least one $NO_2$ exposure at or above potential health effect benchmark levels, using modeled 2002 air quality (as is), both with and without modeled indoor sources.**

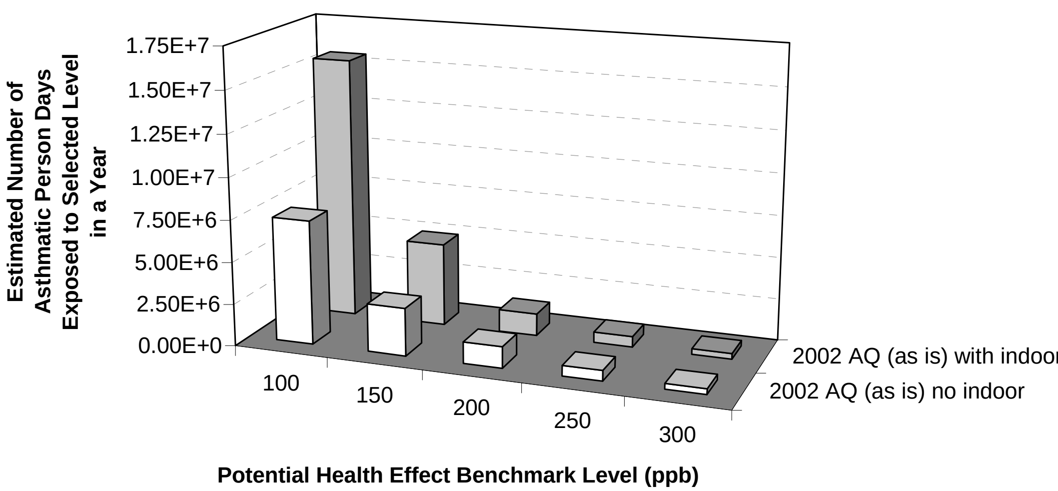



**Figure 8-15. Estimated number asthmatic person-days in the Atlanta model domain with an $NO_2$ exposure at or above potential health effect benchmark levels, using modeled 2002 air quality (as is), both with and without modeled indoor sources.**

As an example, Figure 8-16 (a, b, c) summarizes the percent of total time spent in each microenvironment for simulation year 2002 that was associated with estimated exposure concentrations at or above 100, 200, and 300 ppb (results for years 2001 and 2003 were similar). These estimated exposures did not include the contribution from indoor sources. Time spent in the indoor microenvironments contributed little to the occurrence of estimated exposures at or above the selected benchmark levels. Most indoor microenvironments contributed < 1% of exposures to 1-h concentrations above 100 ppb and none of them contributed at all to exceedances of the 200 and 300 ppb benchmark levels. Most of the time associated with the high short-term exposures was associated with the transportation microenvironments (In-Vehicle or In-Public Transport) or outdoors (Out-Near Road, Out-Parking Lot, Out-Other). The time spent outdoors near roadways exhibited an increase in contribution of exceedances of potential health benchmark levels, increasing from around 25 to 29% of time associated with concentrations of 100 and 300 ppb, respectively. The in-vehicle microenvironment showed a corresponding decrease, estimated as contributing to 65% of the time associated with 100 ppb exceedances, while contributing to 58% of 1-hour daily maximum exposures at or above 300 ppb. While more persons are likely to spend time inside a vehicle than outdoors near roads, there is attenuation of the estimated on-road concentration that penetrates the in-vehicle microenvironment, leading to lowered concentrations. The result of this is that exposures above 300 ppb occur less frequently in-vehicles when compared with the outdoor near-road microenvironment that has no attenuation of concentrations.

The microenvironments where the exposure exceedances occur were also identified for the estimated exposures that included indoor source contributions (Figure 8-17). While the transportation-associated microenvironments remained important for exposures above the selected levels, the time spent in the indoor microenvironments was also important for exceedances of hourly levels of 100 ppb, contributing to approximately 26% (inside a home) and 33% (inside bar/restaurant) of the time persons were exposed (Figure 8-17a). This is likely a result of the indoor source contribution to each individual's exposure concentrations and is consistent with what was observed regarding the effect of indoor sources on the total person-days of exposure. However, the importance of the indoor microenvironments decreases with the increasing benchmark levels. Exposures at or above 200-300 ppb occur rarely in the indoor microenvironments, even when considering the indoor source contributions. The exposures at the higher benchmarks are associated mainly with the transportation microenvironments, increasing from about 39% of the time exposures occurred at the lowest potential health effect benchmark level (100 ppb) to comprising 100% of the time exposures occurred at the highest benchmark level (300 ppb, Figure 8-17c).

In the above analysis of persons exposed, the results show the number or percent of those with at least one day on which the 1-hour exposure was at or above the selected potential health effect benchmark level. Given that the benchmark is for a relatively short averaging time (i.e., 1-hour) it may be possible that individuals are exposed to concentrations at or above the potential health effect benchmark levels on several days in a given year. Since APEX simulates the longitudinal diary profile for each individual, the number of days with a 1-hour daily maximum exposure above a selected level is retained for each person. Figure 8-18 presents such an analysis for the year 2002, where the estimated exposures did not include indoor source $NO_2$ contributions. Nearly all simulated asthmatics (98.7%) experienced up to six exposures at or above 100 ppb, with nearly 78% experiencing at least six exposures at or above the 150 ppb level. Multiple exposures at or above the higher potential health effect benchmark levels were less frequent, with around 58, 28, and 12 percent of asthmatics exposed annually to four or more 1-hour $NO_2$ concentrations greater than or equal to 200, 250, and 300 ppb, respectively.

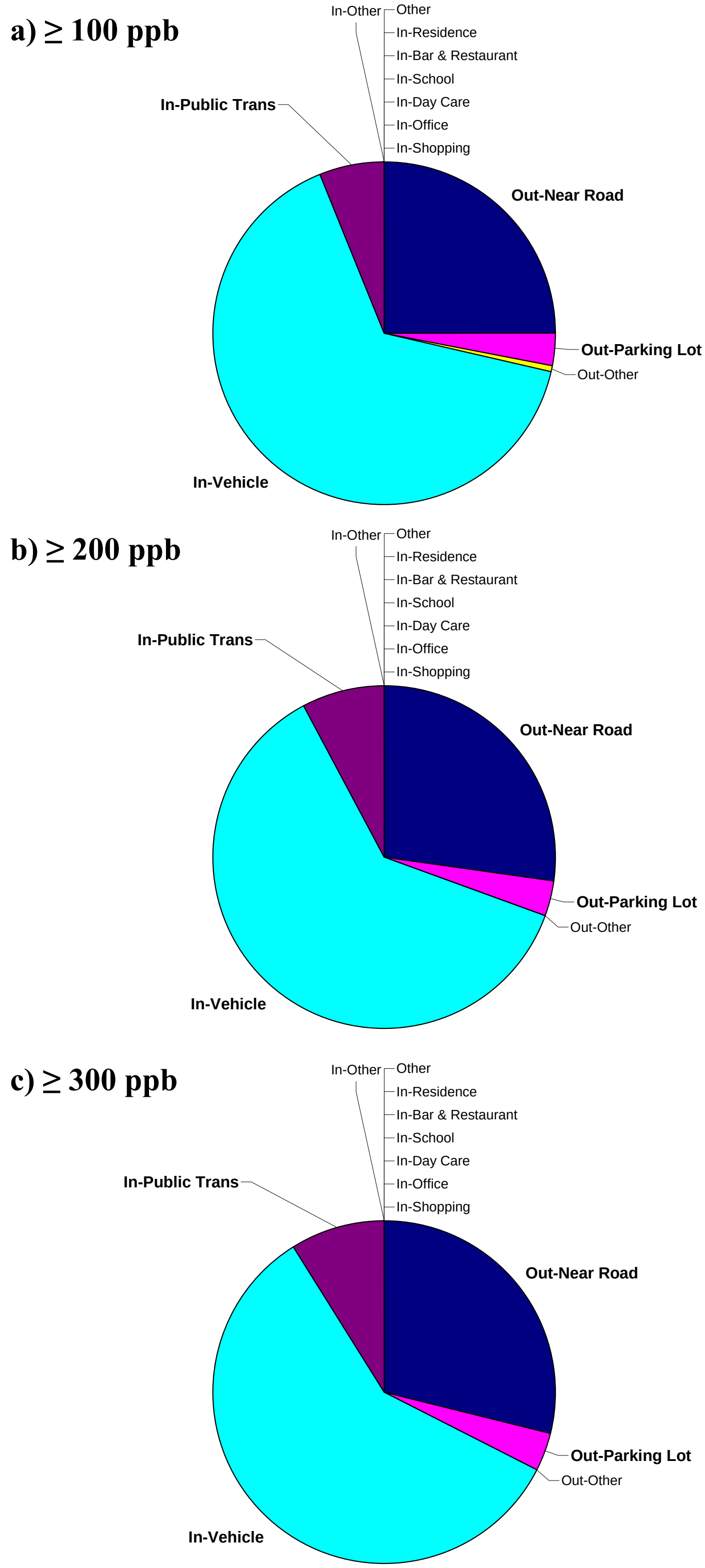



**Figure 8-16. Fraction of time all simulated persons in the Atlanta model domain spend in the twelve microenvironments that corresponds with exceedances of the potential $NO_2$ health effect benchmark levels, a) ≥ 100 ppb, b) ≥ 200 ppb, and c) ≥ 300 ppb, year 2002 air quality (as is) without indoor sources.**

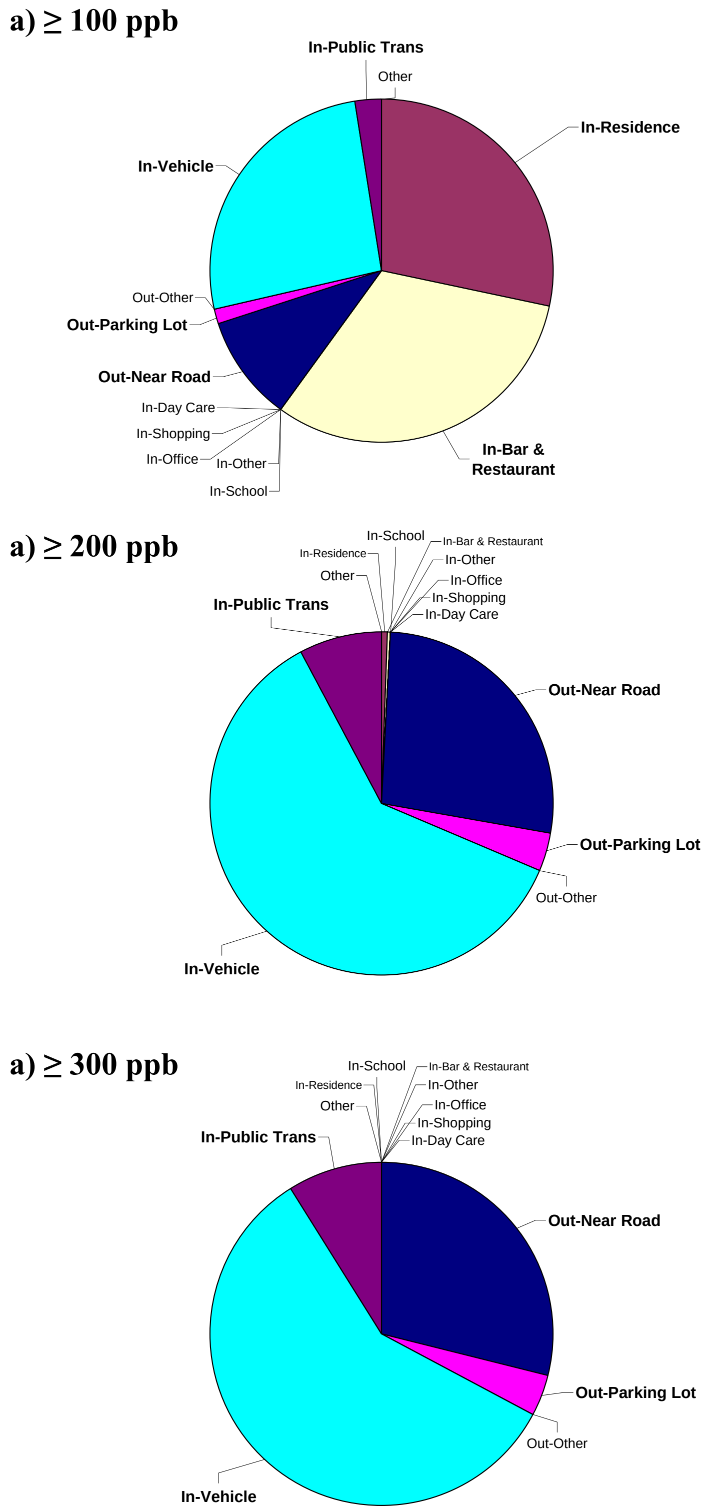



**Figure 8-17. Fraction of time all simulated persons in the Atlanta model domain spend in the twelve microenvironments that corresponds with exceedances of the potential $NO_2$ health effect benchmark levels, a) ≥ 100 ppb, b) ≥ 200 ppb, and c) ≥ 300 ppb, year 2002 air quality (as is) with indoor sources.**

The contribution of indoor sources to the occurrence of repeated exposure exceedances was also evaluated. Figure 8-18 illustrates that nearly all asthmatics (about 93%) would be exposed at least six times to either the 1-hour daily maximum 100 ppb or 150 ppb concentration level in a year when considering exposure to ambient $NO_2$ combined with indoor source emissions. This is approximately 15% more persons than was estimated for the simulations without indoor source contributions. However, the percent of asthmatics experiencing multiple exposures above the 200, 250 and 300 ppb was only about 1-4% greater than that observed for asthmatics without indoor sources. This is consistent with the person-day results that indicate the indoor source emissions contribute primarily to numbers of exposures experienced at or above the 100 or 150 ppb benchmark levels.

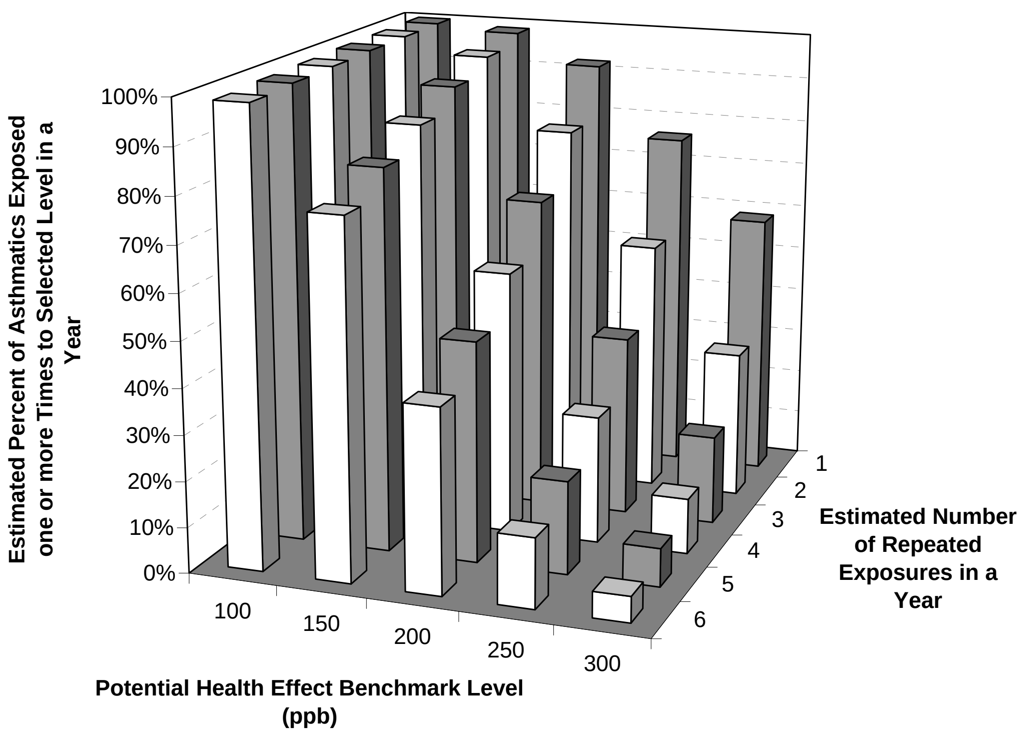



**Figure 8-18. Estimated percent of all asthmatics in the Atlanta modeling domain with repeated $NO_2$ exposures above potential health effect benchmark levels, using modeled 2002 air quality (as is), without indoor sources.**

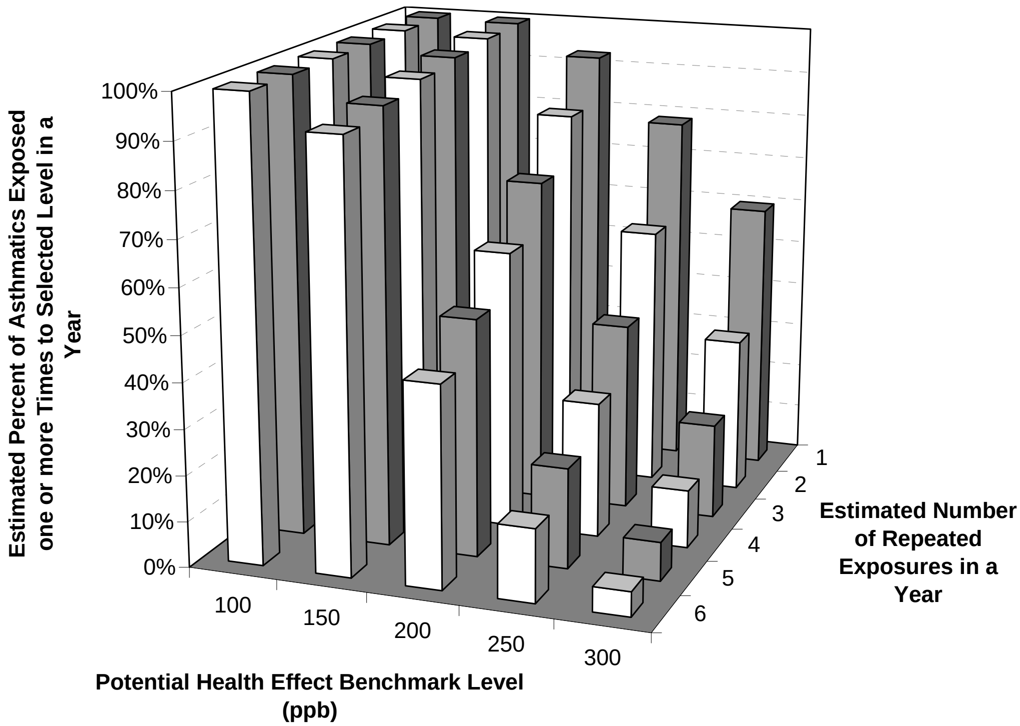



**Figure 8-19. Estimated percent of all asthmatics in the Atlanta modeling domain with repeated $NO_2$ exposures above potential health effect benchmark levels, using modeled 2002 air quality (as is), with indoor sources.**

### *8.9.4.3 Estimated Number of 1-hour Exposures Above Selected Levels (current standard)*

To simulate just meeting the current annual average $NO_2$ standard, the potential health effect benchmark levels were adjusted in the exposure model, rather than adjusting all of the hourly concentrations for each receptor and year simulated (see section 8.8). Similar to what was performed for the as is air quality, estimates of short-term exposures (i.e., 1-hour daily maximum) were generated for the total population and population subgroups of interest (i.e., asthmatics and asthmatic children).

When considering the estimated exposures associated with air quality simulated to just meet the current annual average $NO_2$ standard, the number of persons experiencing concentrations at or above the potential health effect benchmarks is increased in comparison with as is air quality. Figure 8-20 illustrates the percent of asthmatics estimated to experience at least one exposure at or above the selected potential health effect benchmark concentrations, with air quality adjusted to just meet the current standard. The exposure results for both including and excluding indoor source contributions are presented. While it was estimated that about 92, 76, and 59% of asthmatics would be exposed to 200, 250, and 300 ppb (1-hour average) at least once in a year for the as is air quality, it was estimated that nearly all asthmatics would experience at least one exposure above any of the potential health effect benchmark levels in a year when air quality is adjusted to just meet the current standard. Exposure estimates where indoor sources were included were not greatly different than the results without indoor source contributions, with nearly all asthmatics estimated to have at least one exposure at or above even the highest potential health effect benchmark level.

For air quality simulated to just meet the current standard, repeat exposures at the selected potential health effect benchmarks are more frequent than that estimated for the modeled as is air quality. Figure 8-21 illustrates this using the simulated asthmatic population for year 2002 data as an example. Nearly all asthmatics (>97%) were estimated to be exposed at or above any one of the selected levels for at least six times in a year. Results for where the exposures were estimated considering the contribution from indoor sources were similar, only slightly higher (data not shown).

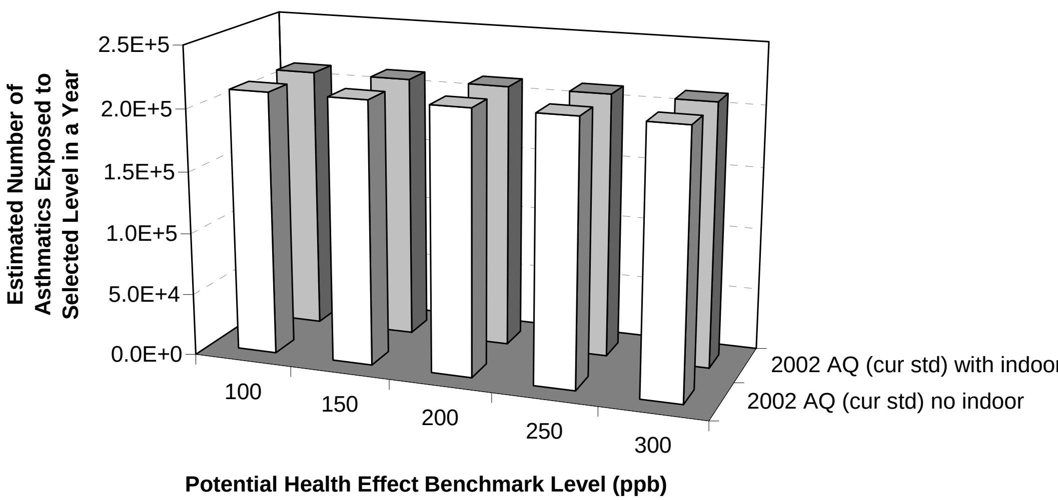



**Figure 8-20. Estimated number of all asthmatics in the Atlanta modeling domain with at least one $NO_2$ exposure at or above the potential health effect benchmark level, using modeled 2002 air quality just meeting the current standard (cur std), with and without modeled indoor sources.**

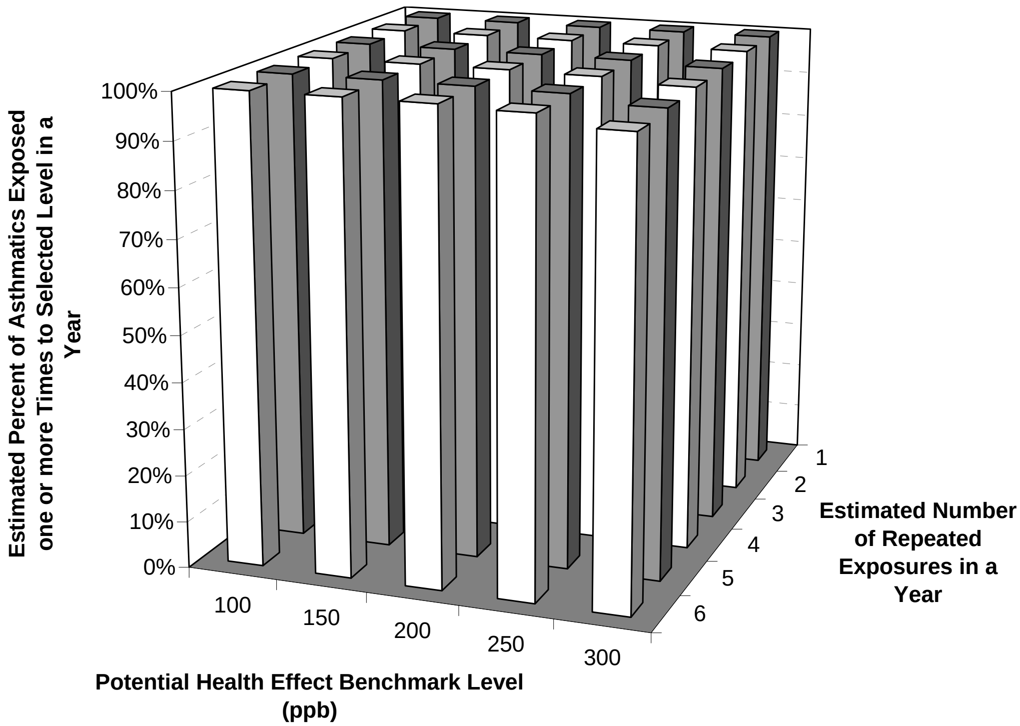



**Figure 8-21. Estimated percent of asthmatics in the Atlanta modeling domain with repeated $NO_2$ exposures above health effect benchmark levels, using modeled 2002 air quality just meeting the current standard, without modeled indoor sources.**

#### *8.9.4.4 Estimated Number of 1-hour Exposures Above Selected Levels (alternative standards)*

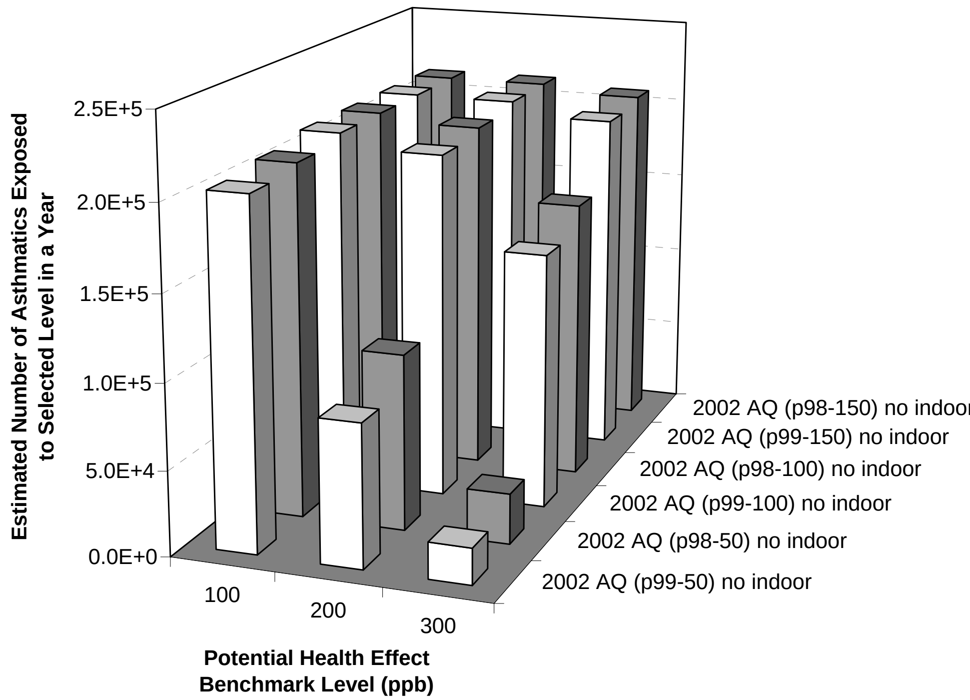
To simulate just meeting the alternative $NO_2$ standards, the potential health effect benchmark level was adjusted in the exposure model, rather than adjusting all of the hourly concentrations for each receptor and year simulated (see section 8-8). Similar to exposure analyses performed with the as is air quality, estimates of short-term exposures (i.e., 1-hour daily maximum) were generated for the total population and population subgroups of interest (i.e., asthmatics and asthmatic children). Due to limitations on the number of concentration levels allowed in an APEX simulation, only the potential health effect benchmark levels of 100, 200, 300 ppb were evaluated for the alternative 1-hour daily maximum standards.

In considering exposures estimated to occur associated with air quality simulated to just meet the alternative $NO_2$ 1-hour daily maximum standards, the number of persons experiencing concentrations at or above the potential health effect benchmarks varied, depending on the form and level of the standard. Figure 8-22 illustrates the different forms (a 98$^{th}$ or 99$^{th}$ percentile) at various 1-hour concentration levels of the standard. The number of persons exposed at least once at each of the 98th and 99th percentiles alternative standards and considering a potential benchmark level of 100 ppb is similar to that observed for the as is air quality and for air quality adjusted to just meet the current standard. That is, most persons are exposed at least once to 100 ppb in a year, regardless of the standard form and level chosen. It is not until the level of the 1-hour daily maximum standard approaches 50 ppb for either of the percentile forms that the number of persons exposed to the higher benchmark levels is substantially reduced. For example, while nearly all asthmatics are exposed to 100 ppb at least once in a year as was observed in the above analyses, the percent of asthmatics exposed to at least one 1-hour concentration at or above the 200 or 300 ppb is reduced to about 49% and 14% of the subpopulation, respectively, when considering the 50 ppb, 98th percentile standard.

The estimated number of repeated $NO_2$ exposures above selected levels can be sharply reduced for potential alternative standards at the lower end of the range of alternative standards considered. As an example, Figure 8-23 illustrates the number of multiple exposures above the potential health effect benchmark levels using a 50 ppb, 99th percentile alternative standard. This is the first instance where multiple exposures of the 100 ppb benchmark are estimated to be reduced, with about 57% of asthmatics estimated to contain greater than six in a year. A greater reduction in the number of multiple exposures is observed when considering the 200 ppb benchmark level. For example, only 5% of asthmatics are estimated to be exposed four or more times, compared with 58% using the 2002 air quality as is.

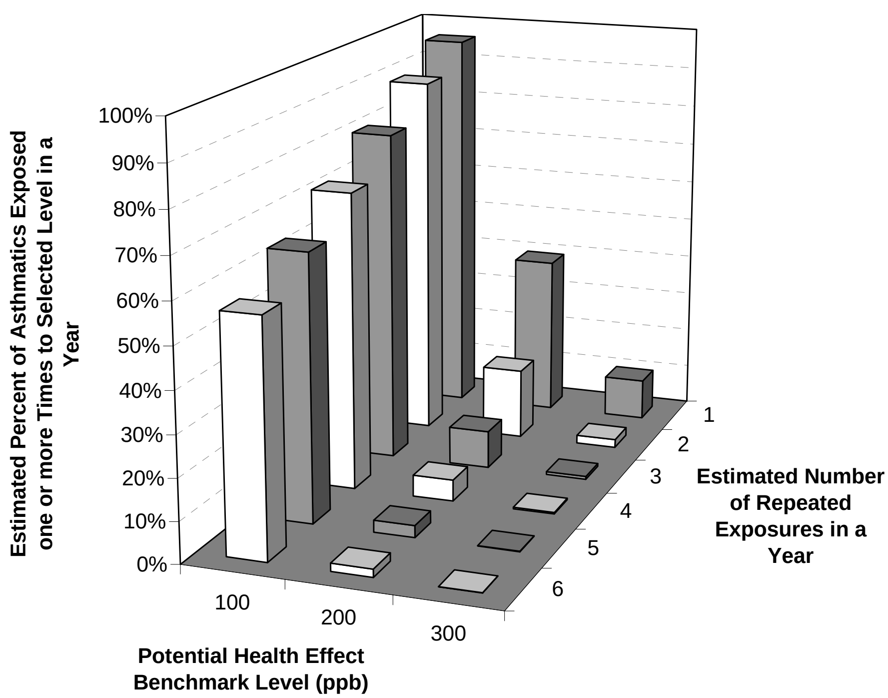
The effect of indoor source contributions to the exposures was also evaluated for the same level and form of alternative standard (50 ppb, 99th percentile). Figure 8-24 illustrates what has been consistently shown in the above analyses, the indoor sources primarily affect the numbers of persons and the number of times a person is exposed at or above 100 or 150 ppb, with limited contribution to the higher potential health effect benchmark levels.

In addition, for comparison with the results presented in Figure 8-23, the percent of asthmatics exposed to the selected health effect benchmark levels considering the 100 ppb, 99th percentile alternative standard is presented in Figure 8-25. A greater proportion of asthmatics have multiple exposures at all of the 1-hour benchmarks, nearly all of which were estimated to have at least six exposures at or above a 1-hour concentration of 100 ppb.




1

**Figure 8-22. Estimated percent of asthmatics in the Atlanta modeling domain with $NO_2$ exposures at or above potential health effect benchmark levels, using modeled 2002 air quality adjusted to just meeting potential alternative standards, without indoor sources.**




2

**Figure 8-23. Estimated percent of asthmatics in the Atlanta modeling domain with multiple $NO_2$ exposures at or above potential health effect benchmark levels, using modeled 2002 air quality adjusted to just meeting a 50 ppb level 99$^{th}$ percentile form alternative standard, without indoor sources.**

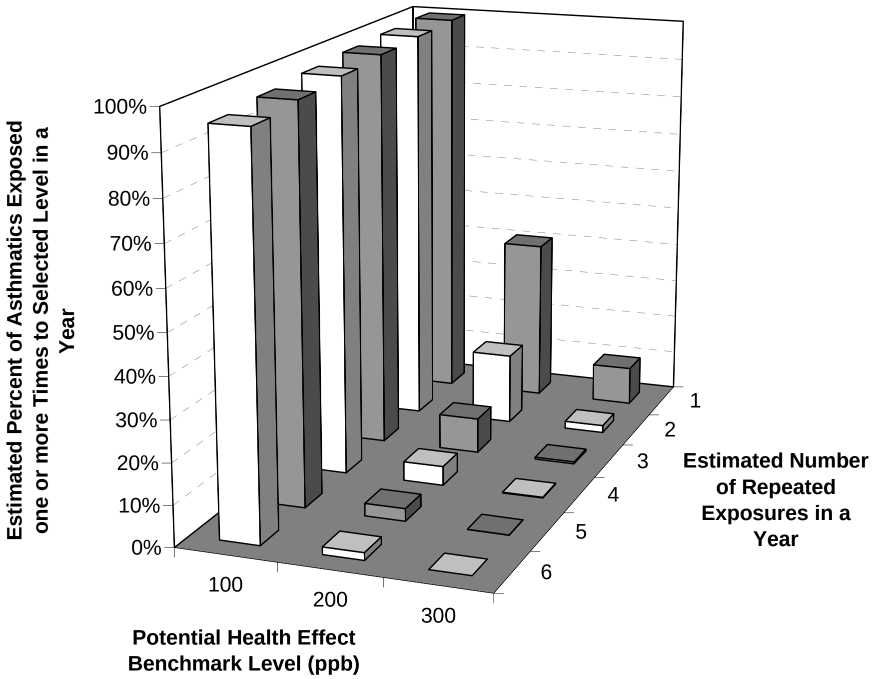



**Figure 8-24. Estimated percent of asthmatics in the Atlanta modeling domain with multiple $NO_2$ exposures at or above potential health effect benchmark levels, using modeled 2002 air quality adjusted to just meeting a 50 ppb level 99th percentile form alternative standard, with indoor sources.**

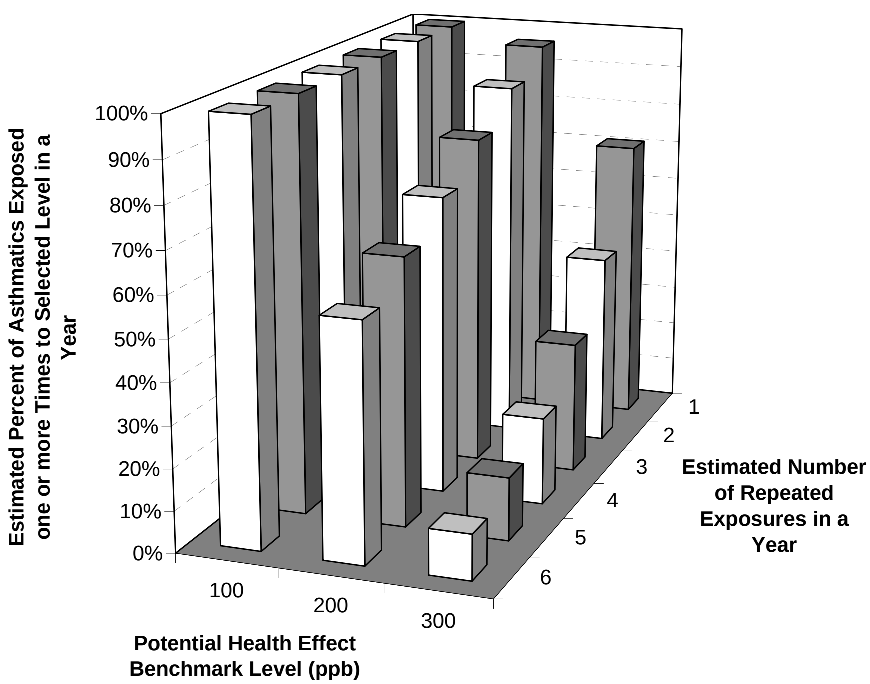



**Figure 8-25. Estimated percent of asthmatics in the Atlanta modeling domain with multiple $NO_2$ exposures at or above potential health effect benchmark levels, using modeled 2002 air quality adjusted to just meeting a 100 ppb level 99th percentile form alternative standard, without indoor sources.**

# 8.10 VARIABILITY AND UNCERTAINTY

## 8.10.1 Introduction

The methods and the model used in this assessment conform to the most contemporary modeling methodologies available. APEX is a powerful and flexible model that allows for the realistic estimation of air pollutant exposure to individuals. Since it is based on human activity diaries and accounts for the most important variables known to affect exposure, it has the ability to effectively approximate actual conditions. In addition, the input data selected were the best available data to generate the exposure results. However, there are constraints and uncertainties with the modeling approach and the input data that limit the realism and accuracy of the model results.

All models have limitations that require the use of assumptions. Limitations of APEX lie primarily in the uncertainties associated with data distributions input to the model. Broad uncertainties and assumptions associated with these model inputs, utilization, and application include the following, with more detailed analysis summarized below and presented previously (see EPA, 2007g; Langstaff, 2007). Identified uncertainties include:

- The CHAD activity data used in APEX are compiled from a number of studies in different areas, and for different seasons and years. Therefore, the combined data set may not constitute a representative sample for a particular study scenario.
- Commuting pattern data were derived from the 2000 U.S. Census. The commuting data address only home-to-work travel. The population not employed outside the home is assumed to always remain in the residential census tract. Furthermore, although several of the APEX microenvironments account for time spent in travel, the travel is assumed to always occur in basically a composite of the home and work block. No other provision is made for the possibility of passing through other blocks during travel.
- APEX creates seasonal or annual sequences of daily activities for a simulated individual by sampling human activity data from more than one subject. Each simulated person essentially becomes a composite of several actual people in the underlying activity data.

- The APEX model currently does not capture certain correlations among human activities that can impact microenvironmental concentrations (for example, cigarette smoking leading to an individual opening a window, which in turn affects the amount of outdoor air penetrating the microenvironment).
- Certain aspects of the personal profiles are held constant, though in reality they change as individuals age. This is only important for simulations with long timeframes, particularly when simulating young children (e.g., over a year or more).

### 8.10.2 Input Data Evaluation

Modeling results are heavily dependent on the quality of the data that are input to the system. As described above, several studies were reviewed, and data from these studies were used to develop the parameters and factors that were used to build the microenvironments in this assessment. A constraint on this effort is that there are a limited number of $NO_2$ exposure studies to use for evaluation.

The input data used in this assessment were selected to best simulate actual conditions that affect human exposure. Using well characterized data as inputs to the model lessens the degree of uncertainty in exposure estimates. Still, the limitations and uncertainties of each of the data streams affect the overall quality of the model output. These issues and how they specifically affect each data stream are discussed in this section.

### 8.10.3 Meteorological Data

Meteorological data are taken directly from monitoring stations in the assessment areas. One strength of these data is that it is relatively easy to see significant errors if they appear in the data. Because general climactic conditions are known for each area simulation, it would have been apparent upon review if there were outliers in the dataset. However, there are limitations in the use of these data. Because APEX only uses one temperature value per day, the model does not represent hour-to-hour variations in meteorological conditions throughout the day that may affect both $NO_2$ formation and exposure estimates within microenvironments.

### 8.10.4 Air Quality Data

Air quality data used in the exposure modeling was determined through use of EPA's recommended regulatory air dispersion model, AERMOD (version 07026 (EPA, 2004)), with meteorological data discussed above and emissions data based on the EPA's National Emissions Inventory for 2002 (EPA, 2007e) and the CAMD Emissions Database (EPA, 2007f) for stationary sources and mobile sources determined from local travel demand modeling and EPA's MOBILE6.2 emission factor model. All of these are high quality data sources. Parameterization of meteorology and emissions in the model were made in as accurate a manner as possible to ensure best representation of air quality for exposure modeling. Thus, the resulting air quality values are likely free of systematic errors to the best approximation available through application of modeled data.

However, determining the most appropriate source characteristics for modeling emissions from mobile sources presents several technical challenges and involves a number of uncertainties. Unlike typical stationary emission sources simulated by AERMOD, for which source characteristics such as release height and effluent parameters can be clearly defined and measured, emissions from mobile sources represent an aggregate of emissions from non-stationary sources of various sizes, shapes, and speeds. Since mobile source emissions (other than aircraft) are emitted near the ground, the plumes can be significantly influenced by the turbulent wake generated by the emitting vehicle, as well as turbulence generated by nearby vehicles and other roughness elements such as sound barriers, median barriers, trees, buildings, etc. Representative source characteristics for mobile emissions may also depend on the pollutant of interest, and whether the pollutant is primarily associated with direct vehicle exhaust, as in the case of $NO_2$, or includes secondary sources, such as re-entrained road dust, tire wear and brake wear for PM. Emissions associated with vehicle exhaust may experience some buoyancy due to the exhaust temperature exceeding the ambient temperature. Such buoyancy effects might be negligible for vehicles moving at highway speeds, where mechanically-induced turbulence would likely dominate the initial plume characteristics, but could be a significant factor for slow moving vehicles on a cold day during rush hour. In addition to the influence of roughness elements, characteristics of the roadway itself may be a factor. For example, thermally-induced turbulence generated by direct sunlight on dark asphalt could enhance the initial plume spread compared to the same conditions for a more reflective concrete road surface. The best approach for determining source characteristics for mobile emissions may also depend on the scope and nature of the application. Characterizing mobile sources for a large-scale urban study, such as the Atlanta $NO_2$ modeling, may necessitate a different approach than characterizing mobile sources for a particular highway project within a more localized modeling domain. A detailed treatment accounting for influences of specific local features may be possible for the latter. However, for larger scale applications such as this, a simplified approach with the goal of characterizing emissions based on a reasonable estimate of the aggregate effect of these various factors is necessitated by practical limitations.

The factor of 1.7 times the vehicle height used to account for vehicle-induced turbulence is cited in Gilles et al. (2005) based on some field measurements for an unpaved road. The factor of 1.7 is somewhat less than the typical formula for the turbulent wake downwind of a building, which is 2.5 times the building height. This difference seems reasonable based on the more aerodynamic shape of vehicles as compared to buildings. This value could be conservative since it may not account for the other influences mentioned above. However, those influences may vary significantly across the modeling domain and are difficult to quantify within the current model formulations. While some differences may be expected between paved and unpaved roads, these differences are probably minor compared to other uncertainties.

#### 8.10.5 Population and Commuting Data

The population and commuting data are drawn from U.S. Census data from the year 2000. This is a high quality data source for nationwide population data in the U.S. However, the data do have limitations. The Census used random sampling techniques instead of attempting to reach all households in the U.S., as it has in the past. While the sampling techniques are well established and trusted, they introduce some uncertainty to the system. The Census has a quality section (http://www.census.gov/quality/) that discusses these and other issues with Census data.

In addition to these data quality issues, certain simplifying assumptions were made in order to better match reality or to make the data match APEX input specifications. For example, the APEX dataset does not differentiate people that work at home from those that commute within their home tract, and individuals that commute over 120 km a day were assumed to not commute daily. In addition to emphasizing some of the limitations of the input data, these assumptions introduce uncertainty to the results.

Furthermore, the estimation of block-to-block commuter flows relied on the assumption that the frequency of commuting to a workplace block within a tract is proportional to the amount of commercial and industrial land in the block. This assumption introduces additional uncertainty.

### 8.10.6 Activity Pattern Data

It is probable that the CHAD data used in the system is the most subject to limitations and uncertainty of all the data used in the model. Much of the data used to generate the daily diaries are over 20 years old. While the trends in people's daily activities may not have changed much over the years, it is certainly possible that some differences do exist. In addition, the CHAD data are taken from numerous surveys that were performed for different purposes. Some of these surveys collected only a single diary-day while others went on for several days. Some of the studies were designed to not be representative of the U.S. population, although a large portion of the data are from National surveys. Furthermore, study collection periods occur at different times of the year, possibly resulting in seasonal differences. A few of these limitations are corrected by the approaches used in the exposure modeling (e.g., weighting by US population demographics for a particular location, adjusting for effects of temperature on human activities).

A sensitivity analysis was performed to evaluate the impact of the activity pattern database on APEX model results for $O_3$ (see Langstaff (2007) and EPA (2007g)). Briefly, exposure results were generated using APEX with all of the CHAD diaries and compared with results generated from running APEX using only the CHAD diaries from the National Human Activity Pattern Study (NHAPS), a nationally representative study in CHAD. There was agreement between the APEX exposure results for the 12 cities evaluated (one of which was Atlanta), whether all of CHAD or only the NHAPS component of CHAD is used. The absolute difference in percent of persons above a particular concentration level ranged from -1% to about 4%, indicating that the exposure model results are not being overly influenced by any single study in CHAD. It is likely that similar results would be obtained here for $NO_2$ exposures, although remains uncertain due to different averaging times (1-hour vs. 8-hour average).

### 8.10.7 Air Exchange Rates

There are several components of uncertainty in the residential air exchange rate distribution used for this analysis. EPA (2007g) details an analysis of uncertainty due to extrapolation of air exchange rate distributions between-CMSAs and within-CMSA uncertainty due to sampling variation. In addition, the uncertainty associated with estimating daily air exchange rate distributions from air exchange rate measurements with varying averaging times is discussed. The results of those investigations are briefly summarized here.

#### *8.10.7.1 Extrapolation of AER among cities*

Location-specific distributions were assigned in the APEX model, as detailed in the indoors-residential microenvironment. Since specific data for all of the locations targeted in this analysis were not available, data from another location were used based on similar influential characteristics. Such factors include age composition of housing stock, construction methods, and other meteorological variables not explicitly treated in the analysis, such as humidity and wind speed patterns. In order to assess the uncertainty associated with this extrapolation, between-CSA uncertainty was evaluated by examining the variation of the geometric means and standard deviations across cities and studies.

The analysis showed a relatively wide variation across different cities in the air exchange rate geometric mean and standard deviation, stratified by air-conditioning status and temperature range. This implies that the air exchange rate modeling results would be very different if the matching of modeled locations to study locations was changed. For example, the $NO_2$ exposure estimates may be sensitive to the assumption that the Atlanta air exchange rate distributions can be represented by the measured Research Triangle Park, NC air exchange rate data.

#### *8.10.7.2 Within MSA uncertainty*

There is also variation within studies for the same location (e.g., Research Triangle Park, NC), but this is much smaller than the variation across CMSAs. This finding tends to support the approach of combining different studies for a CMSA. Within-city uncertainty was assessed by using a bootstrap distribution to estimate the effects of sampling variation on the fitted geometric means and standard deviations for each CMSA. The bootstrap distributions assess the uncertainty due to random sampling variation but do not address uncertainties due to the lack of representativeness of the available study data or the variation in the lengths of the AER monitoring periods.

1,000 bootstrap samples were randomly generated for each AER subset (of size N), producing a set of 1,000 geometric mean and geometric standard deviation pairs. The analysis indicated that the geometric standard deviation uncertainty for a given CSA/air-conditioning-status/temperature-range combination tended to have a range of at most from *fitted GSD-1.0* $hr^{-1}$

to *fitted GSD+1.0 $hr^{-1}$*, but the intervals based on larger AER sample sizes were frequently much narrower. The ranges for the geometric means tended to be approximately from *fitted GM-0.5 $hr^{-1}$* to *fitted GM+0.5 $hr^{-1}$*, but in some cases were much smaller. See EPA (2007g) for details.

#### *8.10.7.3 Variation in AER measurement averaging times*

Although the averaging periods for the air exchange rates in the study data varied from one day to seven days, the analyses did not take the measurement duration into account and treated the data as if they were a set of statistically independent daily averages. To investigate the uncertainty of this assumption, correlations between consecutive 24-hour air exchange rates measured at the same house were investigated using data from the Research Triangle Park Panel Study (EPA, 2007g). The results showed extremely strong correlations, providing support for the simplified approach of treating multi-day averaging periods as if they were 24-hour averages.

### 8.10.8 Air Conditioning Prevalence

Because the selection of an air exchange rate distribution is conditioned on the presence or absence of an air-conditioner, for each modeled area, the air conditioning status of the residential microenvironments was simulated randomly using the probability that a residence has an air conditioner, i.e., the residential air conditioner prevalence rate. For this study we used location-specific data from the American Housing Survey of 2004. EPA (2007g) details the specification of uncertainty estimates in the form of confidence intervals for the air conditioner prevalence rate, and compares these with prevalence rates and confidence intervals developed from the Energy Information Administration's Residential Energy Consumption Survey (RECS) of 2001 for more aggregate geographic subdivision (e.g., states, multi-state Census divisions and regions).

Air conditioning prevalence rates for were 97% for Atlanta, with reported standard errors of 1.2% (AHS, 2004). Estimated 95% confidence intervals were also small and span approximately 4.6%. The RECS prevalence estimates for Atlanta and confidence intervals compared well with a value of 95.0% and a 95% confidence interval spanning 5.8%.

### 8.10.9 Indoor Source Estimation

Other indoor $NO_2$ emission sources, such as gas pilot lights, gas heating, or gas clothes drying were not included in this analysis, due to lack of data for characterization.

The data used to estimate the average number of daily food preparation events is older than the time period assessed (1992 versus 2001-2003) and may therefore be unrepresentative of current conditions, and may lead to under- or over-estimates of exposure to exceedances of threshold concentrations of concern. For example, if the population of Atlanta in 2003 prepares food at home less frequently than the 1992 survey population, then the number of such exposures may be over-estimated.

As noted above, it was assumed that the probability that a food preparation event included stove use was the same no matter what hour of the day the food preparation event occurred. If such probabilities differ, then the diurnal allocation of cooking events may differ from the actual pattern. To the extent that the gas stove usage patterns may correlate with ambient concentration patterns, the number of exposures to exceedances of threshold concentrations of concern may be under- or over-estimated. For example, if gas stove usage and ambient concentrations are positively correlated (e.g., if cooking tends to occur during evening rush hour) and the diurnal allocation assumed here results in a lower correlation (e.g., if the diurnal allocation understates the probability of gas stove usage at times of high ambient concentrations) then the number of such exposures may be under-estimated. As another example, if the diurnal pattern allocation assumed here understates the probability of gas stove usage at times when simulated subjects are assumed to be at home, then the number of such exposures may be under-estimated.

The durations of the CARB (2001) cooking tests ranged from 21 minutes to 3 hours with an average of about 70 minutes. For implementation in APEX it was assumed that each cooking event lasts exactly an hour. That is, the randomly selected net concentration contribution was added to hourly average indoor concentration for the hour it was selected to occur. Because the mass balance algorithm leads to carryover from one hour to the next, some of the indoor cooking impact will influence subsequent hours. However, the impact of the cooking event may be overstated or understated for cooking events longer or shorter than 1 hour.

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