Technical Support Document for the Nonroad Land-based Diesel Engines Standards Air Quality Modeling Analyses

U.S. Environmental Protection Agency
Office of Air Quality Planning and Standards
Emissions Analysis and Monitoring Division
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Table of Contents

I Introduction 1

II Emissions Inventory Estimates 1

III Episodic Ozone Modeling 2
A. Model Configuration 3
1. Episodic Meteorology and Ambient Air Quality..... 3
2. Domain and Grid Configuration 3
3. Meteorological Modeling 5
B. Model Performance Evaluation 7
1. Statistical Definitions 7
2. Domainwide Model Performance (Eastern U.S.) 8
3. Local-scale Model Performance (Eastern U.S.).................. 10
4. Domainwide Model Performance (Western U.S.) 13
5. Local-scale Model Performance (Western U.S.) 15
F. Ozone Modeling Results 16
1. Projected Future Ozone Design Values 16
2. Impacts of the NLDE Rule on One Hour Ozone 19
a. Effects on future ozone design values................. 19
b. Effects on model-predicted ozone....................... 22
c. Ozone increases 23

IV Particulate Matter Modeling over the Continental U.S. 31
A. REMSAD Model Description.. 31
1. Gas Phase Chemistry 31
2. PM Chemistry 32
B. REMSAD Modeling Domain 33
C. REMSAD Inputs 34
1. Meteorological Data 35
2. Initial and Boundary Conditions, and Surface Characteristics .. 37
D. Model Performance Evaluation 39
1. Statistical Definitions 41
2. Results of REMSAD Performance Evaluation 42
a. PM2.5 Performance 42
b. Sulfate Performance 43
c. Elemental Carbon Performance 43
d. Organic Aerosol Performance 44
e. Nitrate Performance 44
f. PMFINE-Other (crustal) Performance 45
g. Summary of Model Performance
Results using IMPROVE Data 45

E. Visibility Calculations 46
F. Projected Future PM2.5 Design Values.. 46

V References 47

Appendix A 8-Hour Ozone Design Values for 1999-2001 and 2020 and 2030 Base Case and Control Case Scenarios.
Appendix B Maps Showing 1-Hour and 8-Hour Design Values
Appendix C 2020 Eastern U.S. Ozone Metrics.
Appendix D 2030 Easrtern U.S. Ozone Metrics.
Appendix E 2020 Western U.S. Ozone Metrics.
Appendix F 2030 Western U.S. Ozone Metrics.
Appendix G IMPROVE Monitoring Sites used in the REMSAD Model Performance Evaluation.
Appendix H Annual PM2.5 Design Values for 1999-2001 and 2020 and 2030 Base Case and Control Case Scenarios.

I. Introduction

This document describes the procedures and results of the air quality modeling analyses used to support the Nonroad Land-based Diesel Engine (NLDE) proposed rulemaking. The air quality modeling was conducted to support several components of the rulemaking including:

(a) an assessment of the need for the NLDE program,
(b) an assessment of the costs and benefits associated with the rulemaking, and
(c) an assessment of the expected impact of the program on ozone and PM levels.

The air quality model applications include episodic regional scale ozone modeling for the eastern and western U.S. and annual particulate matter (PM) modeling on a continental scale covering the 48 contiguous States. For both ozone and PM, 1996 Base Year simulations were made to examine the ability of the modeling systems to replicate observed concentrations of these pollutants. This was followed by simulations for several future-year Base Case scenarios (i.e., 2020 and 2030). The results of the future base case model runs were used to support the need for the NLDE emissions reductions to help mitigate unhealthy concentrations of ozone and PM. In this regard, the predictions from these model runs were used to determine the extent of future ozone and PM nonattainment. Additional simulations were performed for 2020 and 2030 to quantify the impacts of the NLDE controls on air quality. The outputs of the base and control case model runs were also used to calculate portions of the monetized benefits of the rule as part of the cost-benefits analysis.

The remainder of this report includes a description of the ozone and PM modeling systems, the time periods modeled, the Base Year model performance evaluations, and the results of the future Base Case and Control Case model simulations. The air quality modeling input and output data sets can be obtained upon request by sending an email to ASDinfo@epa.gov or by calling (734) 214-4636.

II. Emissions Inventory Estimates

In order to complete the requisite ozone and PM modeling, it was necessary to first develop a national mass emissions inventory. This mass emissions inventory was then used as the basis for developing input files for the air quality modeling. The development and details of these inventories for each of the scenarios (i.e., 1996 Base Year, 2020 Base Case, 2020 Control Case, 2030 Base Case, and 2030 Control Case) are described elsewhere (EPA, 2003a).

The mass inventories were prepared at the county-level for on-highway mobile, stationary area sources, and nonroad sources. Emissions for electric generating units (EGUs) and large industrial sources (non-EGUs) were prepared as individual point sources. These inventories contain annual and typical summer season day emissions for the following pollutants: oxides of nitrogen (NO_x), volatile organic compounds (VOC), carbon monoxide (CO), sulfur dioxide (SO_2), primary particulate matter with an aerodynamic diameter less than or equal to 10 micrometers and 2.5 micrometers (PM_{10} and $PM_{2.5}$), and ammonia (NH_3). The 2020 and 2030 Base Case inventories were prepared by applying growth and control assumptions to the 1996 Base Year inventory. The 2020 and 2030 Control Case inventories are developed from the 2020 and 2030 Base Case inventories, respectively, by applying NLDE control and fuel measures to the nonroad emission source sector.

The annual and summer day mass emissions inventories for each scenario were processed using the SMOKE (Houyoux, 2000) to create the appropriate emissions inputs for REMSAD and CAMx model runs, respectively. The emissions processing produced hourly, gridded, speciated emissions. For PM modeling the annual emissions for stationary area, point, and nonroad sources were processed to generate separate sets of emissions representing typical weekday, Saturday, and Sunday emissions for each season. For ozone modeling the summer day emissions were process to generate typical summer weekday, Saturday, and Sunday emissions. On-highway emissions were obtained in model-ready form from the Heavy-Duty Diesel Rule modeling exercise. Hourly biogenic emissions were calculated using the Biogenic Emissions Inventory System (BEIS3.09) model. Biogenic emissions were not altered for any of the scenarios modeled.

III. Episodic Ozone Modeling

Air quality modeling analyses for ozone were conducted with the Comprehensive Air Quality Model with Extensions (CAMx). CAMx is non-proprietary computer modeling tool that can be used to evaluate the impacts of proposed emissions reductions on future air quality levels. For more information on the CAMx model, please see the model user's guide (Environ, 2002)[1]. Version 3.10 of the CAMx model was employed for these analyses.

The modeling analyses were completed for two separate 36/12 km resolution domains, one covering the eastern U.S. and the other covering the western U.S. as shown in Figures III-1 and III-2, respectively. For the eastern U.S. domain, the model was applied and evaluated over three episodes that occurred during the summer of 1995 Base Year. For the western U.S. modeling, two episodes that occurred during the summer of 1996 were modeled using Base Year emissions. Subsequently, episodic ozone model runs were made for 2020 and 2030 Base and Control Case scenarios for both domains and all episodes.

The model outputs from the 1996 Base Year and 2020 and 2030 Base Cases, combined with current air quality data, were used to identify areas expected to exceed the ozone National Ambient Air Quality Standards (NAAQS) in 2020 and 2030. These "nonattainment" areas will require additional emission reductions to attain and maintain the ozone NAAQS. The costs, benefits, and expected impacts of the proposed controls were determined by comparing the model

[1] http://www.camx.com/pdf/CAMx3.UsersGuide.020410.pdf

results in the future year control runs against the baseline simulations of the same year. Ultimately, the modeling supports the conclusions that there will potentially be several metropolitan areas with predicted ozone concentrations at or above the NAAQS in the 2020 and 2030 Base Case scenarios without additional emission reductions; and that the proposed nonroad emissions reductions are expected to substantially improve ozone levels in the future.

A. Model Configuration

1. Episodic Meteorologyand Ambient Air Quality

There are several considerations involved in selecting episodes for an ozone modeling analysis (EPA, 1999a). In general, the goal should be to model several differing sets of meteorological conditions leading to ambient ozone levels similar to an area's design value. Warm temperatures, light winds, cloud-free skies, and stable boundary layers are some of the typical characteristics of ozone episodes. On a synoptic scale, these conditions usually result from a combination of high pressure aloft (e.g., at the 500 millibar pressure level) and at the surface. Of course at a smaller scale, the conditions that lead to local ozone exceedances can vary from location to location based on factors such as wind direction, sea/lake breezes, etc. The meteorological and resultant ozone patterns for the five separate modeling episodes used in this analysis are listed in Table III-1 and are discussed in more detail in previous technical support documents for the Tier-2/Low Sulfur rule (EPA, 1999b) and the Heavy-Duty Engine rule (EPA, 2000). These previous discussions conclude that the selected episodes contain measured ozone concentrations that are representative of design values over most of the U.S. The first three days of each period are considered ramp-up days and the results from these days were not used in the analyses. In all, 49 episode days were modeled; 30 days in the eastern simulations and 19 days in the western simulations.

Table III-1. Dates of CAMx Modeling Episodes.

	Eastern U.S. Modeling	**Western U.S. Modeling**
Episode 1	June 12-24, 1995	July 5-15, 1996
Episode 2	July 5-15, 1995	July 18-31, 1996
Episode 3	August 7-21, 1995	

2. Domain and Grid Configuration

As with episode selection, there are also several considerations involved in selecting the domain and grid configuration to be used in the ozone modeling analysis. The modeling domain should encompass the area of intended analysis with an additional buffer of grid cells to minimize the effects of uncertain boundary condition inputs. When possible, grid resolution should be equivalent to the resolution of the primary model inputs (emissions, winds, etc.) and equivalent to the scale of the air quality issue being addressed. The CAMx modeling was performed for each of two domains of varying extent and resolution as described and shown below.

Table III-2. Details of the CAMx Modeling Domains.

	Eastern US Domain		**Western US Domain**	
	Coarse Grid	**Fine Grid**	**Coarse Grid**	**Fine Grid**
Map Projection	latitude/longitude	latitude/longitude	latitude/longitude	latitude/longitude
Grid Resolution	1/2˚ longitude, 1/3˚ latitude (~ 36 km)	1/6˚ longitude, 1/9˚ latitude (~ 12 km)	1/2˚ longitude, 1/3˚ latitude (~ 36 km)	1/6˚ longitude, 1/9˚ latitude (~ 12 km)
East/West extent	-99 W to -67 W	-92 W to -69.5 W	-127W to -99 W	-125 W to -103 W
North/South extent	26 N to 47 N	32 N to 44 N	26 N to 52 N	31 N to 49 N
Vertical extent	Surface to 4 km	Surface to 4 km	Surface to 4.8 km	Surface to 4.8 km
Dimensions	64 by 63 by 9	137 by 110 by 9	56 by 78 by 11	132 by 162 by 11

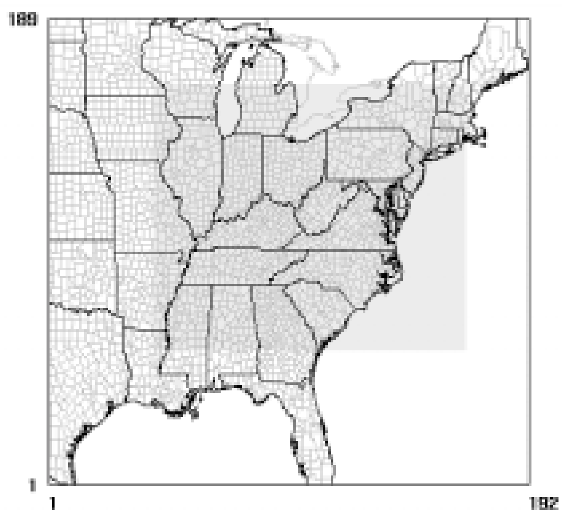

Figure III-1. Map of the Eastern U.S. modeling domain. The outer box denotes the entire modeling domain (36 km) and the inner box shaded indicates the fine grid location (12 km).

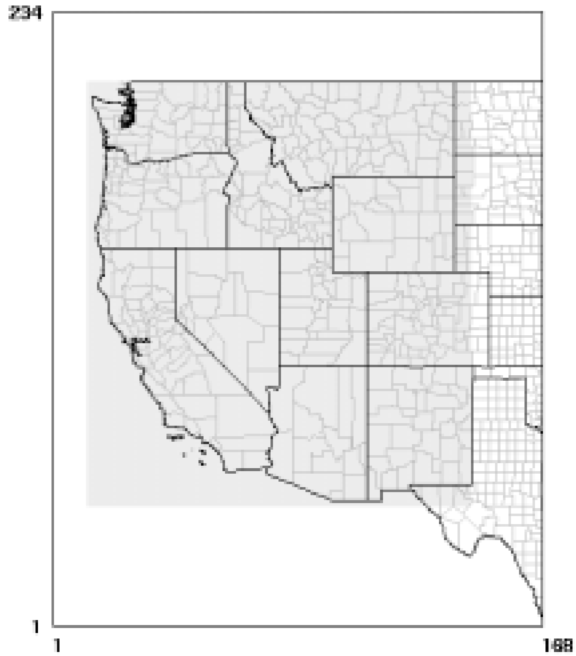

Figure III-2. Map of the Western U.S. modeling domain. The outer box denotes the entire modeling domain (36 km) and the inner shaded box indicates the fine grid location (12 km).

3. Meteorological and Other Model Inputs

The air quality model requires certain meteorological inputs that, in part, govern the formation, transport, and destruction of pollutant material. In particular, the CAMx model used in these analyses requires seven meteorological input files: wind (u- and v-vector wind components), temperature, water vapor mixing ratio, atmospheric air pressure, cloud cover, rainfall, and vertical diffusion coefficient. Fine grid values of wind, pressure, and vertical diffusivity are used; the other fine grid meteorological inputs are interpolated from the coarse grid files.

<u>Eastern U.S. Domain:</u> The gridded meteorological data for the three historical 1995 episodes were developed by the New York Department of Environment and Conservation using the Regional Atmospheric Modeling System (RAMS), version 3b. RAMS (Pielke *et. al.*, 1992) is a numerical meteorological model that solves the full set of physical and thermodynamic equations which govern atmospheric motions. The output data from RAMS, which was run in a polar stereographic projection and a sigma-p coordinate system, was then mapped to the CAMx grid. Two separate meteorological CAMx inputs, cloud fractions and rainfall rates, were developed based on observed data.

RAMS was run in a nested-grid mode with three levels of resolution: 108 km, 36 km, and 12 km with 28-34[2] vertical layers. The top of the surface layer was 16.7 m in the 36 and 12km grids. The two finer grids were at least as large as their CAMx counterparts. In order to keep the model results in line with reality, the simulated fields were nudged to an European Center for Medium-Range Weather Forecasting analysis field every six hours. This assimilation data set was bolstered by every four-hourly special soundings regularly collected as part of the North American Research Strategy on Tropospheric Ozone field study in the northeast U.S.

A limited model performance evaluation (Sistla, 1999) was completed for a portion of the 1995 meteorological modeling (July 12-15). Observed data not used in the assimilation procedure were compared against modeled data at the surface and aloft. In general, there were no widespread biases in temperatures and winds. Furthermore, the meteorological fields were compared before and after being processed into CAMx inputs. It was concluded that this preprocessing did not distort the meteorological fields.

Western U.S. Domain: The gridded meteorological data for the two historical 1996 episodes were developed using the Fifth-Generation NCAR / Penn State Mesoscale Model (MM5). MM5 (Grell *et. al.*, 1995) is a numerical meteorological model that solves the full set of physical and thermodynamic equations which govern atmospheric motions. MM5 was run in a nested-grid mode with three levels of resolution: 108 km, 36km, and 12 km with 23 vertical layers. The model was simulated in five day segments with an eight hour ramp-up period. The MM5 runs were started at 0)Z, which is 4:00 p.m. PST. The first eight hours of each five day period were removed before being input into CAMx. The CAMx runs start at midnight, and each day runs from midnight to midnight (PST).

MM5 is a terrain-following sigma-pressure coordinate model and was run using a Lambert conformal map projection, therefore the data were processed to match the CAMx grid structure. There was also an issue in that several of the CAMx grid boundaries extended slightly beyond their counterpart MM5 12 km and 36 km domain boundaries (mostly over the Pacific Ocean). In these cases, data from the next outer grid were mapped to these areas. A preprocessor generates model-ready CAMx files for wind, temperature, water vapor, pressure, and vertical diffusion from the MM5 output.

The standard version of MM5 was revised for this project to output the internally-calculated vertical diffusivities generated as part of the MRF boundary layer scheme. When the MRF boundary layer option is employed these K_v values represent non-local vertical exchanges. This approach should provide the most representative mixing field; one that captures both large- and small-scale vertical diffusive fluxes.

Unlike the eastern ozone modeling, the cloud fraction and rainfall rate inputs were derived

[2] The inner nests were modeled with 34 layers while the outer 108 km domain was modeled with 28 layers.

from the meteorological model as opposed to interpolating observed data to the model grid. This alternative procedure was used because of the relatively sparse meteorological observation network in the West. Cloud fractions were diagnosed from the MM5 results based on the assignment of a critical relative humidity, which if exceeded, indicated the presence of a cloud. The fractional extent of the cloud was a function of the amount the model humidity exceeds the threshold value. Rainfall rates are extracted directly from MM5.

Other Model Inputs: In addition to the meteorological data, the photochemical grid model requires several other types of data. In general, most of these miscellaneous model files were taken from existing regional modeling applications. Clean conditions were used to initialize the model and as lateral and top boundary conditions as in previous regional modeling applications. The model also requires information regarding land use type and surface albedo for all layer 1 grid cells in the domain. Existing regional data obtained from OTAG were used for these non-day-specific files. Photolysis rates were developed using the JCALC preprocessor (SAI, 1996). Turbidity values were set equal to a constant thought to be representative of regional conditions.

B. Model Performance Evaluation

The goal of the Base Year modeling was to reproduce the atmospheric processes resulting in high ozone concentrations over the eastern United States during the three 1995 episodes selected for modeling. Note that the Base Year of the emissions was 1996 while the eastern U.S. episodes are for 1995. The effects on model performance of using 1996 Base Year emissions for the 1995 episodes are not known, but are not expected to be major.

An operational model performance evaluation for surface ozone for the five episodes was performed in order to estimate the ability of the modeling system to replicate Base Year ozone concentrations. This evaluation is comprised principally of statistical assessments of model versus observed pairs. The robustness of an operational evaluation is directly proportional to the amount and quality of the ambient data available for comparison.

1. Statistical Definitions

Below are the definitions of those statistics used for the evaluation. The format of all the statistics is such that negative values indicate model ozone predictions that were less than their observed counterparts. Positively-valued statistics indicate model overestimation of surface ozone. Statistics were not generated for the first three days of an episode to avoid the initialization period. The operational statistics were principally generated on a regional basis in accordance with the primary purpose of the modeling which is to assess the need for, and impacts of, a national emissions control program. However, a local assessment of model performance was also completed to ensure that the model did not significantly overestimate the need for controls in individual areas. The statistics were calculated for (a) the entire domain, (b) four quadrants (i.e., Midwest, Northeast, Southeast, Southwest), and (c) 47 local areas. The statistics calculated for each of these sets of areas are described below.

Domainwide unpaired peak prediction accuracy: This metric simply compares the peak concentration modeled anywhere in the selected area against the peak ambient concentration anywhere in the same area. The difference of the peaks (model - observed) is then normalized by the peak observed concentration.

Peak prediction accuracy: This metric averages the paired peak prediction accuracy calculated for each monitor in the subregion. It characterizes the ability of the model to replicate peak (afternoon) ozone over a subregion. The daily peak model versus daily peak observed residuals are paired in space but not by hour.

Mean normalized bias: This performance statistic averages the normalized (by observation) difference (model - observed) over all pairs in which the observed values were greater than 60 ppb. A value of zero would indicate that the model over predictions and model under predictions exactly cancel each other out.

Mean normalized gross error: The last metric used to assess the performance is similar to the above statistic, except in this case it is the absolute value of the residual which is normalized by the observation, and then averaged over all sites. A zero gross error value would indicate that all model concentrations (in which their observed counterpart was greater than 60 ppb) exactly matched the ambient values.

2. Domainwide Model Performance (Eastern U.S.)

As with previous regional photochemical modeling studies, the degree that model predictions replicate observed concentrations varies by day and location over the large eastern U.S. modeling domain. From a qualitative standpoint, there appears to be considerable similarity on most days between the observed and simulated ozone patterns. Additionally, where possible to discern, the model appears to follow the day-to-day variations in synoptic-scale ozone fairly closely. More quantitative comparisons of the model predictions and ambient data are provided below.

When all hourly observed ozone values (greater than 60 ppb) are compared to their modeled counterparts for the thirty episode modeling days for the eastern U.S., the mean normalized bias is -1.1 percent and the mean normalized gross error is 20.5 percent As shown in Table III-3, the model generally underestimates observed ozone values for the June and July episodes, but predicts higher than observed amounts for the August episode.

Table III-3. Performance statistics for hourly ozone in the Eastern U.S. CAMx simulations.

	Average Accuracy of the Peak	**Mean Normalized Bias**	**Mean Normalized Gross Error**
June 1995	-7.3	-8.8	19.6
July 1995	-3.3	-5.0	19.1
August 1995	9.6	8.6	23.3

Depending on the episode and region, the normalized biases can range from an underestimation of 18 percent to an overestimation of 16 percent. Gross errors tend to average between 17 and 25 percent. As shown in Table III-4, when the model domain is subdivided into four quadrants, it is found that most of the underestimations in the June and July episodes are driven by the Northeast and Midwest quadrants (i.e., the two northern ones). Conversely, most of the overestimated ozone in the August episode is due to the Midwest, Southeast and Southwest quadrants. Hourly ozone is consistently underestimated in the Northeast quadrant. The model does slightly better in replicating the peak values for each monitoring site than it does at replicating the mean values, especially in the Northeast where the underpredictions are not as large for the highest ozone observations.

Table III-4. Regional/Episodic performance statistics for NLDE hourly ozone predictions.

	Average Accuracy of the Peak			**Mean Normalized Bias**			**Mean Normalized Gross Error**		
	June	*July*	*August*	*June*	*July*	*August*	*June*	*July*	*August*
Whole Grid	-7.3	-3.3	9.6	-8.8	-5.0	8.6	19.6	19.1	23.3
Northeast	-14.7	-5.0	-4.3	-18.4	-7.2	-6.0	24.7	19.1	22.6
Midwest	-7.3	-6.2	15.5	-8.7	-7.2	15.5	18.0	19.4	23.7
Southeast	-2.9	1.9	15.1	-3.0	1.3	14.7	17.4	19.1	24.1
Southwest	-0.9	1.3	7.0	0.7	3.1	10.3	19.0	20.0	22.6

At present, there are no generally accepted set of numerical criteria by which one can judge the adequacy of model performance for regional applications. In view of this, EPA determined the acceptability of modeling for this rule by comparison against the performance results of regional models from previous analyses. For instance, the Heavy Duty Engine (HDE) simulations were determined to be appropriate for use based on comparisons to previously accepted modeling analyses (e.g., OTAG and Tier-2). As shown in Table III-5, model performance in the Base Year NLDE simulations is generally similar or better than other regional ozone modeling efforts. In particular, the gross error metric is almost universally improved in the more recent NLDE modeling. In general, the NLDE/CAMx modeling results are approximately

3-6 ppb higher on average than what was generated in the HDE/UAM-V modeling. In some previous regional modeling applications, there had been a tendency in some regions for the model to underestimate ozone in the early parts of an episode and then overestimate ozone at the end of an episode. However, in general, there does not appear to be any such bias trend in the NLDE BaseYear modeling.

Table III-5. Regional/Episodic performance statistics for HDE hourly ozone predictions. Bold numbers indicate HDE statistics that have improved in the NLDE simulations (see Table III-4).

	Average Accuracy of the Peak			**Mean Normalized Bias**			**Mean Normalized Gross Error**		
	June	*July*	*August*	*June*	*July*	*August*	*June*	*July*	*August*
Whole Grid	**-10.5**	**-5.8**	7.7	**-13.2**	**-9.6**	5.0	**22.3**	**22.3**	**23.6**
Northeast	**-15.1**	**-6.6**	**-5.2**	**-20.3**	**-12.1**	**-8.8**	**27.0**	**21.2**	**24.2**
Midwest	**-13.1**	**-11.1**	11.4	**-15.4**	**-14.2**	9.6	**21.6**	**23.6**	22.1
Southeast	**-5.4**	0.6	14.7	**-7.2**	**-2.8**	12.1	**18.4**	**21.0**	**24.6**
Southwest	0.2	**3.9**	**8.8**	**1.0**	**4.9**	**10.5**	**21.6**	**23.4**	**26.5**

Table III-6 presents the results from the eight-8-hour ozone evaluation. In general, the gross error is noticeably less for the eight-hour ambient versus observed ozone comparisons. However, model estimates during the August episode clearly over predict the observed values in regions outside the Northeast.

Table III-6. Regional/Episodic performance statistics for NLDE 8-hour ozone predictions.

	Average Accuracy of the Peak			**Mean Normalized Bias**			**Mean Normalized Gross Error**		
	June	*July*	*August*	*June*	*July*	*August*	*June*	*July*	*August*
Whole Grid	-3.9	0.9	13.9	-5.7	-2.1	11.0	17.5	16.4	22.6
Northeast	-13.5	-2.4	-1.6	-15.4	-4.9	-3.8	21.3	14.6	20.8
Midwest	-4.0	-0.9	20.6	-5.8	-4.4	17.6	16.0	16.7	23.7
Southeast	1.3	5.3	20.5	0.9	4.0	18.4	16.4	17.5	24.1
Southwest	5.0	8.2	16.2	3.9	3.6	12.4	17.8	18.1	21.1

3. Local-scale Model Performance (Eastern U.S.)

The CAMx modeling results were also evaluated at a “local” level. The purpose of this analysis was to ensure that areas determined to need the nonroad engine emissions reductions based on projected exceedances of the ozone standard were not unduly influenced by local overestimation of ozone in the model Base Year. For this analysis, the modeling domain was broken up into 51 local subregions as shown in Figure III-3. The primary statistics for each of the 51 subregions is shown in Table III-7.

As noted above, there is no set of established statistical benchmarks to determine the adequacy of a regional modeling operation evaluation. However, the performance statistics for the eastern U.S. modeling were compared to the recommended performance ranges for urban attainment modeling (EPA, 1991). The results indicate that model performance for the June episode was within the recommended ranges for 69% of the local areas examined. For the July and August episodes, the percent of local areas with performance within the recommended ranges was 80% and 61%, respectively. This is an improvement from the HDE model performance where the numbers were 57%, 45%, and 55% for the June, July, and August episodes, respectively.

Local scale model performance is poorest in the southeastern U.S. in the August episode where over predictions occurred. In fact, areas along the Gulf Coast (New Orleans, Beaumont/Port Arthur, Baton Rouge, etc.) tend to be universally overestimated. This is likely due to the model tendency to generate large amounts of ozone along coastal areas where low stability and high emissions densities can coexist.

With the exception of the July episode, the model tends to underestimate observed ozone by approximately 15% in the local areas of the Northeast (e.g., New York City, Philadelphia, Boston). The local 8-hour metrics (not shown) generally do not greatly differ from their hourly counterparts. There is a slight tendency toward greater overprediction of the 8-hour values.

Table III-7. Local performance statistics for NLDE hourly ozone predictions.

	Average Accuracy of the Peak			**Mean Normalized Bias**			**Mean Normalized Gross Error**		
	June	*July*	*August*	*June*	*July*	*August*	*June*	*July*	*August*
Dallas	-9.6	-12.3	2.2	-10.6	-11.5	3.2	16.6	18.7	15.7
Houston/Galveston	-3.0	-5.1	0.3	-3.5	-3.9	2.2	20.8	19.0	25.7
Beaumont/Port Arthur	14.0	16.7	8.8	16.0	19.3	12.9	20.4	24.5	24.6
Baton Rouge	15.6	24.7	31.4	22.6	26.6	37.4	26.1	31.0	40.5
New Orleans	15.6	29.1	42.1	15.9	28.9	48.9	21.9	32.0	50.2
St. Louis	-0.5	-4.0	8.4	-0.6	0.6	10.5	17.0	18.4	18.2
Memphis	-7.7	-4.9	13.7	-5.9	-0.3	13.6	15.5	19.3	22.0
Alabama	5.2	-1.7	16.0	6.5	6.7	23.1	14.4	16.6	25.2
Atlanta	-3.1	5.4	19.0	-3.4	6.8	26.1	16.7	20.1	31.0

Nashville	-2.9	7.8	31.5	-2.4	9.1	36.1	18.1	24.7	37.4
Eastern TN	-14.2	-16.0	-2.7	-21.0	-17.1	-5.9	22.7	20.7	18.3
Charlotte	8.3	-2.1	6.0	5.8	4.1	14.5	13.0	16.3	18.2
Greensboro	-1.7	-1.1	17.2	-4.2	1.2	18.2	14.1	15.3	21.7
Raleigh-Durham	-11.8	1.3	-2.3	-10.7	4.2	-1.9	14.6	13.9	16.9
Evansville/Owensboro	1.2	-0.9	28.3	4.5	5.4	32.8	15.1	21.2	33.9
Indianapolis	-8.3	-13.5	15.9	-3.6	-14.4	18.0	13.1	19.3	19.7
Louisville	2.8	4.2	36.6	4.8	6.1	42.1	14.7	17.9	42.5
Cincinnati/Dayton	-4.7	-8.5	29.0	0.1	-5.6	32.7	12.8	19.1	33.5
Columbus	-8.5	-14.5	9.2	-6.2	-11.0	14.2	14.6	17.3	18.7
West Virginia	-8.8	-5.7	12.7	-7.5	-3.2	13.7	15.7	16.6	24.5
Chicago	-9.9	-4.3	10.4	-17.1	-11.1	3.5	24.5	23.5	22.3
Milwaukee	-14.8	-12.9	21.5	-16.5	-16.9	12.3	19.1	23.3	18.2
Muskegon/Grand Rapids	-10.8	-12.3	3.1	-11.6	-12.9	1.7	17.7	20.4	16.4
Gary/South Bend	-13.0	-10.0	11.8	-15.0	-14.5	9.3	19.2	24.4	20.7
Detroit	-17.2	-5.8	3.9	-20.1	-13.2	-3.2	25.1	22.5	23.4
Pittsburgh	-10.0	-3.2	9.2	-9.2	-2.1	7.9	23.1	16.1	20.4
Central PA	-6.0	-7.6	1.0	-8.5	-6.0	1.1	21.9	15.5	18.6
Norfolk	-9.0	0.0	8.3	-13.4	-5.6	5.7	19.1	18.6	24.7
Richmond	-1.2	4.8	2.6	-1.3	10.7	4.5	8.4	18.3	20.3
Baltimore/Washington	-4.7	-3.1	1.7	-6.8	-5.2	0.7	18.6	15.6	23.4
Delaware	-6.1	-5.2	2.3	-6.3	-0.2	7.5	12.9	11.6	16.2
Philadelphia	-14.1	-1.8	-8.7	-22.0	-10.5	-13.9	26.4	19.5	28.9
New York City	-16.2	-3.9	-12.2	-24.6	-14.1	-17.9	31.3	22.5	29.8
Hartford	-16.9	-5.0	-9.9	-18.5	-4.0	-7.7	23.6	18.2	20.1
Boston	-13.7	-4.7	-15.6	-19.6	-9.2	-19.6	25.9	20.9	26.5
Maine	-20.4	-4.7	-6.9	-25.0	-9.4	-6.9	25.3	19.0	15.5
Longview/Shreveport	-2.1	11.3	7.7	0.8	11.1	11.4	16.2	16.5	17.9
Kansas City	-8.5	-7.8	-4.3	-7.9	-1.5	-8.3	15.7	13.0	12.4
Western NY	-23.1	-20.6	-9.0	-25.6	-20.5	-12.1	28.1	23.8	19.0
Northeast OH	-4.0	-6.5	6.9	-6.6	-6.8	7.7	20.4	15.5	16.5
South Carolina	-2.5	1.3	11.4	-3.4	1.5	15.7	12.5	17.7	19.4
Gulf Coast	0.5	23.1	29.3	4.5	30.0	33.7	15.4	31.6	34.9

FL West Coast	-6.4	22.8	41.2	-7.3	11.9	42.8	11.3	22.7	43.7
FL East Coast	-15.9	16.2	23.3	-16.8	16.6	26.3	18.0	18.4	29.4
Jackson	0.6	10.9	21.0	1.8	10.0	24.0	16.0	16.0	24.9
Central MI	-6.9	-10.4	12.0	-9.6	-14.8	6.6	18.1	18.7	17.5
Macon/Columbus	-9.5	-11.1	21.6	-8.8	-5.7	26.4	10.9	13.0	26.9
Austin/San Antonio	-14.1	-19.6	-1.9	-11.0	-15.5	4.1	14.1	17.2	12.4
Oklahoma City/Tulsa	-12.3	-5.6	-5.2	-12.9	-3.2	-2.8	17.2	14.6	12.6
Ft. Wayne/Lima	-9.1	-13.1	3.9	-8.3	-14.1	5.1	16.0	18.2	10.6
Bangor/Hancock Co.	-17.8	-6.9	-17.7	-24.4	-8.5	-19.9	25.2	15.3	21.0

4. Domainwide Model Performance (Western U.S.)

Model performance statistics for the western U.S. NLDE Base Year simulations were also calculated for the two 1996 ozone episodes. The first three days of each simulation were considered ramp-up days and were not used in the statistical calculations. Thus, there were 19 episode days used in the model performance evaluation. The statistics were calculated for the entire model domain[3] and for nine subregions. Again, the model performance evaluation consists solely of comparisons against ambient surface ozone data. There is insufficient available data in terms of ozone precursors or ozone aloft to allow for a more complete assessment of model performance.

When all hourly observed ozone values (greater than 60 ppb) are compared to their model counterparts for the 19 episode modeling days, the mean normalized bias is -21.4 percent and the mean normalized gross error is 26.1 percent. The eight-hour model ozone averages are also biased low (-19.2%) with a mean normalized gross error of 23.5%. In general, the daily peak values were not as underestimated as the mean values.

[3] Although the modeling was at 36/12km, nearly all of the model/ambient pairs were in the 12km fine grid.

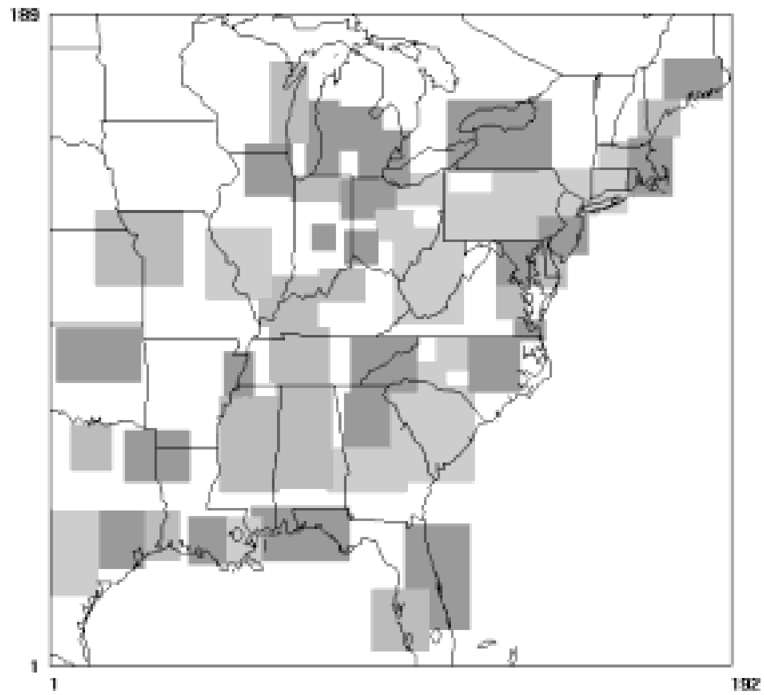

Figure III-3. Map of the 51 local-scale evaluation zones.

Table III-8. Domainwide ozone performance statistics for the July 1996 CAMx Base Year**.**

	Average Accuracy of the Peak	Mean Normalized Bias	Mean Normalized Gross Error
1-hour ozone	-20.5	-21.4	26.1
8-hour ozone	-17.3	-19.2	23.5

The EPA determined the adequacy of model performance for the western U.S. by comparison to performance results from the only comparable set of regional modeling for ozone in the western U.S. which was done for the Tier-2/Low Sulfur rulemaking. As shown in Table III-9, model performance in the Base Year NLDE simulations is better than what was exhibited in the Tier-2 UAM-V modeling. The improvements in Base Year performance from the Tier-2 modeling are attributable to the use of more representative on-road mobile emissions estimates from the State of California and improved biogenic estimates from the BEIS-3 model.

Table III-9. Domainwide model performance statistics for hourly ozone predictions for two sets of western U.S. modeling.

	Average Accuracy of the Peak		**Mean Normalized Bias**		**Mean Normalized Gross Error**	
	Tier-2	NLDE	Tier-2	NLDE	Tier-2	NLDE
Domainwide	-38.3	-20.5	-39.5	-21.4	39.9	26.1

5. Local-Scale Model Performance (Western U.S.)

The local-scale model performance areas in the western U.S. are shown in Figure III-4 and the performance statistics are given in Table III-10. A comparison of performance in the local-scale areas of the western U.S. against the recommended ranges for accuracy, bias, and error for attainment demonstration modeling indicates that three of the nine regions exhibit performance within these ranges.

Table III-10. Local performance statistics for NLDE hourly ozone predictions.

	Average Accuracy of the Peak	**Mean Normalized Bias**	**Mean Normalized Gross Error**
Seattle	-11.4	-11.6	23.5
Portland	-20.2	-25.1	26.9
San Francisco / Sacramento	-23.8	-25.4	26.6
San Joaquin Valley	-20.7	-20.0	23.3
Los Angeles	-25.2	-23.1	33.2
Phoenix / Tucson	-6.4	-9.9	22.5
Salt Lake City	-21.1	-19.9	21.7
Denver	-12.2	-14.5	17.9
El Paso	-23.8	-26.5	27.1

The model underestimates observed ozone in all nine local areas, ranging from 10 to 27 percent. Based on gross error values, local scale model performance is poorest in the local performance areas in southern California. The local 8-hour statistics (not shown) generally do not greatly differ from their hourly counterparts. There is a slight tendency toward less underestimation of the 8-hour values. While the Base Year model performance is considerably better than in the previously-used Tier-2 rulemaking, the modeling still generally underestimates observed ozone (greater than 60 ppb) by about 20 percent. However, it was determined that the use of these modeling simulations was the best approach for assessing the need for, and the effects of, the proposed rule.

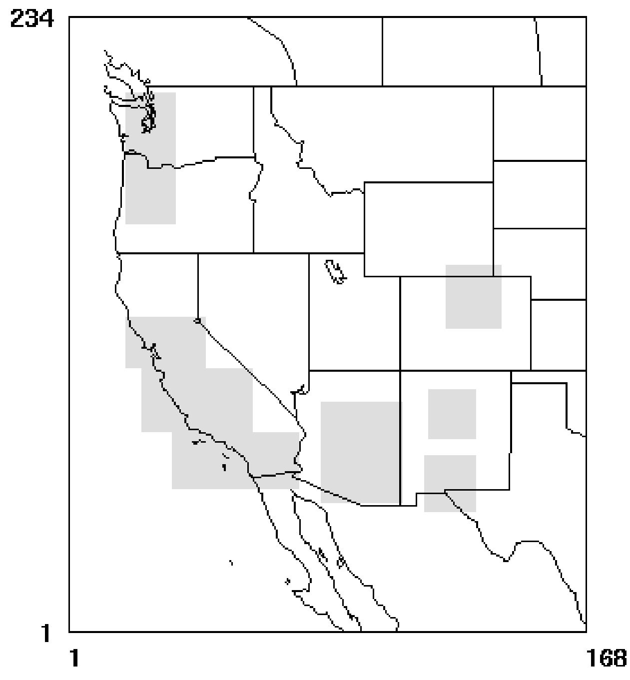

Figure III-4. Map of the nine local-scale performance evaluation areas in the western U.S.

C. Ozone Modeling Results

The NLDE CAMx modeling output was analyzed to provide information to (a) support the determination of the need for NLDE, and (b) examine the air quality impacts of the rulemaking. The procedures and results of each of these analyses are described below.

1. Projected Future Ozone Design Values

The CAMx simulations were performed for Base Cases in 1996, 2020, and 2030 considering growth and expected emissions controls that will affect future air quality. The effects of the nonroad engine reductions (i.e., Control Cases) were modeled for the two future years. As a means of assessing the future levels of air quality with regard to the ozone NAAQS, future-year estimates of ozone design values were calculated using relative reduction factors (RRFs) applied to 1999-2001 ozone design values (EPA, 2003b). The procedures for determining the RRFs are similar to those in EPA's draft guidance for modeling for an 8-hour ozone standard (EPA, 1999a). Hourly model predictions were processed to determine daily maximum 8-hour concentrations for each grid cell for each non-ramp-up day modeled. The RRF for a monitoring site was determined by first calculating the multi-day mean of the 8-hour daily maximum predictions in the nine grid cells surrounding the site using only those predictions greater than or equal to 70 ppb[4], as recommended in the guidance. This calculation was performed for the Base Year scenario and each of the future-year baselines. The RRF for a site is the ratio of the mean prediction in the future-year scenario to the mean prediction in the Base Year scenario. RRFs were calculated on a site-by-site basis. The future-year design value projections were then calculated by county, based on the highest resultant design values for a site within that county from the RRF application. The current and future Base and Control 8-hour county maximum ozone design values are provided in Appendix A. County population for 2000, 2020, and 2030 are also included in this appendix.

As shown in Table III-11, the modeling projects that 30 counties across the U.S. will have design values greater than the 8-hour NAAQS in 2020. By 2030 that number is expected to rise to 32 counties as a result of projected emissions growth. In all, based on present-day population figures, over 39 million people live in areas that are projected to be violating the NAAQS in 2020 and/or 2030. While this projection reflects a need for additional ozone precursor emissions controls, it should be noted that this reflects a considerable improvement from the 111 million people in 289 counties residing in counties that currently exceed the 8-hour NAAQS. Table III-12 indicates that 15 counties with a total population over 24 million are projected to have design values greater than the 1-hour NAAQS in 2020 and 2030. Appendix B contains maps of the projected design values across the U.S. for the 1- and 8-hour standards for the 2020 and 2030 Control Cases

Table III-11. Current and estimated future 8-hour ozone design values for counties projected to exceed the standard in 2020 and/or 2030.

State	County	1999-2001 Design Value	2020 Base	2030 Base	2000 Population
California	Los Angeles	105	121	123	9,519,338
Illinois	Cook	88	85	86	5,376,741
Texas	Harris	110	104	106	3,400,578
California	Orange	77	101	101	2,846,289
Michigan	Wayne	88	86	88	2,061,162
California	San Bernardino	129	133	135	1,709,434
California	Riverside	111	107	108	1,545,387
New York	Westchester	92	86	87	923,459
Connecticut	Fairfield	97	92	93	882,567
Connecticut	New Haven	97	87	89	824,008
Georgia	Fulton	107	88	88	816,006
California	Fresno	108	93	93	799,407
Michigan	Macomb	88	84	85	788,149
California	Ventura	101	94	94	753,197

[4]For the one-hour NAAQS we used a cut-off of 80 ppb. Please see the Tier 2 Air Quality Modeling TSD for more details (EPA 1999b).

New Jersey	Middlesex	103	92	93	750,162
Pennsylvania	Montgomery	100	89	90	750,097
California	Kern	109	94	94	661,645
New Jersey	Hudson	93	87	88	608,975
Pennsylvania	Bucks	105	94	95	597,635
New Jersey	Ocean	109	94	95	510,916
New Jersey	Camden	103	87	88	508,932
Indiana	Lake	90	84	85	484,564
New York	Richmond	98	87	88	443,728
New Jersey	Mercer	105	94	95	350,761
New Jersey	Gloucester	101	88	88	254,673
Texas	Galveston	98	90	91	250,158
Maryland	Harford	104	86	87	218,590
Connecticut	Middlesex	99	88	90	155,071
Georgia	Bibb	98	85	85	153,887
Wisconsin	Kenosha	95	87	89	149,577
New Jersey	Hunterdon	100	88	89	121,989
Georgia	Henry	107	85	85	119,341

Table III-12. Current and estimated future 1-hour ozone design values for counties projected to exceed the standard in 2020 and/or 2030.

State	**County**	**1999-2001 Design Value**	**2020 Base**	**2030 Base**	**2000 Population**
California	Los Angeles	169	184	185	9,519,338
Texas	Harris	182	171	175	3,400,578
California	Orange	114	132	132	2,846,289
California	San Bernardino	170	200	202	1,709,434
California	Riverside	149	140	141	1,545,387
Connecticut	Fairfield	143	133	136	882,567
Connecticut	New Haven	146	129	131	824,008
Georgia	Fulton	156	126	126	816,006
New Jersey	Middlesex	142	126	127	750,162
Pennsylvania	Bucks	142	127	128	597,635
New Jersey	Mercer	145	126	127	350,761
Texas	Galveston	164	150	152	250,158
Texas	Brazoria	154	137	139	241,767
Connecticut	Middlesex	147	131	133	155,071
California	Imperial	166	137	137	142,361

2. Impacts of the NLDE Rule on Future Year Ozone

The impacts of the proposed emissions reductions from nonroad engines were examined in terms of:

- effects on projected future ozone design values; and
- effects on model-predicted ozone levels and the number/duration/extent of predicted high ozone events
- ozone increases (i.e., "disbenefits")

The effects of the NLDE controls on future ozone design values were determined on a county-by-county basis as well as for consolidated metropolitan statistical areas (CMSAs) or metropolitan statistical areas (MSAs)[5]. The effects of the NLDE controls on model-predicted ozone concentrations was examined for those CMSAs/MSAs that have a current or projected future case design value exceeding the 1- hour or 8-hour ozone NAAQS. In the East there are 84 such areas and in the West there are 10 areas. The results of nearly all of the analyses indicate that the proposed NLDE rule will provide an net improvement in ozone air quality nationally.

a. Effect on projected future ozone design values

The counties with projected 8-hour design values exceeding the NAAQS (i.e., nonattainment counties) for the 2020 and 2030 Base and Control Cases are listed in Table III-13. In 2020, three nonattainment counties are projected to come into attainment as a result of the NLDE controls. However, one county, Bronx Co., NY, is currently in attainment but is projected to violate the standard in 2020 as a result of the rule. The net effect is a 2.2 percent increase in the population living in nonattainment counties. It is important to note that ozone nonattainment designations are historically based on larger geographical areas than counties. Bronx Co., NY is the only county within the New York City CMSA in which increases are detected in 8-hour violations in 2020. Considering a larger area, the modeling indicates that projected violations over the entire New York City CMSA will be reduced by 6.8 percent. Upon full turnover of the fleet in 2030, the net impact of the rule on projected 8-hour nonattainment is a 2.0 percent decrease in the population living in nonattainment counties as two additional counties are no longer projected to violate the NAAQS.

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[5] For those calculations it was necessary to assign the model grid cells to individual CMSA/MSAs. The rules for assigning grid cells to CMSA/MSAs is as follows. The first step was to assign grid cells to States based on the fraction of the grid cells' area in a State. Next, grid cells were assigned to an individual CMSA/MSAs if: a) the grid is wholly contained within the CMSA/MSA or b) partially within the area, but *not* also partially within another CMSA/MSA. Grid cells that partially overlap two or more CMSA/MSAs are assigned to the county, and thereby the corresponding CMSA/MSA, which contains the largest portion of the grid cell. Each grid cell in the "coarse" or 36 km grid portion of the domain was divided into nine 12 km grids before applying the preceding methodology.

Table III-13. Lists of counties projected to violate the 8-hour NAAQS in 2020 and 2030 for the Base Case and NLDE Control Case.

2020 Base	2020 Control	2030 Base	2030 Control
Bibb	Bronx	Bibb	Bronx
Bucks	Bucks	Bucks	Bucks
Camden	Camden	Camden	Camden
Cook	Cook	Cook	Cook
Fairfield	Fairfield	Fairfield	Fairfield
Fresno	Fresno	Fresno	Fresno
Fulton	Fulton	Fulton	Galveston
Galveston	Galveston	Galveston	Gloucester
Gloucester	Gloucester	Gloucester	Harris
Harford	Harris	Harford	Hudson
Harris	Hudson	Harris	Hunterdon
Henry	Hunterdon	Henry	Kenosha
Hudson	Kenosha	Hudson	Kern
Hunterdon	Kern	Hunterdon	Los Angeles
Kenosha	Los Angeles	Kenosha	Macomb
Kern	Mercer	Kern	Mercer
Los Angeles	Middlesex (CT)	Lake	Middlesex (CT)
Mercer	Middlesex (NJ)	Los Angeles	Middlesex (NJ)
Middlesex (CT)	Montgomery	Macomb	Montgomery
Middlesex (NJ)	New Haven	Mercer	New Haven
Montgomery	Ocean	Middlesex (CT)	Ocean
New Haven	Orange	Middlesex (NJ)	Orange
Ocean	Richmond	Montgomery	Richmond
Orange	Riverside	New Haven	Riverside
Richmond	San Bernardino	Ocean	San Bernardino
Riverside	Ventura	Orange	Ventura
San Bernardino	Wayne	Richmond	Wayne
Ventura	Westchester	Riverside	Westchester
Wayne		San Bernardino	
Westchester		Ventura	
		Wayne	
		Westchester	
30 Total	**28 Total**	**32 Total**	**28 Total**

Another way to assess the impact of the rule on ozone concentrations is to calculate the effects in all counties with projected future year design values including both attainment and nonattainment counties. This approach helps assess the degree to which the rule will not only help nonattainment counties to attain the NAAQS, but will also help attainment counties maintain attainment. In the 1999-2001 ambient design value data set, there were sites in 522 counties for with valid 8-hour design values and sites in 510 counties with valid 1-hour design values.

Table III-14 shows the average change in future year eight-hour and one-hour ozone design values. Average changes are shown for 1) all counties with design values in 1999-2001, 2) counties with design values that did not meet the standard in 1999-2001, and 3) counties that met the standard, but were within 10 percent of it in 1999-2001. This last category is intended to reflect counties that meet the standard, but will likely benefit from help in maintaining that status in the face of growth. The average and population-weighted average over all counties in Table III-14 demonstrates a broad improvement in ozone air quality. The average across nonattainment counties shows that the rule will certainly help bring these counties into attainment. The average over counties within ten percent of the standard shows that the rule will also help those counties to maintain the standard. All of these metrics show a decrease in 2020 and a larger decrease in 2030 (due to fleet turnover), indicating the overall improvement in ozone air quality.

Table III-15 presents counts of counties by the size and direction of their change in design value in 2020 and 2030. For the 8-hour NAAQS, 96 percent of counties show a decrease in 2020, 97 percent in 2030. For the 1-hour NAAQS, 97 percent of counties show a decrease in 2020, 98 percent in 2030.

Table III-14. Average change in projected future year ozone design values (ppb).

Design Value	***Average***	***Number of Counties***	***2020 Control minus Base***	***2030 Control minus Base***
8-Hour	All	522	-1.8	-2.8
	All, population-weighted	522	-1.6	-2.6
	Nonattainment counties[6]	289	-1.9	-3.0
	Counties within 10 percent of the standard[7]	130	-1.7	-2.6
1-Hour	All	510	-2.4	-3.8
	All, population-weighted	510	-2.3	-3.6
	Nonattainment counties[8]	73	-2.9	-4.5
	Counties within 10 percent of the standard[9]	130	-2.4	-3.8

[6] Counties whose present-day design values exceeded the 8-hour standard ($\geq$ 85 ppb).

[7] Counties whose present-day design values were less than but within 10 percent of the 8-hour standard ($77 \leq DV < 85$ ppb).

[8] Counties whose present-day design values exceeded the 1-hour standard ($\geq$ 125 ppb).

[9] Counties whose present-day design values were less than but within 10 percent of the 1-hour standard ($112 \leq DV < 125$ ppb) in 1999-2001.

Table III-15. Numbers of counties projected to be in different design value change bins as a result of the rule in 2020 and 2030.

Design value change	***2020***		***2030***	
	8-Hour	***1-Hour***	***8-Hour***	***1-Hour***
≥ 2ppb increase	1	1	1	1
1 ppb increase	1	5	3	2
No change	21	10	10	5
1 ppb decrease	140	69	42	22
2-3 ppb decrease	357	356	333	193
4 ppb decrease	2	69	133	287
Total	522	510	522	510

b. Effects on model-predicted ozone concentrations

The impacts of NLDE controls on model-predicted ozone concentrations were quantified using a number of metrics (i.e., measures of ozone concentrations). These metrics include:

(1) peak 8-hour ozone concentrations,
(2) the number of 8-hour exceedances,
(3) the number of modeled episode days with 8-hour exceedances,
(4) total amount of 8-hour ozone >= 85 ppb,
(5) total amount of 8-hour ozone >= 85 ppb weighted by 2000 population.

(1) The peak 8-hour ozone represents the highest 8-hour average ozone prediction within the area (i.e., CMSA or MSA) across all episodes modeled.

(2) The number of exceedances is the total number of grid cells with predicted exceedances in the area across all days modeled. This exceedance metric counts each grid cell every day there is a predicted exceedance in that grid. Thus, an individual grid cell can be counted more than once if there are multiple days with predicted exceedances in that grid.

(3) The number of exceedance days is simply a count of the total number days with predicted exceedances in the area. The count is not a function of the number of cells >= 85 ppb; a single cell is sufficient to trigger the count.

(4) The total amount of ozone above 85 ppb in an area is determined by taking the difference between the predicted daily maximum 8-hour average ozone concentration and 85 ppb in each grid cell and then summing this amount across all grid cells in the area and days modeled. This

metric is sometimes referred to as the "amount of nonattainment".

(5) This metric is similar to the amount of nonattainment (#4) except that each grid cell value is weighted by the population in that grid.

The tables with data for each of these metrics are included in Appendices C, D, E, and F for the 2020 and 2030 eastern and western modeling. Based on these metrics, the following conclusions can be made regarding the impacts of the proposed emissions reductions in the NLDE rule:

- Local peak 8-hour concentrations will be reduced by as much as 6 percent in 2020 and by as much as 8 percent in 2030. The average reduction in peak 8-hour ozone is 2.7 percent in 2020 and 4.1 percent in 2030. No areas are projected to experience increases in peak ozone as a result of the rule.

- In terms of the extent of projected exceedances in the future, the rule is expected to result in a significant reduction in the total area exceedance-level ozone in the future years. In 2020, the reduction is expected to be 14% and by 203o, the reduction in the total exceedance increases to 21%..

- The number of exceedance days is expected to drop by 13% due to NLDE in 2020 and 18% in 2030.

- The total amount of nonattainment is expected to be reduced by 16% and 22% in 2020 and 2030, respectively. When the ozone changes are weighted by population, the overall reduction is 10% in 2020 and 15% in 2030. When weighted by population there are some areas (e.g., Chicago, New York City) that experience small increases in this metric. This issue is discussed in more detail in the next section.

c. Ozone Increases

As shown above, the proposed rule will generally reduce ozone levels at the national and local scales and thereby provide significant ozone-related health benefits. However, this is not exclusively the case at the local level, when all times and locations are considered. Due to the complex photochemistry of ozone production, emissions of nitrogen oxides (NOx) can lead to both the formation and destruction of ozone, depending on the relative quantities of NOx, VOC, and ozone catalysts such as the OH and HO_2 radicals. In areas dominated by fresh emissions of NOx, ozone catalysts are removed via the production of nitric acid which slows the ozone formation rate. Because NOx is generally depleted more rapidly than VOC, this effect is usually short-lived and the emitted NOx can lead to ozone formation later (i.e., further downwind). The terms "NOx disbenefits" or "ozone disbenefits" refer to the ozone increases that can result from NOx emissions reductions in these localized areas. According to the NARSTO Ozone Assessment, these disbenefits are generally limited to small regions within specific urban cores and are surrounded by larger regions in which NOx control is beneficial[10].

EPA maintains that the most appropriate criteria for determining the value of a particular emissions reduction strategy is the net air quality change projected to result from the rule, evaluated on a nationwide basis and for all pollutants that are health and/or welfare concerns. The primary tool for assessing the net impacts of this rule is the air quality simulation modeling discussed here.

There are several known issues with the modeling with respect to the disbenefit issue. First, the future year modeling conducted by EPA does not contain any local governmental actions beyond the controls proposed in this rule. It is possible that significant local controls of VOC and/or NOx could modify the conclusions regarding ozone changes in some areas. Second, as discussed in the Preamble to the proposed rule the modeled NOx reductions are greater than those actually included in the proposal. This could lead to an exaggeration of the benefits and disbenefits expected to result from the rule. Third, this modeling is subject to the limitations and uncertainties of photochemical grid modeling. While the air quality simulations conducted for the rule represent state-of-the-science analyses, any changes to the underlying chemical mechanisms, grid resolution, and emissions/meteorological inputs could result in revised conclusions regarding the strength and frequency of ozone disbenefits.

Based only on the reductions from today's rule, our modeling predicts that periodic ozone disbenefits will occur most frequently in New York City, Los Angeles, and Chicago. Smaller and even less frequent disbenefits also occur in Boston, Detroit, and San Francisco. However as shown in the Appendices C and D, despite these localized increases, the net ozone impact of the rule nationally is positive for the majority of the analysis metrics. Tables III-16 and III-17 shows that even within the few CMSAs/MSAs that experience periodic ozone increases, these disbenefits are infrequent relative to the benefits accrued at ozone levels above the NAAQS. Furthermore, and most importantly the overall air quality impact of the proposed controls is projected to be strongly positive due to the expected reductions in fine particulate matter (see section D, below).

[10] NARSTO Synthesis Team (2000). An Assessment of Tropospheric Ozone Pollution: A North American Perspective.

Table III-16. Comparison of model projected disbenefits resulting from the rule in 2020.

Considered 94 CMSA/MSAs	Cells > 85 ppb in 2020 Base, % that Increase	Cells > 85 ppb in 2020 Control, % resulting from rule	Cells > 85 in Base or Control, Largest increase (ppb)	Percentage reduction in cells >= 85 ppb
Composite East	3.4%	0.6%	10.7	-13.7%
Composite West	13.1%	1.5%	6.2	-8.3%
Areas w/ disbenefits				
New Haven-Bridgeport-Stamford, CT	29.4%	10.4%	2.2	-5.9%
Chicago	20.1%	3.1%	9.2	-8.5%
New York City	15.1%	3.9%	10.7	-6.7%
Los Angeles	14.4%	1.7%	6.2	-6.5%
Detroit	13.5%	0.0%	3.2	-15.5%
New Orleans, LA	2.2%	0.1%	0.6	-2.4%
Milwaukee	1.8%	0.0%	0.2	-22.8%
Philadelphia	1.4%	0.6%	1.3	-19.6%
Washington-Baltimore	0.4%	0.0%	0.3	-35.9%
Houston	0.4%	0.0%	0.7	-10.6%
Areas w/ no disbenefits				
Baton Rouge, LA	0.0%	0.0%	0	-3.1%
Lake Charles, LA	0.0%	0.0%	0	-4.7%
Buffalo-Niagara Falls, NY	0.0%	0.0%	0	-5.9%
Beaumont-Port Arthur, TX	0.0%	0.0%	0	-6.6%
Benton Harbor, MI	0.0%	0.0%	0	-6.8%
Biloxi-Gulfport-Pascagoula, MS	0.0%	0.0%	0	-7.8%
Atlanta, GA	0.0%	0.0%	0	-8.3%
New London - Norwich CT	0.0%	0.0%	0	-9.4%
Barnstable-Yarmouth, MA	0.0%	0.0%	0	-10.7%
Macon, GA	0.0%	0.0%	0	-11.1%
Louisville, KY-IN	0.0%	0.0%	0	-13.2%

Harrisburg-Lebanon-Carlisle,	0.0%	0.0%	0	-14.0%
Grand Rapids-Muskegon-	0.0%	0.0%	0	-14.0%
Columbus, GA-AL	0.0%	0.0%	0	-15.6%
Memphis, TN-AR-MS	0.0%	0.0%	0	-17.3%
Richmond-Petersburg, VA	0.0%	0.0%	0	-17.9%
Huntington-Ashland, WV-KY-	0.0%	0.0%	0	-20.0%
Pensacola, FL	0.0%	0.0%	0	-21.2%
Bakersfield, CA	0.0%	0.0%	0	-21.4%
Hartford, CT	0.0%	0.0%	0	-21.4%
Phoenix, AZ	0.0%	0.0%	0	-23.9%
Lancaster, PA	0.0%	0.0%	0	-25.0%
Providence, RI	0.0%	0.0%	0	-25.0%
Toledo, OH	0.0%	0.0%	0	-25.0%
Shreveport, LA	0.0%	0.0%	0	-26.7%
Evansville-Henderson, IN-KY	0.0%	0.0%	0	-27.3%
St. Louis, MO-IL	0.0%	0.0%	0	-28.6%
Cincinnati	0.0%	0.0%	0	-29.5%
Chattanooga, TN	0.0%	0.0%	0	-31.8%
Charleston, WV	0.0%	0.0%	0	-33.3%
Pittsburgh, PA	0.0%	0.0%	0	-34.1%
Nashville, TN	0.0%	0.0%	0	-36.7%
Sheboygan, WI	0.0%	0.0%	0	-37.5%
Youngstown-Warren, OH	0.0%	0.0%	0	-37.5%
Columbus, OH	0.0%	0.0%	0	-37.9%
Birmingham, AL	0.0%	0.0%	0	-39.3%
Augusta-Aiken, GA-SC	0.0%	0.0%	0	-40.0%
Reading, PA	0.0%	0.0%	0	-40.0%
Boston	0.0%	0.0%	0	-40.5%
Cleveland	0.0%	0.0%	0	-44.3%
Norfolk-Virginia Beach-Newport	0.0%	0.0%	0	-50.0%
Sarasota-Bradenton, FL	0.0%	0.0%	0	-54.5%
Canton-Massillon, OH	0.0%	0.0%	0	-55.0%
Springfield, MA	0.0%	0.0%	0	-57.1%
Charlotte-Gastonia-Rock Hill,	0.0%	0.0%	0	-63.2%
Jamestown, NY	0.0%	0.0%	0	-66.7%
Little Rock, AR	0.0%	0.0%	0	-66.7%

Scranton-Wilkes Barre, PA	0.0%	0.0%	0	-69.2%
Allentown-Bethlehem-Easton,	0.0%	0.0%	0	-70.0%
Janesville-Beloit, WI	0.0%	0.0%	0	-72.7%
Dallas	0.0%	0.0%	0	-75.0%
San Diego, CA	0.0%	0.0%	0	-75.0%
Longview-Marshall, TX	0.0%	0.0%	0	-75.0%
Parkersburg-Marietta, WV	0.0%	0.0%	0	-75.0%
Erie, PA	0.0%	0.0%	0	-80.0%
Indianapolis, IN	0.0%	0.0%	0	-80.0%
Areas w/ no exceedances in control				
Dayton-Springfield, OH	0.0%		0	-100.0%
Tulsa, OK	0.0%		0	-100.0%
York, PA	0.0%		0	-100.0%
Areas w/ no exceedances in base or control				
Austin-San Marcos, TX				
Clarksville-Hopkinsville, TN-KY				
Columbia, SC				
Dover, DE				
Fayetteville, NC				
Fresno, CA				
Fort Wayne, IN				
Greensboro-Winston Salem, NC				
Greenville-Spartanburg, SC				
Hickory-Morganton, NC				
Huntsville, AL				
Johnson City, TN				
Johnstown, PA				
Knoxville, TN				
Lima, OH				
Merced, CA				
Modesto, CA				
Montgomery, AL				
Raleigh-Durham, NC				
Roanoke, VA				
Rocky Mount, NC				
Sacramento, CA				
San Francisco, CA				
Sharon, PA				
Visalia-Tulare, CA				

Table III-17. Comparison of model projected disbenefits resulting from the rule in 2030.

Considered 84 CMSA/MSAs over the Eastern U.S. (2030)	of cells > 85 ppb in base, % that increase	of cells > 85 ppb in control, % due to the rule	Largest Increase (ppb), cells > 85 in base or control	percent reduction in cells >= 85 ppb (8-hour averages)
Composite Eastern U.S.	3.0%	0.7%	16.1	-20.5%
Composite Western U.S.	11.0%	2.4%	9.3	-13.3%
Areas w/ disbenefits				
New Haven-Bridgeport-Stamford, CT	23.1%	1.8%	2.1	-15.4%
Chicago	16.9%	5.2%	14.2	-13.2%
New York City	14.0%	3.1%	16.1	-13.5%
Detroit	9.6%	1.2%	4.2	-21.6%
New Orleans, LA	2.2%	0.0%	0.8	-4.6%
Philadelphia	1.3%	0.0%	1.8	-28.4%
Houston	0.3%	0.2%	0.9	-13.5%
Phoenix	0.0%	5.1%	1.4	-35.0%
Areas w/o disbenefits				
Baton Rouge, LA	0.0%	0.0%	0	-4.9%
Lake Charles, LA	0.0%	0.0%	0	-7.7%
Beaumont-Port Arthur, TX	0.0%	0.0%	0	-8.6%
Biloxi-Gulfport-Pascagoula, MS	0.0%	0.0%	0	-8.8%
Buffalo-Niagara Falls, NY	0.0%	0.0%	0	-11.1%
Benton Harbor, MI	0.0%	0.0%	0	-11.3%
Macon, GA	0.0%	0.0%	0	-15.9%
Atlanta, GA	0.0%	0.0%	0	-16.0%
New London - Norwich CT	0.0%	0.0%	0	-22.2%
Grand Rapids-Muskegon-Holland, MI	0.0%	0.0%	0	-23.9%
Louisville, KY-IN	0.0%	0.0%	0	-24.1%
Memphis, TN-AR-MS	0.0%	0.0%	0	-26.2%
Pensacola, FL	0.0%	0.0%	0	-26.4%
Barnstable-Yarmouth, MA	0.0%	0.0%	0	-26.7%
Columbus, GA-AL	0.0%	0.0%	0	-26.7%
Harrisburg-Lebanon-Carlisle, PA	0.0%	0.0%	0	-27.9%
Chattanooga, TN	0.0%	0.0%	0	-28.6%

Providence, RI	0.0%	0.0%	0	-29.8%
Richmond-Petersburg, VA	0.0%	0.0%	0	-30.0%
Bakersfield, CA	0.0%	0.0%	0	-31.3%
Charleston, WV	0.0%	0.0%	0	-33.3%
Hartford, CT	0.0%	0.0%	0	-33.3%
Milwaukee	0.0%	0.0%	0	-33.9%
Huntington-Ashland, WV-KY-OH	0.0%	0.0%	0	-34.5%
Shreveport, LA	0.0%	0.0%	0	-36.4%
Sheboygan, WI	0.0%	0.0%	0	-37.5%
Augusta-Aiken, GA-SC	0.0%	0.0%	0	-40.0%
Cincinnati	0.0%	0.0%	0	-44.0%
St. Louis, MO-IL	0.0%	0.0%	0	-44.2%
Boston	0.0%	0.0%	0	-47.8%
Pittsburgh, PA	0.0%	0.0%	0	-48.9%
Birmingham, AL	0.0%	0.0%	0	-49.1%
Lancaster, PA	0.0%	0.0%	0	-50.0%
Reading, PA	0.0%	0.0%	0	-50.0%
Toledo, OH	0.0%	0.0%	0	-50.0%
Washington-Baltimore	0.0%	0.0%	0	-53.9%
Evansville-Henderson, IN-KY	0.0%	0.0%	0	-54.5%
Canton-Massillon, OH	0.0%	0.0%	0	-57.1%
Cleveland	0.0%	0.0%	0	-58.0%
Nashville, TN	0.0%	0.0%	0	-59.6%
Norfolk-Virginia Beach-Newport News	0.0%	0.0%	0	-61.5%
Columbus, OH	0.0%	0.0%	0	-64.7%
Little Rock, AR	0.0%	0.0%	0	-66.7%
Charlotte-Gastonia-Rock Hill, NC-SC	0.0%	0.0%	0	-71.4%
Springfield, MA	0.0%	0.0%	0	-71.4%
Parkersburg-Marietta, WV	0.0%	0.0%	0	-75.0%
San Diego, CA	0.0%	0.0%	0	-75.0%
Sarasota-Bradenton, FL	0.0%	0.0%	0	-75.0%
Youngstown-Warren, OH	0.0%	0.0%	0	-77.8%
Allentown-Bethlehem-Easton, PA	0.0%	0.0%	0	-80.0%
Longview-Marshall, TX	0.0%	0.0%	0	-80.0%
Scranton-Wilkes Barre, PA	0.0%	0.0%	0	-81.5%
Erie, PA	0.0%	0.0%	0	-81.8%

Jamestown, NY	0.0%	0.0%	0	-83.3%
Janesville-Beloit, WI	0.0%	0.0%	0	-84.6%
Indianapolis, IN	0.0%	0.0%	0	-87.5%
Areas w/ no exceedances in control				
Dallas	0.0%		0	-100.0%
Dayton-Springfield, OH	0.0%		0	-100.0%
Tulsa, OK	0.0%		0	-100.0%
York, PA	0.0%		0	-100.0%
Areas w/ no exceedances in base or control				
Austin-San Marcos, TX			0	
Clarksville-Hopkinsville, TN-KY			0	
Columbia, SC			0	
Dover, DE			0	
Fayetteville, NC			0	
Fort Wayne, IN			0	
Greensboro-Winston Salem, NC			0	
Greenville-Spartanburg, SC			0	
Hickory-Morganton, NC			0	
Huntsville, AL			0	
Johnson City, TN			0	
Johnstown, PA			0	
Knoxville, TN			0	
Lima, OH			0	
Montgomery, AL			0	
Raleigh-Durham, NC			0	
Roanoke, VA			0	
Rocky Mount, NC			0	
Sharon, PA			0	

IV. Particulate Matter Modeling over the Continental U.S.

A. REMSAD Model Description

The REgional Modeling System for Aerosols and Deposition (REMSAD) Version 7.01 (ICF Kaiser, 2002) model was used as the tool for simulating Base Year and future concentrations of PM in support of the NLDE air quality assessments. Model runs were made for the 1996 Base Year as well as for the 2020 and 2030 Base and Control scenarios. As described below, each of these emissions scenarios was simulated using 1996 meteorological data in order to provide the annual mean PM concentrations, nitrogen deposition, and estimates of visibility needed for the PM "exposure" analysis and benefits calculations.

The basis for REMSAD is the atmospheric diffusion equation (also called the species continuity or advection/diffusion equation). This equation represents a mass balance in which all of the relevant emissions, transport, diffusion, chemical reactions, and removal processes are expressed in mathematical terms. REMSAD employs finite-difference numerical techniques for the solution of the advection/diffusion equation.

REMSAD was run using a latitude/longitude horizontal grid structure in which the horizontal grids are generally divided into areas of equal latitude and longitude. The vertical layer structure of REMSAD is defined in terms of sigma-pressure coordinates. The top and bottom of the domain are defined as 0 and 1 respectively. The vertical layers are defined as a percent of the atmospheric pressure between the top and bottom of the domain. For example, a vertical layer of 0.50 sigma is exactly halfway between the top and bottom of the domain as defined by the local atmospheric pressure. Usually, the vertical layers are defined to match the vertical layer structure of the meteorological model used to generate the REMSAD meteorological inputs.

1. Gas Phase Chemistry

REMSAD simulates gas phase chemistry using a reduced-form version of Carbon Bond (CB4) chemical mechanism termed "micro-CB4" (mCB4) which treats fewer VOC species compared to the full CB4 mechanism. The inorganic and radical parts of the reduced mechanism are identical to CB4. In this version of mCB4 the organic portion is based on one primary species (VOC) and one primary and secondary carbonyl species (CARB). The VOC species was incorporated with kinetics representing an average anthropogenic hydrocarbon species. A second primary VOC species representing biogenic emissions is also included with kinetic characteristics representing isoprene. The intent of the mCB4 mechanism is to (a) provide a physically faithful representation of the linkages between emissions of ozone precursor species and secondary PM precursors species, (b) treat the oxidizing capacity of the troposphere, represented primarily by the concentrations of radicals and hydrogen peroxide, and (c) simulate the rate of oxidation of the nitrogen oxide (NO_x) and sulfur dioxide (SO_2) PM precursors. Box model testing of mCB4 has found that it performs very closely to the full CB4 that is contained in UAM-V (Whitten, 1999).

REMSAD version 7.01 includes several updates to the mCB4 mechanism relative to earlier versions of REMSAD. A new treatment for the NO_3 and N_2O_5 species has been implemented which results in improved agreement with rigorous solvers such as Gear and eliminates nitrogen mass inconsistencies. Also, several additional reactions have been added to the mCB4 mechanism which may be important for regional scale and annual applications where wide ranges in temperature, pressure, and concentrations may be encountered. The reactions are OH + H, OH + NO_3, and HO_2 + NO_3. For the same reason three reactions involving peroxy nitric acid (PNA), which were included in the original CB4 mechanism, were added to mCB4.

2. PM Chemistry

Primary PM emissions in REMSAD are treated as inert species. They are advected and deposited without any chemical interaction with other species. Secondary PM species, such as sulfate and nitrate are formed through chemical reactions within the model. SO_2 is the gas phase precursor for particulate sulfate, while nitric acid is the gas phase precursor for particulate nitrate. Several other gas phase species are also involved in the secondary reactions.

There are two pathways for sulfate formation; gas phase and aqueous phase. Aqueous phase reactions take place within clouds, rain, and/or fog. In-cloud processes can account for the majority of atmospheric sulfate formation in many areas. In REMSAD, aqueous SO_2 reacts with hydrogen peroxide (H_2O_2), ozone (O_3), and/or oxygen (O_2) to form aerosol sulfate. REMSAD version 7 has been upgraded to include all three aqueous phase sulfate reactions. Previous versions only contained the hydrogen peroxide reaction. The rate of the aqueous phase reactions depends on the concentrations of the chemical reactants as well as cloud water content. SO_2 also reacts with OH radicals in the gas phase to form aerosol sulfate. The aqueous phase and gas phase sulfate is typically added together to get the total sulfate concentration.

An equilibrium algorithm is used to calculate particulate nitrate concentrations. REMSAD version 7.01 uses the MARS-A equilibrium algorithm (Saxena, et al., 1986) and (Kim et al., 1993). In REMSAD, particulate nitrate is calculated in an equilibrium reaction between nitric acid, sulfate, and ammonia. Nitric acid is a product of gas phase chemistry and is formed through the mCB4 reactions. The acids are neutralized by ammonia with sulfate reacting more quickly than nitric acid. An equilibrium is established among ammonium sulfate and ammonium nitrate which strongly favors ammonium sulfate. If the available ammonia exceeds twice the available sulfate then particulate nitrate is allowed to form as ammonium nitrate. Nitrate is then partitioned between particulate nitrate and gas phase nitric acid. The partitioning of nitrate depends on the availability of ammonia as well meteorological factors such as temperature and relative humidity.

Organic aerosols can contribute a significant amount to the PM in the atmosphere. Primary organic aerosols (POA) are treated as a directly emitted species in REMSAD. In REMSAD version 7. A calculation of the production of secondary organic aerosols (SOA) due to atmospheric chemistry processes has been added. A peer review of the REMSAD model (Seigneur et al., 1999) recommended an SOA module based on the equilibrium approach of Pankow (Odum et al., 1997) and (Griffin et al., 1999). The implementation of the SOA treatment in version 7 of REMSAD follows the recommendation of the peer review. This includes SOA formation from anthropogenic and biogenic organic precursors. For both anthropogenic and biogenic organics REMSAD includes gas phase secondary organic species and the corresponding aerosol phase species.

B. REMSAD Modeling Domain

The REMSAD domain used for the NLDE modeling is shown in Figure IV-1. The geographic characteristics of the domain are as follows:

120 (E-W) X 84 (N-S) grid cells
Cell size (~36 km)
    ½ degree longitude (0.5)
    1/3 degree latitude (0.3333)
E-W range: 66 degrees W - 126 degrees W
N-S range: 24 degrees N - 52 degrees N
Vertical extent: Ground to 16,200 meters (100mb) with 12 layers

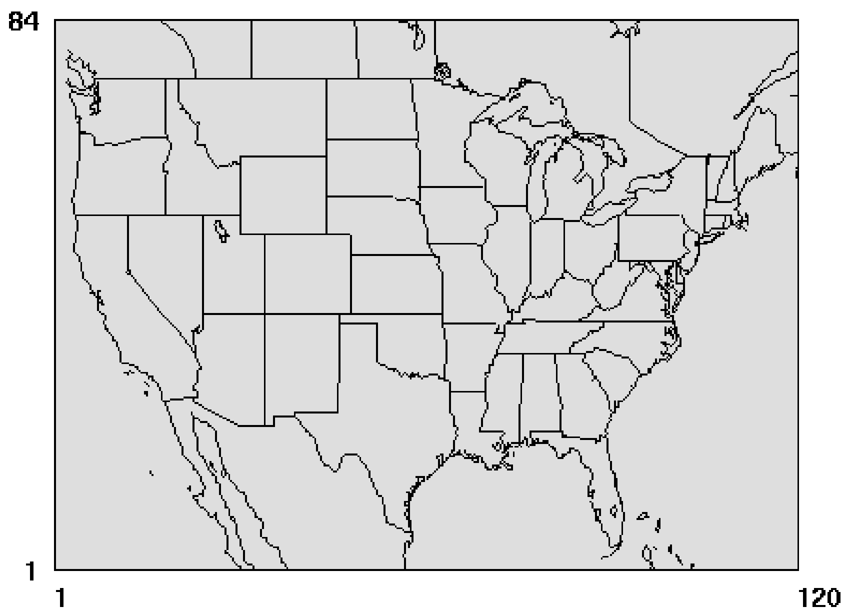


Figure IV-1. REMSAD Modeling Domain.

C. REMSAD Inputs

Input data for REMSAD can be classified into six categories: (1) simulation control, (2) emissions, (3) initial and boundary concentrations, (4) meteorological, (5) surface characteristics, and (6) chemical rates. The REMSAD predictions of pollutant concentrations are calculated from the emissions, advection, and dispersion processes coupled with the formation and deposition of secondary PM species within every grid cell of the modeling domain. To adequately replicate the full three-dimensional structure of the atmosphere, the REMSAD program uses hourly input data for a number of variables. Table IV-1 lists the required REMSAD input files.

Table IV-1. List of REMSAD input files.

Data type	Files	Description
Control	CONTROL	Simulation control information
Emissions	PTSOURCE EMISSIONS	Elevated source emissions Surface emissions
Initial and boundary concentrations	AIRQUALITY BOUNDARY	Initial concentrations Lateral boundary concentrations
Meteorological	WIND TEMPERATURE PSURF H2O VDIFFUSION RAIN	X,Y-components of winds 3D array of temperature 2D array of surface pressure 3D array of water vapor 3D array of vertical turbulent diffusivity coefficients 3D array of cloud water mixing ratio 3D array of rain water mixing ratio 2D array of rainfall rates
Surface characteristics	SURFACE TERRAIN	Gridded land use Terrain heights
Chemical rates	CHEMPARAM RATES	Chemical reaction rates Photolysis rates file

1. Meteorological Data

REMSAD requires input of winds (u- and v-vector wind components), temperatures, surface pressure, specific humidity, vertical diffusion coefficients, and rainfall rates. The meteorological input files were developed from a 1996 annual MM5 model run that was developed for previous projects. MM5 is the Fifth-Generation NCAR / Penn State Mesoscale Model. MM5 (Grell *et. al.*, 1994) is a numerical meteorological model that solves the full set of physical and thermodynamic equations which govern atmospheric motions. MM5 was run in a nested-grid mode with 2 levels of resolution: 108 km, and 36km with 23 vertical layers sigma layers extending from the surface to the 100 mb pressure level. The model was simulated in five day segments with an eight hour ramp-up period. The MM5 runs were started at 00Z, which is 7:00 p.m. EST. The first eight hours of each five day period were removed before being input into REMSAD. Figure IV-2 shows the MM5 and REMSAD 36km domain superimposed on each other. Table IV-2 lists the vertical grid structures for the MM5 and REMSAD domains. Further detailed information concerning the development and evaluation of the 1996 MM5 datasets can be found in (Olerud, 2000**).**

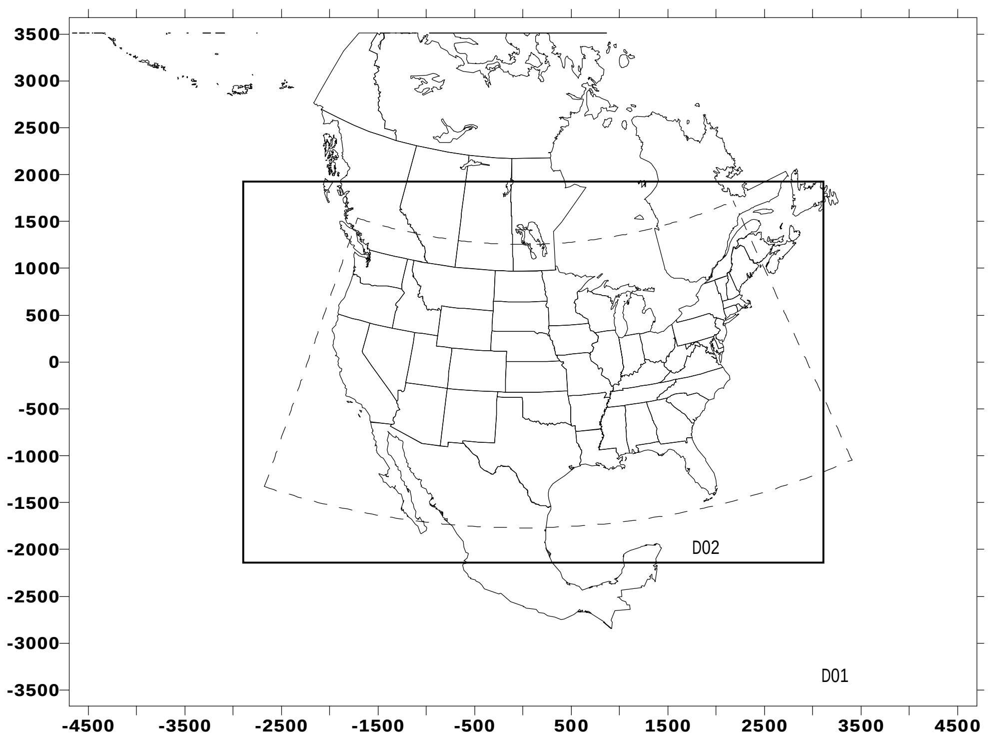


Figure IV-2. MM5 36km Domain (solid box) and REMSAD Domain (dashed lines).

Table IV-2. Vertical Grid Structure for 1996 MM5 and NLDE REMSAD Domains. Layer heights represent the top of each layer. The first layer is from the ground up to 38 meters.

REMSAD Layer	MM5 Layer	Sigma	Approximate Height(m)	Pressure(mb)
0	0	1.000	0.0	1000.0
1	1	0.995	38.0	995.5
2	2	0.988	91.5	989.2
	3	0.980	152.9	982.0
3	4	0.970	230.3	973.0
	5	0.956	339.5	960.4
4	6	0.938	481.6	944.2
	7	0.916	658.1	924.4
5	8	0.893	845.8	903.7
	9	0.868	1053.9	881.2
6	10	0.839	1300.7	855.1
	11	0.808	1571.4	827.2
7	12	0.777	1849.6	799.3
	13	0.744	2154.5	769.6
8	14	0.702	2556.6	731.8
	15	0.648	3099.0	683.2
9	16	0.582	3805.8	623.8
	17	0.500	4763.7	550.0
10	18	0.400	6082.5	460.0
	19	0.300	7627.9	370.0
11	20	0.200	9510.5	280.0
	21	0.120	11465.1	208.0
	22	0.052	13750.2	146.0
12	23	0.000	16262.4	100.0

The physical options selected for this configuration of MM5 include the following:

1. One-way nested grids
2. Nonhydrostatic dynamics
3. Four-dimensional data assimilation (FDDA):
   - Analysis nudging of wind, temperature, and mixing ratios
   - Nudging coefficients range from 1.0×10^{-5} s^{-1} to 3.0×10^{-4} s^{-1}
4. Explicit moisture treatment:

- 3-D predictions of cloud and precipitation fields
- Simple ice microphysics (summer) and Mixed ice microphysics (winter)
- Cloud effects on surface radiation
- Moist vertical diffusion in clouds
- Normal evaporative cooling

5. Boundary conditions:
    - Time and inflow/outflow relaxation
6. Cumulus cloud parameterization schemes:
    - Anthes-Kuo (108-km grid)
    - Kain-Fritsch (36-km grid)
7. No shallow convection
8. Full 3-dimensional Coriolis force
9. Drag coefficients vary with stability
10. Vertical mixing of momentum in mixed layer
11. Virtual temperature effects
12. PBL process parameterization: MRF scheme
13. Surface layer parameterization:
    - Fluxes of momentum, sensible and latent heat
    - Ground temperature prediction using energy balance equation
    - 24 land use categories
14. Atmospheric radiation schemes:
    - Simple cooling
    - Long- and short-wave radiation scheme
15. Sea ice treatment:
    - Forced Great Lakes/Hudson Bay to permanent ice under very cold conditions
    - 36-km treatment keyed by observations of sea ice over the Great Lakes
16. Snow cover:
    - Assumed no snow cover for July and August
    - National Center for Environmental Prediction (NCEP) snow cover for January to June, and for September to December

The MM5 model output cannot be directly input into REMSAD due to differences in the grid coordinate systems and file formats. A postprocessor called MM5-REMSAD was developed to convert the MM5 data into REMSAD format. This postprocessor was used to develop hourly average meteorological input files from the MM5 output. Documentation of the MM5REMSAD code and further details on the development of the input files is contained in (Mansell, 2000).

2. Initial and Boundary Conditions, and Surface Characteristics

Application of the REMSAD modeling system requires data files specifying the initial species concentration fields (AIRQUALITY) and lateral species concentrations (BOUNDARY). Due to the extent of the proposed modeling domains and the regional-scale nature of the REMSAD model, these inputs were developed based on “clean” background concentration values. The NLDE modeling used temporally and spatially (horizontal) invariant data for both initial and boundary conditions. Species concentration values were allowed to decay vertically for most species. Table IV-3 summarizes the initial and boundary conditions used in the NLDE REMSAD modeling.

Table IV-3. REMSAD Initial and Boundary Conditions (ppm)

	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5	Layer 6	Layer 7	Layer 8	Layer 9	Layer 10	Layer 11	Layer 12
NO	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	8.44E-13	5.15E-13	1.72E-13	1.72E-13
NO2	1.00E-04	1.00E-04	1.00E-04	1.00E-04	1.00E-04	1.00E-04	1.00E-04	1.00E-04	8.44E-05	5.15E-05	1.72E-05	1.72E-05
O3	3.50E-02	3.50E-02	3.50E-02	3.50E-02	4.00E-02	4.00E-02	5.00E-02	5.00E-02	6.00E-02	6.00E-02	6.00E-02	7.00E-02
CO	8.00E-02	8.00E-02	8.00E-02	8.00E-02	8.00E-02	8.00E-02	8.00E-02	8.00E-02	8.00E-02	8.00E-02	8.00E-02	8.00E-02
SO2	3.00E-04	3.00E-04	3.00E-04	3.00E-04	3.00E-04	3.00E-04	3.00E-04	3.00E-04	2.53E-04	1.55E-04	5.15E-05	5.15E-05
NH3	1.00E-04	1.00E-04	1.00E-04	1.00E-04	1.00E-04	1.00E-04	1.00E-04	1.00E-04	7.12E-05	2.66E-05	2.95E-06	2.95E-06
VOC	2.00E-02	2.00E-02	2.00E-02	2.00E-02	2.00E-02	2.00E-02	2.00E-02	2.00E-02	1.69E-02	1.03E-02	3.44E-03	3.44E-03
CARB	1.00E-07	1.00E-07	1.00E-07	1.00E-07	1.00E-07	1.00E-07	1.00E-07	1.00E-07	1.00E-07	1.00E-07	1.00E-07	1.00E-07
ISOP	1.00E-09	1.00E-09	1.00E-09	1.00E-09	1.00E-09	1.00E-09	1.00E-09	1.00E-09	1.00E-09	1.00E-09	1.00E-09	1.00E-09
HNO3	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	8.44E-06	5.15E-06	1.72E-06	1.72E-06
PNO3	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	7.12E-06	2.66E-06	2.95E-07	2.95E-07
HG0	2.00E-07	2.00E-07	2.00E-07	2.00E-07	2.00E-07	2.00E-07	2.00E-07	2.00E-07	1.42E-07	5.31E-08	5.90E-09	5.90E-09
HG2G	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	7.12E-13	2.66E-13	2.95E-14	2.95E-14
GSO4	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	7.12E-06	2.66E-06	2.95E-07	2.95E-07
ASO4	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	7.12E-13	2.66E-13	2.95E-14	2.95E-14
NH4N	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	7.12E-06	2.66E-06	2.95E-07	2.95E-07
NH4S	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05	7.12E-06	2.66E-06	2.95E-07	2.95E-07
SOA	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	7.12E-04	2.66E-04	2.95E-05	2.95E-05
POA	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	7.12E-04	2.66E-04	2.95E-05	2.95E-05
PEC	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	7.12E-04	2.66E-04	2.95E-05	2.95E-05
PMFINE	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	7.12E-04	2.66E-04	2.95E-05	2.95E-05
PMCOARS	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	1.00E-03	6.00E-04	1.37E-04	5.07E-06	5.07E-06
HG2P	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	7.12E-13	2.66E-13	2.95E-14	2.95E-14

Application of the REMSAD model requires specification of gridded terrain elevations (TERRAIN) and landuse characteristics (SURFACE). The SURFACE data files provides the fraction of the 11 landuse categories recognized by REMSAD in each grid cell. Landuse characteristics are used in the model for the calculation of deposition parameters. For this task, a landuse/terrain processor, PROC_LUTERR, was developed based on the MM5 TERRAIN preprocessor. Landuse data was obtained from the USGS Global 30 sec. vegetation database which is the same database used in the 1996 MM5 models runs. This dataset provides 24 landuse categories, including urban. For the REMSAD application, the 10 min. (1/6 deg.) datasets was utilized. The processor remapped the 24 USGS vegetation categories to those required for application of REMSAD. It also aggregated the 10 min resolution data to the ~36 km horizontal resolution used for this REMSAD application.

For the TERRAIN input data files, a similar global terrain elevation dataset is also available from NCAR and was used for this task. While it is possible to use the terrain elevations obtained from the MM5 model output data files, it was deemed more appropriate to begin with the USGS 10 min. resolution database due to the various map projections and interpolations involved in developing the required data files for the geodetic coordinates used in REMSAD. However, because proper application of REMSAD will require zero terrain elevations, "dummy" terrain files (with all zeroes) were developed and provided for input to REMSAD.

D. Model Performance Evaluation

The goal of the 1996 Base Year modeling was to reproduce the atmospheric processes resulting in formation and dispersion of fine particulate matter across the U.S. An operational model performance evaluation for $PM_{2.5}$ and its related speciated components (e.g., sulfate, nitrate, elemental carbon etc.) for 1996 was performed in order to estimate the ability of the modeling system to replicate Base Year concentrations. All of the observational data used in this analysis can be found at the CAPITA website:

http://capita.wustl.edu/datawarehouse/Datasets/CAPITA/NAMPM_fine/Data/NAMPM_f.html

This evaluation is comprised principally of statistical assessments of model versus observed pairs. The robustness of any evaluation is directly proportional to the amount and quality of the ambient data available for comparison. Unfortunately, there are few $PM_{2.5}$ monitoring networks with available data for evaluation of the NLDE PM modeling. Critical limitations of the 1996 databases are a lack of urban monitoring sites with speciated measurements and poor geographic representation of ambient concentration in the East. $PM_{2.5}$ monitoring networks were expanded in 1999 to include more than 1000 Federal Reference Method (FRM) monitoring sites. The purpose of this network is to monitor $PM_{2.5}$ mass levels in urban areas. These monitors only measure total $PM_{2.5}$ mass and do not measure PM species. In 2002 a new network of ~300 urban oriented speciation monitor sites began operation across the country. These monitors collect a full range of $PM_{2.5}$ species that are necessary to evaluate models and to develop $PM_{2.5}$ control strategies.

The largest available ambient database for 1996 comes from the **I**nteragency **M**onitoring of **PRO**tected **V**isual **E**nvironments (IMPROVE) network. IMPROVE is a cooperative visibility monitoring effort between EPA, federal land management agencies, and state air agencies. Data is collected at Class I areas across the United States mostly at National Parks, National Wilderness Areas, and other protected pristine areas (IMPROVE 2000). There were approximately 60 IMPROVE sites that had complete annual $PM_{2.5}$ mass and/or $PM_{2.5}$ species data for 1996. Forty two sites were in the West[11] and 18 sites were in the East. Figure IV-3 shows the locations of the IMPROVE monitoring sites used in this evaluation. IMPROVE data is collected twice weekly (Wednesday and Saturday). Thus, there is a total of 104 possible samples per year or 26 samples per season. For this analysis, a 50% completeness criteria was used. That is, in order to be counted in the statistics a site had to have > 50% complete data in all 4 seasons. If any season was missing, an annual average was not calculated for the site. See Appendix G for a list of the IMPROVE sites used in the evaluation. The observed IMPROVE data used for the performance evaluation was $PM_{2.5}$ mass, sulfate ion, nitrate ion, elemental carbon, organic

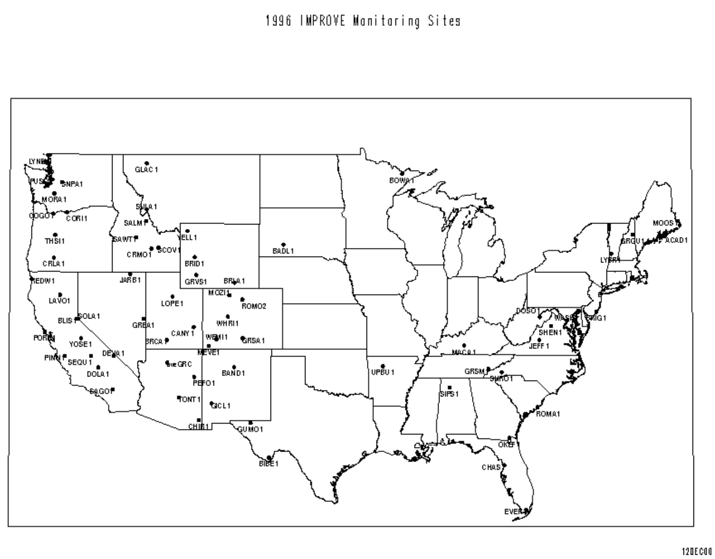
[11]The dividing line between the West and East was defined as the 100th meridian.

aerosols, and crustal material (soils). The REMSAD model output species were postprocessed in order to achieve compatibility with the observation species. The following is the translation of REMSAD output species into $PM_{2.5}$ and related species:

Sulfate Ion:	TSO4 = ASO4 + GSO4
Nitrate Ion:	PNO3
Anthropogenic SOA	SOA1 + SOA2
Biogenic SOA	SOA3 + SOA4
Organic aerosols:	TOA = 1.167POA + SOA1 + SOA2 + SOA3 + SOA4
Elemental Carbon:	PEC
Crustal Material (soils):	PMFINE
$PM_{2.5}$:	$PM_{2.5}$ = PMFINE + ASO4 + GSO4 + NH4S + PNO3 + NH4N + 1.167*POA + PEC + SOA1 + SOA2 + SOA3 + SOA4

where, TSO4 is total sulfate ion, ASO4 is aqueous path sulfate, GSO4 is gaseous path sulfate, NH4S is ammonium associated with sulfate, PNO3 is nitrate ion, NH4N is ammonium associated with nitrate, TOA is total organic aerosols, POA is primary organic aerosol, SOA1 and SOA2 are anthropogenic secondary organic aerosol, SOA3 and SOA4 are biogenic secondary organic aerosol, PEC is primary elemental carbon, and PMFINE is primary fine particles (other unspeciated primary $PM_{2.5}$). $PM_{2.5}$ is defined as the sum of the individual species. POA is multiplied by 1.167 to make modeled organic mass equivalent to monitored organic mass.

Figure IV-3. Map of 1996 IMPROVE monitoring sites used in the REMSAD model



performance evaluation.

1. Statistical Definitions

Below are the definitions of statistics used for the evaluation. The format of all the statistics is such that negative values indicate model predictions that were less than their observed counterparts. Positive statistics indicate model overestimation of observed PM.. The statistics were calculated for the entire REMSAD domain and separated for the east and the west. The dividing line between East and West is the 100^{th} meridian.

Mean Observation: The mean observed value (in ug/m3) averaged over all monitored days in the year and then averaged over all sites in the region.

$$OBS = \frac{1}{N} \sum_{i=1}^{N} Obs_{x,t}^{i}$$

Mean REMSAD Prediction: The mean predicted value (in ug/m3) paired in time and space with the observations and then averaged over all sites in the region.

$$PRED = \frac{1}{N} \sum_{i=1}^{N} Pred_{x,t}^{i}$$

Ratio of the Means: Ratio of the predicted over the observed values. A ratio of greater than 1 indicates on overprediction and a ratio of less than 1 indicates an underprediction.

$$RATIO = \frac{1}{N} \sum_{i=1}^{N} \frac{Pred_{x,t}^{i}}{Obs_{x,t}^{i}}$$

Mean Bias (ug/m3): This performance statistic averages the difference (model - observed) over all pairs in which the observed values were greater than zero. A mean bias of zero indicates that the model over predictions and model under predictions exactly cancel each other out. Note that the model bias is defined such that it is a positive quantity when model prediction exceeds the observation, and vice versa. This model performance estimate is used to make statements about the absolute or unnormalized bias in the model simulation

$$BIAS = \frac{1}{N} \sum_{i=1}^{N} (Pred_{x,t}^{i} - Obs_{x,t}^{i})$$

Mean Fractional Bias (percent): Normalized bias can become very large when a minimum threshold is not used. Therefore fractional bias is used as a substitute. The fractional bias for cases with factors of 2 under- and over-prediction are -67 and + 67 percent, respectively (as opposed to -50 and +100 percent, when using normalized bias, which is not presented here). Fractional bias is a useful model performance indicator because it has the advantage of equally weighting positive and negative bias estimates. The single largest disadvantage in this estimate of model performance is that the estimated concentration (i.e., prediction, Pred) is found in both the numerator and denominator.

$$FBIAS = \frac{2}{N}\sum_{i=1}^{N}\frac{(Pred_{x,t}^{i} - Obs_{x,t}^{i})}{(Pred_{x,t}^{i} + Obs_{x,t}^{i})} * 100$$

Mean Error (ug/m3): This performance statistic averages the absolute value of the difference (model - observed) over all pairs in which the observed values were greater than zero. It is similar to mean bias except that the absolute value of the difference is used so that the error is always positive.

$$ERR = \frac{1}{N}\sum_{i=1}^{N}\left|Pred_{x,t}^{i} - Obs_{x,t}^{i}\right|$$

Mean Fractional Error: Normalized error can become very large when a minimum threshold is not used. Therefore fractional error is used as a substitute. It is similar to the fractional bias except the absolute value of the difference is used so that the error is always positive.

$$FERROR = \frac{2}{N}\sum_{i=1}^{N}\frac{\left|Pred_{x,t}^{i} - Obs_{x,t}^{i}\right|}{Pred_{x,t}^{i} + Obs_{x,t}^{i}} * 100$$

2. Results of REMSAD Performance Evaluation

The statistics described above are presented for the entire domain, the Eastern sites, and the Western sites. The model's ability to replicate annual average $PM_{2.5}$ and $PM_{2.5}$ species concentrations at the IMPROVE sites is as follows:

a. $PM_{2.5}$ Performance

Table IV-4 lists the performance statistics for $PM_{2.5}$ at the IMPROVE sites. For the full domain, $PM_{2.5}$ is underpredicted by 34%. The ratio of the means is 0.66 with a bias of -2.12 ug/m3. It can be seen that most of this underprediction is due to the Western sites. The West is underpredicted by 50% while the East is underpredicted by 18%. The fractional bias is ~24% in the East, while the fractional error is 49.5%. The fractional bias and error in the West is 52.5% and 77% respectively. The observed $PM_{2.5}$ concentrations in the East are relatively high compared to the West. REMSAD displays an ability to differentiate between generally high and low $PM_{2.5}$ areas.

Table IV-4. Annual mean $PM_{2.5}$ performance at IMPROVE sites.

	No. of Sites	Mean REMSAD Predictions (ug/m3)	Mean Observations (ug/m3)	Ratio of Means (pred/obs)	Bias (ug/m3)	Fractional Bias (%)	Error (ug/m3)	Fractional Error (%)
National	54	4.09	6.21	0.66	-2.12	-44.6	3.29	69.4
East	15	9.17	11.15	0.82	-1.98	-24.1	4.57	49.5
West	39	2.13	4.31	0..50	-2.18	-52.5	2.80	77.0

b. Sulfate Performance

Table IV-5 lists the performance statistics for particulate sulfate at the IMPROVE sites. Domainwide, sulfate performance is better than PM2.5 with a sulfate underprediction of 20%. The annual sulfate underprediction in the east is 11% and 40% in the West.

Table IV-5. Annual mean sulfate ion performance at IMPROVE sites.

	No. of Sites	Mean REMSAD Predictions (ug/m3)	Mean Observations (ug/m3)	Ratio of Means (pred/obs)	Bias (ug/m3)	Fractional Bias (%)	Error (ug/m3)	Fractional Error (%)
National	58	1.26	1.59	0.80	-0.32	-39.5	0.80	69.3
East	16	3.50	3.93	0..89	-0.43	-29.2	1.82	60.5
West	42	0.42	0.69	0.60	-0.28	-43.4	0.42	72.6

c. Elemental Carbon Performance

Table IV-6 lists the performance statistics for primary elemental carbon at the IMPROVE sites. Performance for elemental carbon is very good in the east with a 0% bias. There is a domainwide underprediction of 15% and a western underprediction of 29%.

Table IV-6. Annual mean elemental carbon performance at IMPROVE sites.

	No. of Sites	Mean REMSAD Predictions (ug/m3)	Mean Observations (ug/m3)	Ratio of Means (pred/obs)	Bias (ug/m3)	Fractional Bias (%)	Error (ug/m3)	Fractional Error (%)
National	47	0.27	0.32	0.85	-0.05	-13.9	0.17	58.7
East	15	0.487	0.484	1.00	0.003	1.13	0.20	41.7
West	32	0.17	0.24	0.71	-0.07	-21.1	0.16	66.8

d. Organic Aerosol Performance

Table IV-7 lists the performance statistics for primary organic aerosols at the IMPROVE sites. Organic aerosols are underpredicted nationwide. The East and West are equally underpredicted by about 45%. Both the fractional bias and fractional errors are higher than for PM2.5, sulfate, and elemental carbon. It is clear that the model and the emissions inventory are not accounting for all of the organics that were observed. Wild fires which produce a lot of organic aerosol emissions were not included in the modeling. This may be important for model evaluation, but not necessarily for the NLDE analysis. Also, improvements to the REMSAD secondary organic aerosol (SOA) module are currently taking place which will lead to greater SOA production in future model runs.

Table IV-7. Annual mean organic aerosol performance at IMPROVE sites.

	No. of Sites	Mean REMSAD Predictions (ug/m3)	Mean Observations (ug/m3)	Ratio of Means (pred/obs)	Bias (ug/m3)	Fractional Bias (%)	Error (ug/m3)	Fractional Error (%)
National	47	0.94	1.76	0.54	-0.82	-53.9	1.18	82.9
East	15	1.41	2.49	0.56	-1.08	-57.4	1.49	74.9
West	32	0.72	1.41	0.51	-0.69	-52.3	1.04	86.7

e. Nitrate Performance

Table IV-8 lists the performance statistics for nitrate ion at the IMPROVE sites. Nitrate is generally overpredicted in the East and underpredicted in the West. Nitrate is overpredicted by 82% in the east and underpredicted by 55% in the west. Domainwide there is an overprediction of 4%.

It is important to consider these results in the context that the observed nitrate concentrations at the IMPROVE sites are very low. The mean nationwide observations are only 0.40 ug/m3. It is often difficult for models to replicate very low concentrations of secondarily formed pollutants. Nitrate is generally a small percentage of the measured $PM_{2.5}$ at almost all of the IMPROVE sites. Nitrate can be an important contributor to $PM_{2.5}$ in some urban areas (particularly in California) but performance for those areas could not be assessed due to the lack of urban area speciated nitrate data for 1996.

Table IV-8. Annual mean nitrate ion performance at IMPROVE sites.

	No. of Sites	Mean REMSAD Predictions (ug/m3)	Mean Observations (ug/m3)	Ratio of Means (pred/obs)	Bias (ug/m3)	Fractional Bias (%)	Error (ug/m3)	Fractional Error (%)
National	48	0.41	0.39	1.04	0.02	-86.4	0.43	134.1
East	15	1.00	0.55	1.82	0.45	-16.1	0.74	106.2
West	33	0.14	0.32	0.45	-0.18	-118.0	0.29	146.7

f. PMFINE-Other (crustal) Performance

Table IV-9 lists the performance statistics for PMFINE-other or primary crustal emissions. The observations show crustal $PM_{2.5}$ to be generally higher in the West than in the East. But REMSAD is predicting higher crustal concentrations in the East. The largest categories of PMFINE-other are fugitive dust sources such as paved roads, unpaved roads, construction, and animal feed lots. There is a large uncertainty in the handling of these emissions in the inventory. It is apparent that too much fugitive dust is being emitted in the East. It is evident from the performance statistics that further work needs to be done to study the magnitude of these emissions and how they are emitted into the model.

Table IV-9. Annual mean PMFINE (crustal) performance at IMPROVE sites.

	No. of Sites	Mean REMSAD Predictions (ug/m3)	Mean Observations (ug/m3)	Ratio of Means (pred/obs)	Bias (ug/m3)	Fractional Bias (%)	Error (ug/m3)	Fractional Error (%)
National	57	0.85	0.64	1.32	0.21	38.4	0.79	93.7
East	16	1.62	0.53	3.04	1.09	103.1	1.34	115.6
West	41	0.56	0.69	0.81	-0.13	13.2	0.58	85.2

g. Summary of Model Performance Results Using Improve Data

The purpose of this model performance evaluation was to evaluate the capabilities of the REMSAD modeling system in reproducing annual average concentrations for all IMPROVE sites in the contiguous U.S. for fine particulate mass and its associated speciated components. When considering annual average statistics (e.g., predicted versus observed), which are computed and aggregated over all sites and all days, REMSAD underpredicted fine particulate mass ($PM_{2.5}$), by 34%.. $PM_{2.5}$ in the Eastern U.S. was underpredicted by 18%, while $PM_{2.5}$ in the West was underpredicted by 50%. All PM2.5 component species were underpredicted in the west. In the east nitrate and crustal material are significantly overestimated. Elemental carbon shows neither over or underprediction in the east with a bias of 0%. Eastern sulfate is slightly underpredicted with a bias of 11%. Organic aerosol is significantly underpredicted in both the east and west.

It should be noted that $PM_{2.5}$ modeling is an evolving science. There have been few regional or national scale model applications for primary and secondary PM. In fact, this is the one of the first nationwide applications of a full chemistry Eulerian grid model for the purpose of estimating annual average concentrations of $PM_{2.5}$ and its component species. Also, unlike ozone modeling, there is essentially no database of past performance statistics against which to measure the performance of the NLDE PM modeling. Given the state of the science relative to PM modeling, it is inappropriate to judge PM model performance using criteria derived for other pollutants, like ozone. Still, the performance of the NLDE PM modeling is very encouraging, especially considering that the results may be limited by our current knowledge of PM science and chemistry, and by the emissions inventories for primary PM and secondary PM precursor pollutants.

E. Visibility Calculations

Several visibility parameters were calculated from the REMSAD model output for use in the benefits analysis. These included light extinction coefficient (b_{ext}) and deciviews. The extinction coefficient values in units of inverse megameters (1/M) were calculated based on the IMPROVE protocol (IMPROVE, 2000). The reconstructed bext values were calculated as follows:

$$b_{ext} = 10.0 + [3.0 * f(RH) * (1.375 * (GSO4 + ASO4)) + 3.0 * f(RH) * (1.29 * PNO3) + 4.0 * (TOA) + 10.0 * PEC + 1.0 * (PMFINE) + 0.6 * (PMCOARS)]$$

The 10.0 initial value accounts for atmospheric background (i.e., Rayleigh) scattering. f(RH) refers to the relative humidity correction function as defined by IMPROVE (2000). The relative humidity correction factor was calculated from the 3-hour average modeled relative humidity at each grid cell for each time period. The 3-hour average b_{ext} was then calculated. All of the hours in the day were then averaged to derive a daily average b_{ext} for each grid cell. The daily average b_{ext} were averaged to derive the annual average b_{ext}. The annual average b_{ext} were used to calculate the annual average deciviews (dv) using the following formula:

$$dv = 10.0 * \ln\left[\frac{(b_{ext})}{10.0\ Mm^{-1}}\right]$$

F. Projected Future PM2.5 Design Values

In order to assess the need for the NLDE controls and the impacts of these controls on PM2.5 air quality, EPA projected 1999-2001 ambient PM2.5 design values (EPA, 2003b) to the 2020 and 2030 future year Base and Control scenarios. To provide the future-year estimates of PM2.5 concentrations, relative reduction factors (RRFs) were calculated then applied to the ambient data. The procedures for determining the RRFs are similar to those in EPA's draft guidance for demonstrating attainment of air quality goals for PM2.5 and regional haze (EPA, 2000b). One aspect of the procedures in the guidance is to develop RRFs for each component species of PM2.5 and then to apply these to the corresponding species measured at the monitoring site. However, the only extensive nationwide data base of ambient PM2.5 data available at the time of this analysis does not contain speciated data. Thus, the RRFs were calculated for PM2.5 and applied to the monitoring data as described as follows. First, the REMSAD predictions of individual PM2.5 component species were postprocessed to provide annual mean PM2.5 concentrations in each grid cell for the 1996 Base Year and each future year scenario modeled (i.e., 2020 Base and Control and 2030 Base and Control). The gridded data were used to determine RRFs at each monitoring site with valid annual mean PM2.5 data. The RRFs were calculated as the ratio of mean PM2.5 in the future-year scenario to the mean for the 1996 Base Year. This value was then multiplied by the ambient PM2.5 concentration at the monitoring site to provide an estimate of the future PM2.5 concentrations at that site. The annual mean 1999-2001 PM2.5 county maximum design values along with the corresponding future-year estimates, based on RRFs, are provided in Appendix H. Future year 2020 and 2030 county population totals are also included in this appendix.

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Appendix A
8-Hour Ozone Design Values for 1999-2001and 2020 and 2030 Base Case and Control Case Scenarios.

Nonroad Proposal 8-Hr Ozone Design Values

[Note: Nevada Cnty in CA is monitoring nonattainment, but is not included below because model predictions for the location of monitoring sites in this counties are below the 70ppb cut off used for calculating RRFs]

FIPS St	FIPS Cty	State	County	1999 - 2001 DV	2020 Base	2020 Control	2030 Base	2030 Control		2000 Pop	2020 Pop	2030 Pop
1	27	Alabama	Clay	84	67	66	67	65		14,254	15,600	16,298
1	51	Alabama	Elmore	79	63	62	64	62		65,874	88,634	100,566
1	73	Alabama	Jefferson	89	66	64	66	63		662,047	679,713	690,896
1	79	Alabama	Lawrence	82	63	62	63	61		34,803	38,685	40,689
1	89	Alabama	Madison	87	68	67	68	66		276,700	343,075	378,069
1	101	Alabama	Montgomery	85	68	66	68	66		223,510	257,634	275,746
1	117	Alabama	Shelby	96	70	68	70	67		143,293	259,341	320,220
1	119	Alabama	Sumter	75	58	57	59	57		14,798	14,214	13,964
4	13	Arizona	Maricopa	85	80	79	81	80		3,072,149	4,513,344	5,266,724
4	19	Arizona	Pima	72	62	61	62	60		843,746	1,168,864	1,338,830
5	35	Arkansas	Crittenden	92	83	81	83	81		50,866	54,912	57,013
5	97	Arkansas	Montgomery	69	56	55	56	54		9,245	10,446	11,141
5	101	Arkansas	Newton	78	62	60	62	59		8,608	9,490	10,042
5	119	Arkansas	Pulaski	87	72	70	72	69		361,474	382,366	393,433
6	1	California	Alameda	62	60	60	61	60		1,443,741	1,684,320	1,812,462
6	5	California	Amador	91	67	64	67	62		35,100	50,906	59,249
6	9	California	Calaveras	94	70	68	70	66		40,554	56,980	65,483
6	13	California	Contra Costa	82	73	72	74	72		948,816	1,217,061	1,356,529
6	17	California	El Dorado	104	72	69	70	66		156,299	235,742	277,664
6	19	California	Fresno	108	93	91	93	90		799,407	1,010,798	1,121,458
6	25	California	Imperial	92	74	72	74	71		142,361	183,499	204,781
6	27	California	Inyo	79	67	66	67	65		17,945	19,672	20,783
6	29	California	Kern	109	94	92	94	91		661,645	851,039	949,174
6	31	California	Kings	98	80	78	81	77		129,461	171,603	193,641
6	37	California	Los Angeles	105	121	120	123	120		9,519,338	10,068,317	10,397,571
6	39	California	Madera	88	72	70	72	69		123,109	185,860	218,860
6	43	California	Mariposa	91	70	68	70	67		17,130	21,798	24,289
6	47	California	Merced	101	82	80	83	79		210,554	261,895	288,668
6	53	California	Monterey	63	46	44	46	43		401,762	478,637	519,176
6	59	California	Orange	77	101	100	101	100		2,846,289	3,681,637	4,114,415

6	61	California	Placer	101	71	68	70	66		248,399	449,083	555,897
6	65	California	Riverside	111	107	106	108	106		1,545,387	2,176,313	2,500,652
6	67	California	Sacramento	99	76	73	76	70		1,223,499	1,581,115	1,767,164
6	69	California	San Benito	72	57	54	57	53		53,234	74,650	85,672
6	71	California	San Bernardino	129	133	132	135	133		1,709,434	2,298,311	2,602,018
6	73	California	San Diego	94	72	69	72	68		2,813,833	3,720,010	4,194,289
6	77	California	San Joaquin	84	73	71	74	71		563,598	711,131	788,116
6	83	California	Santa Barbara	80	71	70	71	70		399,347	442,321	466,013
6	87	California	Santa Cruz	65	52	50	52	49		255,602	274,436	285,269
6	99	California	Stanislaus	91	76	74	76	73		446,997	576,927	644,333
6	107	California	Tulare	104	82	80	82	79		368,021	461,550	510,533
6	109	California	Tuolumne	92	66	64	65	62		54,501	68,481	75,819
6	111	California	Ventura	101	94	92	94	92		753,197	974,455	1,089,111
6	113	California	Yolo	82	69	68	70	68		168,660	218,397	244,258
8	1	Colorado	Adams	65	61	60	61	60		363,857	478,469	538,611
8	5	Colorado	Arapahoe	76	71	70	72	70		487,967	721,970	843,220
8	13	Colorado	Boulder	72	69	68	69	68		291,288	384,637	433,584
8	31	Colorado	Denver	70	66	66	67	67		554,636	556,044	561,112
8	41	Colorado	El Paso	68	58	57	59	56		516,929	712,813	814,877
8	59	Colorado	Jefferson	81	78	77	78	77		527,056	644,914	707,740
8	69	Colorado	Larimer	74	69	69	70	69		251,494	370,247	431,833
8	83	Colorado	Montezuma	69	65	65	66	65		23,830	33,546	38,492
8	123	Colorado	Weld	70	63	62	63	61		180,936	225,994	249,859
9	1	Connecticut	Fairfield	97	92	92	93	93		882,567	902,450	915,655
9	3	Connecticut	Hartford	88	74	71	75	70		857,183	862,552	868,198
9	7	Connecticut	Middlesex	99	88	85	90	85		155,071	173,619	183,603
9	9	Connecticut	New Haven	97	87	85	89	85		824,008	835,856	844,674
9	11	Connecticut	New London	90	79	76	80	76		259,088	275,818	285,218
9	13	Connecticut	Tolland	90	75	72	76	71		136,364	149,910	157,442
10	1	Delaware	Kent	93	72	70	72	69		126,697	152,443	166,217
10	3	Delaware	New Castle	97	80	78	81	78		500,265	567,457	603,839
10	5	Delaware	Sussex	95	74	72	75	71		156,638	207,387	233,829
11	1	D.C.	Washington	94	82	80	83	79		572,059	544,554	532,846
12	1	Florida	Alachua	79	61	59	60	58		217,955	264,811	289,558
12	3	Florida	Baker	75	58	57	58	56		22,259	29,015	32,536
12	9	Florida	Brevard	76	57	55	57	54		476,230	589,739	648,397
12	31	Florida	Duval	74	59	58	60	58		778,879	936,714	1,020,493
12	33	Florida	Escambia	88	75	74	75	74		294,410	341,459	367,084
12	57	Florida	Hillsborough	84	67	65	67	63		998,948	1,263,223	1,400,587
12	59	Florida	Holmes	74	61	59	61	59		18,564	22,230	24,178
12	71	Florida	Lee	75	54	52	54	51		440,888	628,905	727,235

12	73	Florida	Leon	77	60	59	61	58		239,452	315,384	355,230
12	81	Florida	Manatee	83	64	62	64	61		264,002	384,627	447,858
12	83	Florida	Marion	78	60	59	60	58		258,916	342,354	385,972
12	95	Florida	Orange	81	63	61	63	60		896,344	1,227,393	1,400,894
12	97	Florida	Osceola	77	59	57	59	56		172,493	302,384	371,754
12	99	Florida	Palm Beach	75	58	56	58	54		1,131,184	1,744,032	2,061,168
12	101	Florida	Pasco	79	62	60	62	58		344,765	450,945	505,559
12	103	Florida	Pinellas	83	68	66	68	64		921,482	1,027,556	1,088,025
12	105	Florida	Polk	80	59	57	58	55		483,924	595,133	652,539
12	111	Florida	St Lucie	72	56	54	55	53		192,695	257,927	291,959
12	115	Florida	Sarasota	85	64	61	64	60		325,957	400,330	439,136
12	117	Florida	Seminole	78	60	58	60	57		365,196	569,587	677,953
12	127	Florida	Volusia	74	56	55	56	54		443,343	563,819	626,353
13	21	Georgia	Bibb	98	85	84	85	83		153,887	163,780	169,321
13	51	Georgia	Chatham	76	63	62	63	61		232,048	252,931	264,176
13	57	Georgia	Cherokee	76	56	55	56	54		141,903	231,192	277,881
13	67	Georgia	Cobb	96	74	72	74	70		607,751	878,010	1,019,356
13	77	Georgia	Coweta	96	80	79	80	78		89,215	134,032	157,494
13	85	Georgia	Dawson	83	61	59	60	57		15,999	30,384	37,908
13	89	Georgia	De Kalb	102	84	82	84	81		665,865	736,846	774,881
13	97	Georgia	Douglas	98	78	76	78	75		92,174	136,784	160,103
13	113	Georgia	Fayette	99	79	76	79	75		91,263	144,101	171,680
13	121	Georgia	Fulton	107	88	85	88	84		816,006	899,328	944,173
13	127	Georgia	Glynn	73	59	57	59	57		67,568	81,793	89,253
13	135	Georgia	Gwinnett	94	72	69	72	67		588,448	893,435	1,052,982
13	151	Georgia	Henry	107	85	83	85	81		119,341	188,831	225,194
13	215	Georgia	Muscogee	90	73	71	73	69		186,291	203,643	213,076
13	223	Georgia	Paulding	92	75	73	75	72		81,678	128,988	153,773
13	245	Georgia	Richmond	87	69	67	69	67		199,775	216,710	225,937
13	247	Georgia	Rockdale	104	82	79	82	78		70,111	105,990	124,745
13	261	Georgia	Sumter	86	71	70	71	69		33,200	36,304	38,096
17	1	Illinois	Adams	74	60	58	60	56		68,277	71,558	73,470
17	19	Illinois	Champaign	80	62	60	63	59		179,669	190,977	197,308
17	31	Illinois	Cook	88	85	85	86	86		5,376,741	5,389,403	5,415,053
17	43	Illinois	Du Page	68	64	64	65	65		904,161	1,126,926	1,243,827
17	49	Illinois	Effingham	81	62	60	62	59		34,264	39,077	41,698
17	65	Illinois	Hamilton	77	58	56	58	55		8,621	8,942	9,136
17	83	Illinois	Jersey	89	72	70	73	70		21,668	24,174	25,586
17	89	Illinois	Kane	77	72	71	73	71		404,119	522,657	584,727
17	97	Illinois	Lake	80	73	71	74	71		644,356	820,172	912,421
17	111	Illinois	McHenry	83	77	75	78	75		260,077	355,171	404,813

17	115	Illinois	Macon	78	60	58	60	57		114,706	112,528	111,690
17	117	Illinois	Macoupin	80	62	60	62	60		49,019	52,630	54,535
17	119	Illinois	Madison	82	68	66	68	66		258,941	277,485	287,588
17	143	Illinois	Peoria	78	63	61	63	60		183,433	192,791	198,189
17	157	Illinois	Randolph	78	60	59	60	58		33,893	36,184	37,390
17	163	Illinois	St Clair	82	70	69	71	68		256,082	251,771	249,705
17	167	Illinois	Sangamon	75	57	56	58	55		188,951	203,496	211,534
17	197	Illinois	Will	79	68	67	68	67		502,266	676,751	768,045
17	201	Illinois	Winnebago	76	64	62	65	61		278,418	317,176	337,859
18	3	Indiana	Allen	87	71	68	71	66		331,849	373,222	395,439
18	19	Indiana	Clark	86	68	67	69	67		96,472	117,704	129,061
18	43	Indiana	Floyd	82	67	66	68	66		70,823	85,015	92,614
18	51	Indiana	Gibson	71	52	51	52	50		32,500	33,741	34,514
18	57	Indiana	Hamilton	91	74	71	74	70		182,740	279,810	331,998
18	59	Indiana	Hancock	89	72	70	73	69		55,391	75,428	86,146
18	81	Indiana	Johnson	87	66	64	66	63		115,209	160,081	184,100
18	89	Indiana	Lake	90	84	83	85	84		484,564	492,963	498,991
18	91	Indiana	La Porte	85	75	73	75	73		110,106	113,232	115,188
18	95	Indiana	Madison	87	69	66	69	65		133,358	142,092	146,789
18	97	Indiana	Marion	88	73	71	73	70		860,454	907,240	932,219
18	109	Indiana	Morgan	87	70	67	70	66		66,689	87,224	98,229
18	123	Indiana	Perry	90	65	64	65	63		18,899	19,056	19,202
18	127	Indiana	Porter	90	82	81	83	82		146,798	184,172	203,679
18	129	Indiana	Posey	86	67	65	67	64		27,061	28,879	29,978
18	141	Indiana	St Joseph	84	68	66	68	65		265,559	284,912	295,551
18	163	Indiana	Vanderburgh	84	65	63	65	62		171,922	180,244	185,028
18	167	Indiana	Vigo	79	62	60	62	59		105,848	105,837	105,963
18	173	Indiana	Warrick	81	60	58	60	57		52,383	65,019	71,761
19	45	Iowa	Clinton	79	70	67	70	66		50,149	49,104	48,749
19	85	Iowa	Harrison	74	64	62	64	61		15,666	16,924	17,592
19	113	Iowa	Linn	73	64	62	64	61		191,701	223,880	240,980
19	147	Iowa	Palo Alto	69	58	55	58	54		10,147	9,164	8,707
19	153	Iowa	Polk	60	50	48	50	47		374,601	456,867	500,239
19	163	Iowa	Scott	79	69	67	69	66		158,668	175,894	185,378
19	169	Iowa	Story	66	55	53	55	52		79,981	84,967	87,711
19	181	Iowa	Warren	67	56	54	56	53		40,671	52,190	58,348
20	107	Kansas	Linn	79	69	68	70	67		9,570	4,769	4,493
20	173	Kansas	Sedgwick	81	71	70	71	69		452,869	528,750	568,900
20	209	Kansas	Wyandotte	80	72	70	72	70		157,882	144,783	138,690

21	13	Kentucky	Bell	82	58	57	57	55		30,060	33,087	34,721
21	15	Kentucky	Boone	85	64	62	64	62		85,991	125,566	146,706
21	19	Kentucky	Boyd	86	66	65	66	65		49,752	48,055	47,412
21	29	Kentucky	Bullitt	85	66	65	66	64		61,236	81,834	92,881
21	43	Kentucky	Carter	83	60	59	61	59		26,889	31,905	34,505
21	47	Kentucky	Christian	85	56	55	56	54		72,265	76,756	79,423
21	59	Kentucky	Daviess	79	59	57	59	57		91,545	102,223	108,122
21	61	Kentucky	Edmonson	88	62	60	62	59		11,644	12,812	13,433
21	67	Kentucky	Fayette	81	64	62	64	62		260,512	326,968	362,189
21	83	Kentucky	Graves	83	65	64	65	63		37,028	39,638	41,104
21	89	Kentucky	Greenup	86	66	65	66	64		36,891	36,754	36,758
21	91	Kentucky	Hancock	83	61	60	61	59		8,392	8,624	8,775
21	101	Kentucky	Henderson	77	59	58	60	57		44,829	48,188	50,010
21	111	Kentucky	Jefferson	89	73	72	73	72		693,604	725,700	743,029
21	113	Kentucky	Jessamine	78	62	60	62	60		39,041	55,652	64,443
21	117	Kentucky	Kenton	86	70	68	71	68		151,464	171,352	181,909
21	139	Kentucky	Livingston	87	68	67	68	66		9,804	10,622	11,038
21	145	Kentucky	McCracken	84	67	66	67	65		65,514	74,308	78,993
21	149	Kentucky	McLean	86	64	62	64	62		9,938	10,296	10,458
21	185	Kentucky	Oldham	91	70	68	70	68		46,178	67,362	78,725
21	195	Kentucky	Pike	78	54	53	54	52		68,736	77,184	81,653
21	199	Kentucky	Pulaski	86	66	65	66	64		56,217	68,945	75,701
21	209	Kentucky	Scott	72	52	51	52	50		33,061	48,147	56,246
21	213	Kentucky	Simpson	88	62	61	62	60		16,405	17,755	18,417
21	221	Kentucky	Trigg	82	61	59	61	59		12,597	14,282	15,199
22	5	Louisiana	Ascension	86	78	77	79	77		76,627	116,122	136,632
22	11	Louisiana	Beauregard	78	70	69	71	70		32,986	37,222	39,536
22	15	Louisiana	Bossier	90	79	78	79	78		98,310	123,645	137,122
22	17	Louisiana	Caddo	83	72	71	73	71		252,161	267,902	276,688
22	19	Louisiana	Calcasieu	86	78	77	79	78		183,577	215,763	232,906
22	33	Louisiana	East Baton Rou	91	80	79	81	80		412,852	518,879	574,689
22	43	Louisiana	Grant	81	71	70	72	70		18,698	21,330	22,695
22	47	Louisiana	Iberville	86	77	76	78	76		33,320	33,003	33,048
22	51	Louisiana	Jefferson	89	81	80	82	81		455,466	532,172	572,938
22	55	Louisiana	Lafayette	83	73	72	74	73		190,503	233,196	255,915
22	63	Louisiana	Livingston	88	79	78	80	79		91,814	157,803	191,919
22	71	Louisiana	Orleans	76	70	70	71	70		484,674	430,421	404,817
22	73	Louisiana	Ouachita	80	72	71	73	71		147,250	163,820	172,805
22	77	Louisiana	Pointe Coupee	75	65	64	66	65		22,763	23,109	23,409
22	87	Louisiana	St Bernard	81	74	74	75	75		67,229	70,693	72,688
22	89	Louisiana	St Charles	86	79	79	80	79		48,072	56,744	61,278

22	93	Louisiana	St James	83	76	75	77	76		21,216	22,289	22,945
22	95	Louisiana	St John The Ba	86	78	77	79	78		43,044	48,046	50,791
22	101	Louisiana	St Mary	83	75	75	76	75		53,500	53,475	53,518
22	121	Louisiana	West Baton Rou	88	78	77	79	77		21,601	23,842	25,065
23	5	Maine	Cumberland	80	68	66	69	66		265,612	308,231	330,836
23	9	Maine	Hancock	89	72	69	73	68		51,791	56,083	58,499
23	11	Maine	Kennebec	75	62	59	63	58		117,114	123,081	126,672
23	13	Maine	Knox	80	68	65	68	64		39,618	45,464	48,544
23	17	Maine	Oxford	61	52	50	53	50		54,755	60,048	62,916
23	31	Maine	York	86	74	72	75	72		186,742	215,779	231,214
24	3	Maryland	Anne Arundel	103	83	80	83	78		489,656	598,770	656,196
24	5	Maryland	Baltimore	93	80	78	81	77		754,292	831,729	873,717
24	9	Maryland	Calvert	89	67	65	67	64		74,563	121,253	145,708
24	13	Maryland	Carroll	93	75	73	76	71		150,897	209,221	239,580
24	15	Maryland	Cecil	106	84	81	84	79		85,951	107,523	119,075
24	17	Maryland	Charles	96	73	71	73	70		120,546	171,193	197,639
24	21	Maryland	Frederick	91	73	70	73	69		195,277	273,707	314,624
24	25	Maryland	Harford	104	86	84	87	82		218,590	318,172	370,182
24	29	Maryland	Kent	100	78	76	79	75		19,197	21,272	22,412
24	31	Maryland	Montgomery	89	76	73	76	72		873,341	1,008,558	1,080,468
24	33	Maryland	Prince Georges	97	80	77	81	76		801,515	884,449	929,496
24	43	Maryland	Washington	85	65	63	65	62		131,923	149,914	159,551
25	1	Massachusetts	Barnstable	96	79	76	80	75		222,230	277,219	306,052
25	5	Massachusetts	Bristol	93	78	75	79	74		534,678	583,242	609,773
25	9	Massachusetts	Essex	86	75	76	75	76		723,419	773,032	800,688
25	13	Massachusetts	Hampden	85	73	71	74	70		456,228	450,007	448,459
25	15	Massachusetts	Hampshire	87	75	73	76	72		152,251	164,397	171,127
25	17	Massachusetts	Middlesex	88	74	71	74	71		1,465,396	1,510,184	1,537,905
25	25	Massachusetts	Suffolk	84	69	67	69	67		689,807	659,760	646,962
25	27	Massachusetts	Worcester	85	71	69	72	68		750,963	812,259	846,065
26	5	Michigan	Allegan	87	74	72	75	72		105,665	137,366	153,990
26	19	Michigan	Benzie	89	77	75	77	74		15,998	19,738	21,742
26	21	Michigan	Berrien	87	72	70	73	70		162,453	167,167	169,909
26	27	Michigan	Cass	87	70	68	70	67		51,104	56,079	58,817
26	37	Michigan	Clinton	82	69	67	69	66		64,753	78,498	85,865
26	49	Michigan	Genesee	86	74	72	74	71		436,141	446,891	453,670
26	63	Michigan	Huron	83	71	70	72	69		36,079	37,703	38,663
26	65	Michigan	Ingham	83	70	68	70	67		279,320	290,827	297,581
26	77	Michigan	Kalamazoo	82	66	64	67	63		238,603	262,738	275,735
26	81	Michigan	Kent	84	70	67	70	66		574,335	684,461	742,687
26	91	Michigan	Lenawee	83	70	68	71	67		98,890	108,480	113,789

26	99	Michigan	Macomb	88	84	84	85	86		788,149	890,585	946,209
26	105	Michigan	Mason	91	77	75	78	74		28,274	33,109	35,683
26	113	Michigan	Missaukee	82	69	67	70	67		14,478	17,741	19,439
26	121	Michigan	Muskegon	92	79	77	80	76		170,200	181,910	188,401
26	125	Michigan	Oakland	84	79	79	80	80		1,194,156	1,410,553	1,527,099
26	139	Michigan	Ottawa	84	72	70	73	70		238,314	316,914	358,079
26	147	Michigan	St Clair	85	76	75	77	75		164,235	193,051	208,573
26	163	Michigan	Wayne	88	86	86	88	88		2,061,162	1,897,446	1,818,661
27	3	Minnesota	Anoka	71	63	61	64	61		298,084	418,534	481,468
27	163	Minnesota	Washington	75	66	64	67	63		201,130	326,359	391,832
28	1	Mississippi	Adams	82	70	69	71	69		34,340	33,358	32,941
28	11	Mississippi	Bolivar	82	65	64	66	63		40,633	37,408	35,949
28	33	Mississippi	De Soto	86	71	69	71	69		107,199	173,599	210,077
28	45	Mississippi	Hancock	87	77	76	78	76		42,967	61,659	71,279
28	47	Mississippi	Harrison	89	80	79	81	79		189,601	227,885	248,075
28	49	Mississippi	Hinds	80	64	63	65	62		250,800	268,318	278,025
28	59	Mississippi	Jackson	87	78	78	79	78		131,420	153,814	165,743
28	75	Mississippi	Lauderdale	79	60	59	61	59		78,161	84,485	87,885
28	81	Mississippi	Lee	86	64	63	64	62		75,755	95,564	105,932
28	89	Mississippi	Madison	79	70	69	71	69		74,674	103,364	118,443
28	149	Mississippi	Warren	78	67	66	68	67		49,644	52,773	54,579
29	39	Missouri	Cedar	84	72	71	73	70		13,733	14,933	15,530
29	47	Missouri	Clay	84	74	72	74	72		184,006	243,759	275,253
29	77	Missouri	Greene	75	59	57	59	56		240,391	287,457	312,253
29	99	Missouri	Jefferson	89	72	70	72	69		198,099	264,327	300,317
29	137	Missouri	Monroe	81	65	63	65	62		9,311	9,177	9,142
29	165	Missouri	Platte	81	73	71	73	71		73,781	103,530	119,250
29	183	Missouri	St Charles	90	76	75	77	74		283,883	402,014	466,353
29	186	Missouri	Ste Genevieve	85	69	67	69	66		17,842	20,974	22,653
29	189	Missouri	St Louis	88	76	75	77	74		1,016,315	1,033,549	1,043,340
29	510	Missouri	St Louis City	81	68	67	69	67		348,189	301,448	277,083
31	55	Nebraska	Douglas	62	54	52	54	51		463,585	546,160	589,984
31	109	Nebraska	Lancaster	53	46	44	46	43		250,291	319,321	355,359
32	3	Nevada	Clark	80	68	64	68	63		1,375,765	2,287,193	2,763,400
33	3	New Hampshire	Carroll	66	55	53	55	52		43,666	55,385	61,542
33	5	New Hampshire	Cheshire	72	58	56	58	55		73,825	80,765	84,656
33	9	New Hampshire	Grafton	68	54	52	55	51		81,743	92,895	98,810
33	11	New Hampshire	Hillsborough	83	70	68	70	67		380,841	444,066	477,617
33	13	New Hampshire	Merrimack	70	58	56	58	56		136,225	157,419	168,690
33	15	New Hampshire	Rockingham	81	71	69	72	69		277,359	348,095	385,327
33	17	New Hampshire	Strafford	75	63	61	64	60		112,233	128,703	137,501

33	19	New Hampshire	Sullivan	72	57	55	58	55		40,458	43,846	45,706
34	1	New Jersey	Atlantic	91	74	72	74	71		252,552	287,629	306,558
34	7	New Jersey	Camden	103	87	86	88	86		508,932	511,593	514,403
34	11	New Jersey	Cumberland	97	77	75	78	74		146,438	153,044	156,835
34	15	New Jersey	Gloucester	101	88	86	88	86		254,673	303,325	329,517
34	17	New Jersey	Hudson	93	87	87	88	87		608,975	606,667	607,696
34	19	New Jersey	Hunterdon	100	88	86	89	85		121,989	157,590	176,344
34	21	New Jersey	Mercer	105	94	92	95	92		350,761	369,672	380,558
34	23	New Jersey	Middlesex	103	92	90	93	90		750,162	862,446	922,342
34	25	New Jersey	Monmouth	94	82	80	82	80		615,301	727,885	787,597
34	27	New Jersey	Morris	97	81	79	82	79		470,212	530,791	563,247
34	29	New Jersey	Ocean	109	94	92	95	91		510,916	634,857	700,145
34	31	New Jersey	Passaic	89	78	77	79	77		489,049	503,064	511,915
35	1	New Mexico	Bernalillo	75	69	67	69	68		556,678	673,674	735,366
35	13	New Mexico	Dona Ana	80	62	59	62	58		174,682	235,150	266,803
35	45	New Mexico	San Juan	73	70	69	70	69		113,801	165,573	192,638
36	1	New York	Albany	80	65	62	65	61		294,565	307,100	314,272
36	5	New York	Bronx	83	82	85	83	87		1,332,650	1,273,213	1,247,937
36	13	New York	Chautauqua	89	76	74	76	73		139,750	140,312	141,059
36	15	New York	Chemung	79	64	62	64	61		91,070	89,312	88,691
36	27	New York	Dutchess	87	73	71	74	70		280,150	302,587	315,008
36	29	New York	Erie	92	81	80	82	79		950,265	957,747	964,943
36	31	New York	Essex	78	71	70	71	69		38,851	40,300	41,200
36	41	New York	Hamilton	77	66	64	66	63		5,379	5,710	5,860
36	43	New York	Herkimer	72	63	61	63	61		64,427	64,418	64,650
36	45	New York	Jefferson	87	75	74	76	74		111,738	114,641	116,596
36	53	New York	Madison	78	67	65	67	64		69,441	75,149	78,353
36	63	New York	Niagara	87	77	76	78	76		219,846	221,402	222,977
36	65	New York	Oneida	76	65	63	65	63		235,469	227,206	223,700
36	67	New York	Onondaga	81	68	66	68	65		458,336	463,808	468,164
36	71	New York	Orange	87	75	73	76	73		341,367	402,207	434,472
36	79	New York	Putnam	89	78	76	78	76		95,745	120,410	133,361
36	81	New York	Queens	86	76	75	76	76		2,229,379	2,252,882	2,272,692
36	85	New York	Richmond	98	87	86	88	86		443,728	534,663	582,784
36	91	New York	Saratoga	84	67	64	68	63		200,635	247,509	272,720
36	93	New York	Schenectady	75	62	59	62	58		146,555	145,564	145,427
36	103	New York	Suffolk	91	81	79	82	79		1,419,369	1,527,592	1,587,477
36	111	New York	Ulster	81	68	65	68	65		177,749	190,657	197,999
36	117	New York	Wayne	81	70	69	71	68		93,765	106,121	112,727
36	119	New York	Westchester	92	86	86	87	88		923,459	967,314	992,781
37	3	North Carolina	Alexander	87	64	62	64	61		33,603	38,866	41,560

37	11	North Carolina	Avery	75	54	53	54	52		17,167	19,703	21,132
37	21	North Carolina	Buncombe	83	59	57	58	55		206,330	254,412	279,720
37	27	North Carolina	Caldwell	87	64	62	64	61		77,415	90,861	98,016
37	29	North Carolina	Camden	80	66	65	66	64		6,885	7,992	8,639
37	33	North Carolina	Caswell	90	67	65	67	64		23,501	25,539	26,676
37	37	North Carolina	Chatham	81	60	57	60	56		49,329	61,495	67,885
37	51	North Carolina	Cumberland	88	66	63	66	62		302,963	341,187	361,645
37	59	North Carolina	Davie	96	69	67	69	66		34,835	40,475	43,475
37	61	North Carolina	Duplin	82	63	61	63	59		49,063	53,223	55,448
37	63	North Carolina	Durham	87	65	62	65	61		223,314	281,262	311,720
37	65	North Carolina	Edgecombe	87	68	65	68	64		55,606	56,716	57,541
37	67	North Carolina	Forsyth	94	68	66	68	64		306,067	366,864	398,805
37	69	North Carolina	Franklin	86	64	61	64	60		47,260	59,759	66,374
37	77	North Carolina	Granville	88	66	64	66	62		48,498	56,445	60,614
37	81	North Carolina	Guilford	90	66	64	66	62		421,048	497,827	538,355
37	87	North Carolina	Haywood	87	63	61	62	59		54,033	63,759	68,965
37	99	North Carolina	Jackson	85	59	58	59	56		33,121	44,052	49,697
37	101	North Carolina	Johnston	87	66	63	66	62		121,965	162,050	183,079
37	107	North Carolina	Lenoir	82	63	61	63	60		59,648	63,512	65,712
37	109	North Carolina	Lincoln	91	68	66	68	64		63,780	81,208	90,384
37	117	North Carolina	Martin	79	63	61	63	61		25,593	26,001	26,321
37	119	North Carolina	Mecklenburg	101	75	72	75	70		695,454	941,939	1,070,973
37	129	North Carolina	New Hanover	75	60	58	61	58		160,307	233,447	271,367
37	131	North Carolina	Northampton	82	64	62	64	61		22,086	24,879	26,443
37	145	North Carolina	Person	89	66	64	66	63		35,623	42,087	45,621
37	147	North Carolina	Pitt	84	65	62	65	61		133,798	184,753	211,387
37	157	North Carolina	Rockingham	85	62	59	61	58		91,928	98,875	102,735
37	159	North Carolina	Rowan	99	73	70	73	69		130,340	157,365	171,612
37	173	North Carolina	Swain	73	53	51	52	50		12,968	15,962	17,531
37	179	North Carolina	Union	87	64	61	64	59		123,677	163,429	184,264
37	183	North Carolina	Wake	94	72	68	72	66		627,846	948,294	1,115,401
37	199	North Carolina	Yancey	89	65	63	65	62		17,774	21,503	23,568

39	3	Ohio	Allen	86	71	68	71	67		108,473	105,425	104,133
39	7	Ohio	Ashtabula	89	75	73	76	73		102,728	107,171	109,827
39	17	Ohio	Butler	89	70	68	70	67		332,807	438,817	495,203
39	23	Ohio	Clark	87	68	66	69	64		144,742	141,717	140,693
39	27	Ohio	Clinton	95	71	69	72	67		40,543	53,906	60,919
39	35	Ohio	Cuyahoga	83	71	69	71	68		1,393,978	1,314,252	1,277,539
39	41	Ohio	Delaware	91	73	70	73	69		109,989	162,726	190,545
39	49	Ohio	Franklin	84	70	68	71	68		1,068,978	1,221,199	1,301,984
39	55	Ohio	Geauga	93	77	75	78	74		90,895	113,647	125,915
39	57	Ohio	Greene	85	66	63	66	62		147,886	161,044	168,294
39	61	Ohio	Hamilton	86	71	69	71	68		845,303	844,891	845,159
39	81	Ohio	Jefferson	84	70	68	70	68		73,894	67,057	63,997
39	83	Ohio	Knox	90	73	70	73	69		54,500	64,422	69,708
39	85	Ohio	Lake	91	77	75	78	75		227,511	247,357	258,390
39	87	Ohio	Lawrence	86	66	65	66	64		62,319	63,291	63,930
39	89	Ohio	Licking	88	70	68	70	67		145,491	175,706	191,730
39	95	Ohio	Lucas	85	74	72	75	72		455,054	439,718	433,056
39	97	Ohio	Madison	88	70	68	71	67		40,213	48,425	52,789
39	103	Ohio	Medina	86	70	67	70	66		151,095	197,597	222,583
39	109	Ohio	Miami	84	66	63	66	62		98,868	104,032	107,049
39	113	Ohio	Montgomery	87	69	66	69	65		559,062	547,126	543,119
39	133	Ohio	Portage	92	75	72	75	71		152,061	173,779	185,622
39	135	Ohio	Preble	78	60	57	60	56		42,337	45,627	47,475
39	151	Ohio	Stark	88	71	68	71	67		378,098	386,771	392,398
39	153	Ohio	Summit	92	76	73	76	72		542,899	566,693	580,778
39	155	Ohio	Trumbull	88	70	67	71	66		225,116	227,563	229,495
39	165	Ohio	Warren	88	69	67	69	66		158,383	214,769	244,730
39	167	Ohio	Washington	88	62	61	62	60		63,251	63,089	63,235
39	173	Ohio	Wood	85	72	69	72	68		121,065	137,609	146,682
40	27	Oklahoma	Cleveland	79	66	65	66	65		208,016	258,810	285,452
40	109	Oklahoma	Oklahoma	80	68	67	68	66		660,448	726,990	763,100
40	143	Oklahoma	Tulsa	87	76	75	76	75		563,299	658,823	709,459
41	5	Oregon	Clackamas	68	61	59	61	58		338,391	474,981	546,680
41	9	Oregon	Columbia	53	47	45	47	45		43,560	53,045	57,963
41	39	Oregon	Lane	54	43	41	44	40		322,959	409,094	454,385
41	47	Oregon	Marion	60	50	48	51	47		284,834	353,405	389,154

42	3	Pennsylvania	Allegheny	92	77	75	77	74		1,281,666	1,242,514	1,227,036
42	5	Pennsylvania	Armstrong	92	73	71	73	70		72,392	73,408	74,169
42	7	Pennsylvania	Beaver	89	75	73	75	73		181,412	187,382	191,031
42	11	Pennsylvania	Berks	95	76	74	76	73		373,638	405,375	422,931
42	13	Pennsylvania	Blair	84	64	62	64	61		129,144	129,166	129,691
42	17	Pennsylvania	Bucks	105	94	92	95	93		597,635	701,724	757,778
42	21	Pennsylvania	Cambria	88	70	68	70	67		152,598	141,356	136,383
42	27	Pennsylvania	Centre	80	61	59	61	59		135,758	160,300	173,165
42	33	Pennsylvania	Clearfield	83	65	63	65	62		83,382	86,337	88,108
42	43	Pennsylvania	Dauphin	94	75	73	75	72		251,798	278,696	293,157
42	45	Pennsylvania	Delaware	94	80	79	81	78		550,864	543,058	540,509
42	49	Pennsylvania	Erie	87	74	72	74	71		280,843	289,378	294,654
42	55	Pennsylvania	Franklin	92	69	67	69	66		129,313	141,112	147,622
42	59	Pennsylvania	Greene	92	68	66	68	66		40,672	44,016	45,919
42	69	Pennsylvania	Lackawanna	86	67	64	67	63		213,295	204,671	200,982
42	71	Pennsylvania	Lancaster	96	78	75	78	74		470,658	554,898	600,235
42	73	Pennsylvania	Lawrence	78	62	60	63	60		94,643	96,639	98,062
42	77	Pennsylvania	Lehigh	96	79	77	79	76		312,090	334,897	347,555
42	79	Pennsylvania	Luzerne	84	64	62	65	61		319,250	305,014	298,966
42	81	Pennsylvania	Lycoming	76	59	57	59	56		120,044	123,235	125,235
42	85	Pennsylvania	Mercer	88	70	67	70	66		120,293	125,038	127,856
42	91	Pennsylvania	Montgomery	100	89	88	90	88		750,097	797,026	823,454
42	95	Pennsylvania	Northampton	97	80	78	80	77		267,066	293,034	307,174
42	99	Pennsylvania	Perry	84	65	63	65	62		43,602	55,994	62,541
42	101	Pennsylvania	Philadelphia	88	77	77	78	77		1,517,550	1,323,566	1,228,773
42	117	Pennsylvania	Tioga	81	64	62	64	61		41,373	44,919	46,935
42	125	Pennsylvania	Washington	88	73	72	74	71		202,897	207,824	211,081
42	129	Pennsylvania	Westmoreland	86	70	68	70	67		369,993	376,604	381,310
42	133	Pennsylvania	York	90	72	70	72	69		381,751	426,517	450,509
44	3	Rhode Island	Kent	94	80	77	81	76		167,090	181,472	189,315
44	7	Rhode Island	Providence	87	73	70	74	69		621,602	622,209	624,704
44	9	Rhode Island	Washington	92	77	74	78	74		123,546	152,220	167,321
45	1	South Carolina	Abbeville	85	63	61	62	60		26,167	28,754	30,113
45	3	South Carolina	Aiken	86	68	66	69	66		142,552	170,499	185,233
45	7	South Carolina	Anderson	90	69	67	69	66		165,740	198,222	215,416
45	11	South Carolina	Barnwell	83	63	61	63	61		23,478	24,876	25,657
45	19	South Carolina	Charleston	78	57	55	57	55		309,969	413,794	468,239
45	21	South Carolina	Cherokee	87	66	64	66	63		52,537	59,576	63,288
45	23	South Carolina	Chester	85	65	63	65	62		34,068	39,332	42,141
45	29	South Carolina	Colleton	79	58	57	58	56		38,264	46,471	50,656
45	31	South Carolina	Darlington	86	67	65	68	65		67,394	74,667	78,713

45	37	South Carolina	Edgefield	80	61	59	61	58		24,595	26,612	27,592
45	77	South Carolina	Pickens	87	64	62	64	61		110,757	155,424	178,605
45	79	South Carolina	Richland	93	69	67	69	65		320,677	379,594	410,744
45	83	South Carolina	Spartanburg	93	70	68	70	67		253,791	296,784	319,577
45	87	South Carolina	Union	81	61	59	61	58		29,881	31,148	31,891
45	89	South Carolina	Williamsburg	73	54	53	54	52		37,217	37,898	38,482
45	91	South Carolina	York	82	63	60	63	60		164,614	215,724	242,457
47	1	Tennessee	Anderson	90	63	61	63	60		71,330	80,733	85,682
47	9	Tennessee	Blount	96	70	68	69	66		105,823	136,562	152,562
47	37	Tennessee	Davidson	87	68	66	68	66		569,891	614,007	638,965
47	65	Tennessee	Hamilton	92	71	69	70	68		307,896	347,332	368,296
47	75	Tennessee	Haywood	89	70	68	70	67		19,797	20,645	21,157
47	89	Tennessee	Jefferson	96	70	68	70	67		44,294	58,749	66,300
47	93	Tennessee	Knox	96	69	67	69	66		382,032	473,001	520,715
47	99	Tennessee	Lawrence	83	59	58	59	57		39,926	48,335	52,776
47	141	Tennessee	Putnam	87	64	63	64	62		62,315	77,115	84,957
47	149	Tennessee	Rutherford	86	65	63	65	62		182,023	276,366	325,300
47	155	Tennessee	Sevier	98	70	68	70	67		71,170	121,259	147,616
47	157	Tennessee	Shelby	93	83	82	84	82		897,472	1,021,255	1,086,498
47	163	Tennessee	Sullivan	90	64	63	64	62		153,048	166,896	174,404
47	165	Tennessee	Sumner	93	72	70	72	70		130,449	179,345	204,820
47	187	Tennessee	Williamson	88	64	62	64	61		126,638	206,305	247,716
47	189	Tennessee	Wilson	87	66	64	66	63		88,809	126,983	146,808
48	29	Texas	Bexar	82	69	68	69	68		1,392,931	1,818,579	2,042,324
48	39	Texas	Brazoria	91	82	81	83	82		241,767	322,468	364,672
48	85	Texas	Collin	99	83	80	83	79		491,675	861,692	1,051,712
48	113	Texas	Dallas	93	80	78	80	77		2,218,899	2,554,577	2,737,690
48	121	Texas	Denton	101	83	81	84	80		432,976	674,188	798,468
48	139	Texas	Ellis	88	73	72	74	71		111,360	148,722	168,262
48	141	Texas	El Paso	75	59	56	59	55		679,622	896,883	1,010,581
48	167	Texas	Galveston	98	90	90	91	91		250,158	318,241	353,952
48	183	Texas	Gregg	95	74	73	74	72		111,379	131,531	142,339
48	201	Texas	Harris	110	104	104	106	105		3,400,578	4,151,794	4,549,359
48	245	Texas	Jefferson	85	78	77	79	78		252,051	270,004	279,811
48	339	Texas	Montgomery	91	78	76	78	77		293,768	531,533	654,643
48	361	Texas	Orange	74	67	67	68	68		84,966	92,773	97,011
48	439	Texas	Tarrant	97	82	80	83	80		1,446,219	1,976,530	2,251,918
48	453	Texas	Travis	88	73	72	74	71		812,280	1,100,723	1,255,821
48	469	Texas	Victoria	79	67	66	68	66		84,088	103,302	113,486
49	11	Utah	Davis	79	73	70	74	69		238,994	380,216	453,302
49	35	Utah	Salt Lake	79	74	72	74	71		898,387	1,213,017	1,378,102

49	49	Utah	Utah	78	73	70	73	69		368,536	550,933	645,756
49	57	Utah	Weber	75	65	62	66	62		196,533	242,468	267,013
50	3	Vermont	Bennington	79	64	61	65	60		36,994	39,841	41,416
51	13	Virginia	Arlington	92	80	78	80	78		189,453	197,699	202,553
51	33	Virginia	Caroline	85	65	63	65	62		22,121	27,006	29,528
51	36	Virginia	Charles City	87	70	68	70	68		6,926	7,864	8,407
51	41	Virginia	Chesterfield	86	68	66	68	65		259,903	366,136	422,063
51	59	Virginia	Fairfax	95	80	78	81	78		969,749	1,202,969	1,325,540
51	61	Virginia	Fauquier	82	62	60	62	59		55,139	76,422	87,462
51	69	Virginia	Frederick	83	64	62	64	61		59,209	73,443	80,854
51	87	Virginia	Henrico	90	70	68	71	67		262,300	326,604	360,545
51	107	Virginia	Loudoun	86	71	69	71	68		169,599	259,606	306,614
51	113	Virginia	Madison	87	64	62	64	61		12,520	15,004	16,249
51	139	Virginia	Page	82	59	58	59	57		23,177	25,961	27,418
51	153	Virginia	Prince William	85	68	66	68	65		280,813	404,026	468,438
51	161	Virginia	Roanoke	86	63	61	63	60		85,778	101,646	109,937
51	163	Virginia	Rockbridge	80	57	55	57	54		20,808	22,348	23,236
51	179	Virginia	Stafford	85	65	63	65	62		92,446	137,914	161,575
51	197	Virginia	Wythe	81	56	54	55	53		27,599	30,228	31,621
51	510	Virginia	Alexandria Cit	88	76	75	77	74		128,283	73,706	82,724
51	650	Virginia	Hampton City	87	73	72	74	71		146,437	160,395	168,015
51	800	Virginia	Suffolk City	86	72	71	73	71		63,677	74,434	80,129
53	11	Washington	Clark	59	54	53	54	53		345,238	519,909	611,725
53	33	Washington	King	69	59	57	60	57		1,737,034	2,107,326	2,301,410
53	53	Washington	Pierce	67	57	55	57	54		700,820	944,042	1,071,521
53	67	Washington	Thurston	57	51	50	52	50		207,355	280,103	318,265
54	11	West Virginia	Cabell	88	67	66	68	66		96,784	91,739	89,564
54	25	West Virginia	Greenbrier	83	56	55	56	54		34,453	36,951	38,368
54	29	West Virginia	Hancock	82	68	67	68	66		32,667	30,659	29,778
54	39	West Virginia	Kanawha	90	66	65	66	64		200,073	197,841	197,586
54	69	West Virginia	Ohio	82	63	62	63	61		47,427	46,546	46,276
54	107	West Virginia	Wood	88	61	60	61	59		87,986	87,471	87,560
55	9	Wisconsin	Brown	81	71	69	71	68		226,778	270,348	293,548
55	21	Wisconsin	Columbia	78	67	64	67	63		52,468	64,023	70,105
55	25	Wisconsin	Dane	78	67	65	68	64		426,526	538,843	597,808
55	27	Wisconsin	Dodge	82	71	68	71	67		85,897	101,526	109,834
55	29	Wisconsin	Door	93	80	78	81	77		27,961	33,124	35,898
55	39	Wisconsin	Fond Du Lac	80	69	67	70	66		97,296	106,984	112,168
55	55	Wisconsin	Jefferson	86	74	72	75	71		74,021	79,638	82,748
55	59	Wisconsin	Kenosha	95	87	86	89	86		149,577	183,393	201,186
55	61	Wisconsin	Kewaunee	89	77	75	77	74		20,187	20,915	21,347

55	71	Wisconsin	Manitowoc	92	79	77	80	76		82,887	84,259	85,140
55	73	Wisconsin	Marathon	76	66	64	67	64		125,834	148,400	160,358
55	79	Wisconsin	Milwaukee	89	79	77	80	77		940,164	906,519	891,733
55	85	Wisconsin	Oneida	73	64	62	64	62		36,776	49,768	56,724
55	87	Wisconsin	Outagamie	79	69	67	69	66		160,971	202,072	223,681
55	89	Wisconsin	Ozaukee	95	83	81	84	81		82,317	109,088	123,389
55	101	Wisconsin	Racine	87	78	76	79	76		188,831	209,909	221,262
55	105	Wisconsin	Rock	86	73	70	73	69		152,307	176,556	189,362
55	109	Wisconsin	St Croix	73	64	61	64	60		63,155	78,467	86,455
55	111	Wisconsin	Sauk	77	68	66	68	65		55,225	74,176	84,110
55	117	Wisconsin	Sheboygan	95	82	80	83	80		112,646	125,303	132,146
55	123	Wisconsin	Vernon	72	62	60	62	58		28,056	29,941	30,949
55	127	Wisconsin	Walworth	84	73	70	73	70		93,759	115,771	127,506
55	131	Wisconsin	Washington	84	75	73	76	73		117,493	147,051	162,701
55	133	Wisconsin	Waukesha	86	77	75	78	75		360,767	466,063	521,974
55	139	Wisconsin	Winnebago	80	70	68	70	67		156,763	183,637	197,968
		# Nonattainment Cntys		**289**	**30**	**28**	**32**	**28**				
				110,747,798	42,930,060	43,532,490	46,998,413	46,038,489		168,786,833	199,381,803	215,701,216

Appendix B
Projected Future Ozone Design Values After Implementation of Proposed Nonroad Controls

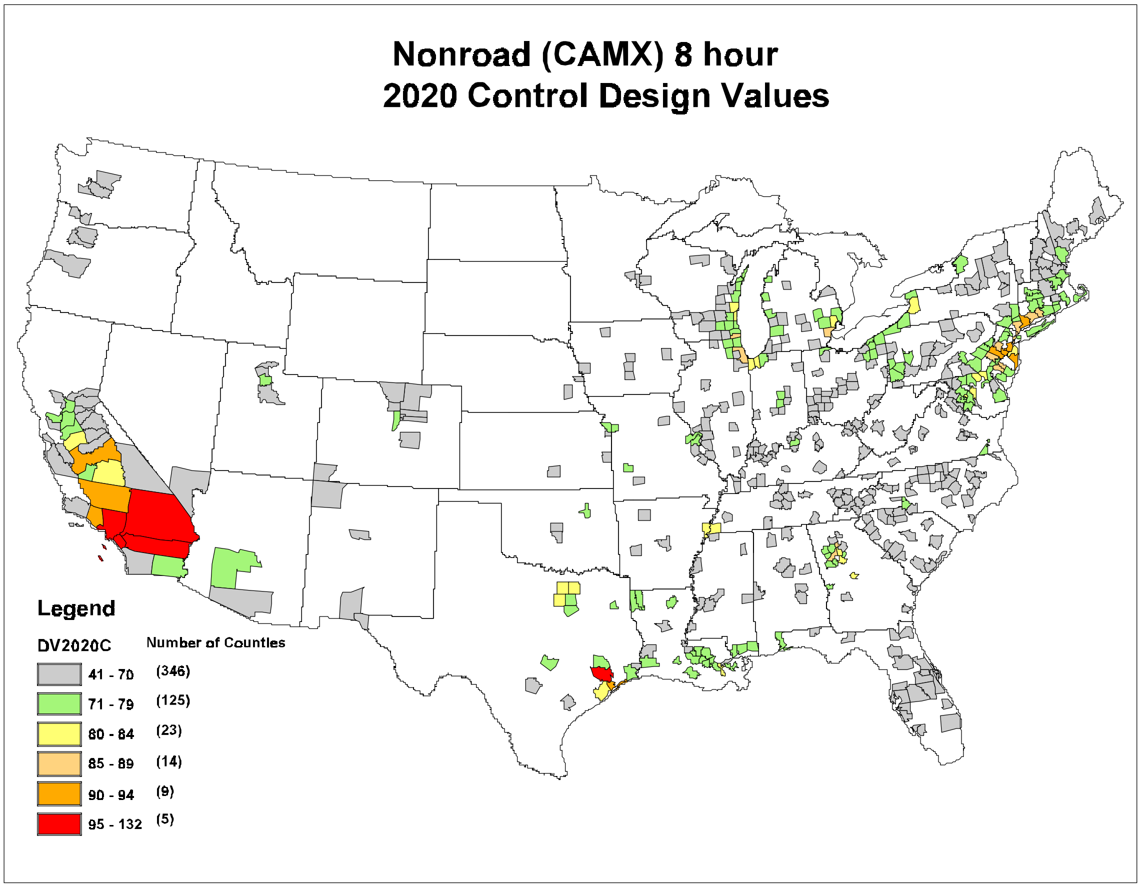

Figure B-1. Estimated future 8-hour ozone design values for the 2020 Control Case.

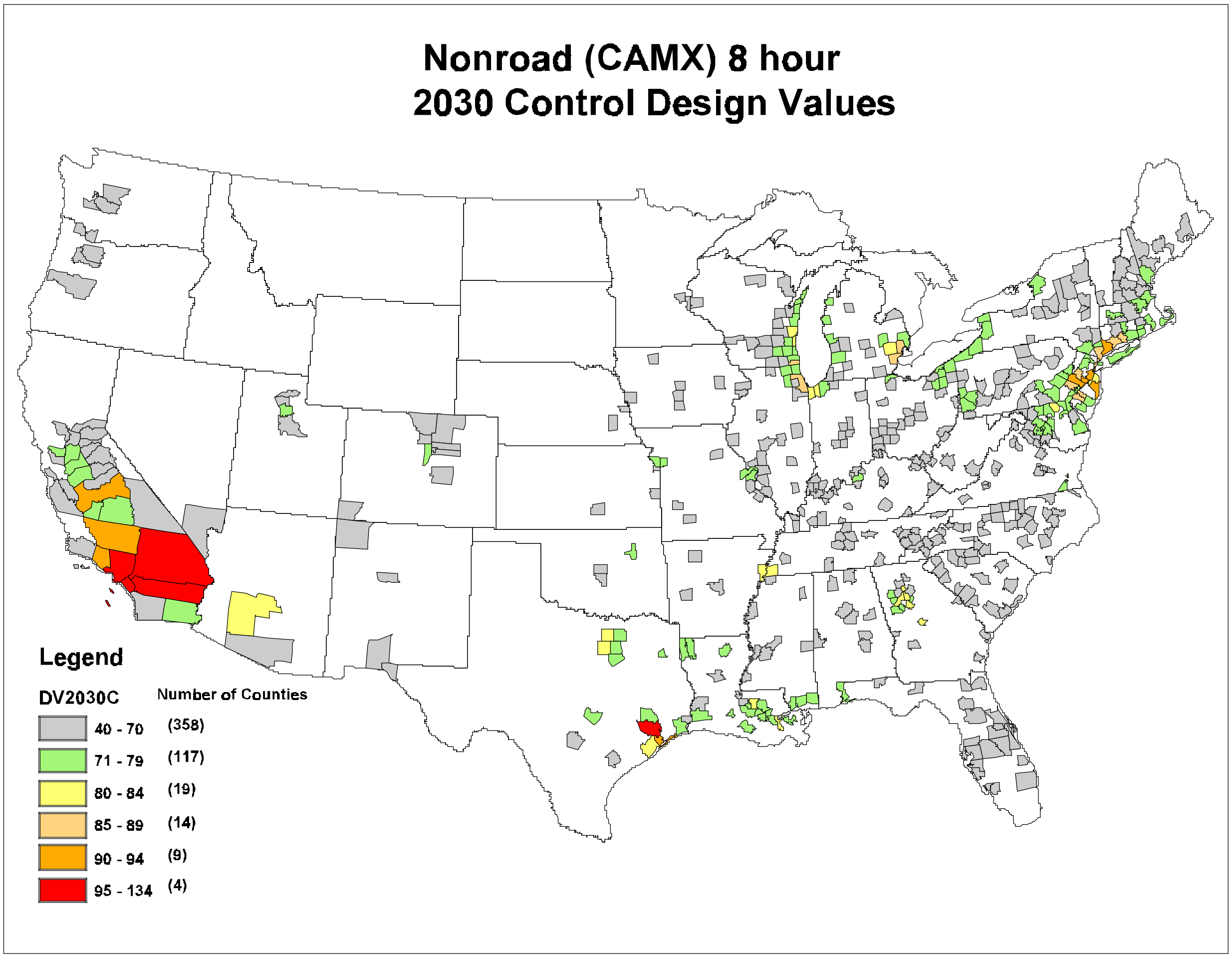

Figure B-2. Estimated future 8-hour ozone design values for the 2030 Control Case.

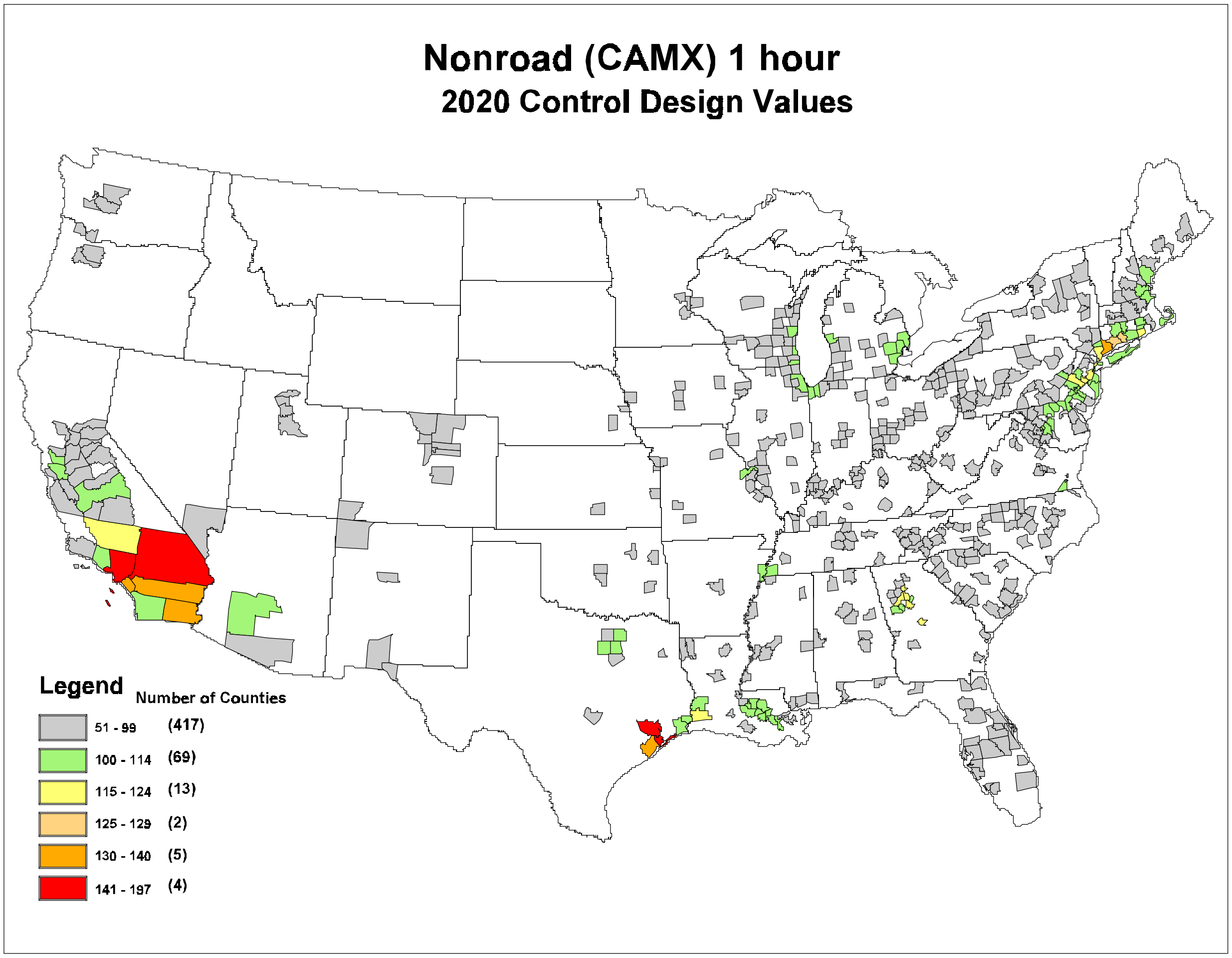

Figure B-3. Estimated future 1-hour ozone design values for the 2020 Control Case.

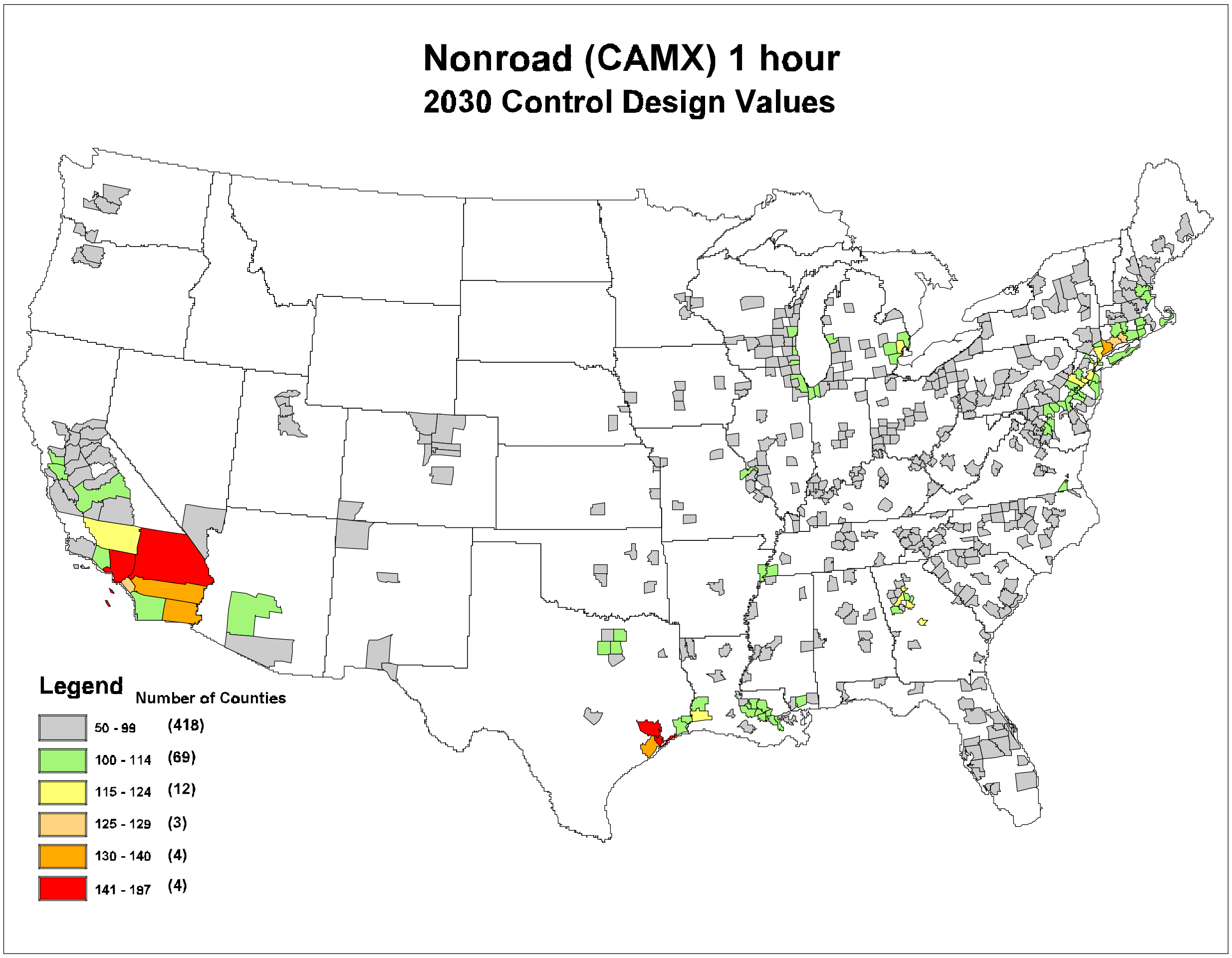

Figure B-4. Estimated future 1-hour ozone design values for the 2030 Control Case.

Appendix C
Effect of Proposed Nonroad Controls on 8-Hour Ozone in 2020 for Selected Eastern U.S. CMSA/MSAs

Table C-1. Modeled episodic peak 8-hour average ozone, before and after the proposed Nonroad emissions reductions in 2020.

Episodic 8-hour Maximum Ozone	2020 Base	2020 Control	Percent Difference
Total	**149**	**145**	**-2.7%**
Boston	104	98	-5.8%
Chicago	138	136	-1.4%
Cincinnati	106	102	-3.8%
Cleveland	101	98	-3.0%
Dallas	87	85	-2.3%
Detroit	120	119	-0.8%
Houston	110	109	-0.9%
Milwaukee	112	110	-1.8%
New York City	130	127	-2.3%
Philadelphia	111	108	-2.7%
Washington-Baltimore	113	110	-2.7%
Allentown-Bethlehem-Easton, PA	89	87	-2.2%
Atlanta, GA	149	145	-2.7%
Augusta-Aiken, GA-SC	90	88	-2.2%
Austin-San Marcos, TX	73	71	-2.7%
Barnstable-Yarmouth, MA	97	93	-4.1%
Baton Rouge, LA	121	120	-0.8%
Beaumont-Port Arthur, TX	107	107	0.0%
Benton Harbor, MI	145	142	-2.1%
Biloxi-Gulfport-Pascagoula, MS	111	110	-0.9%
Birmingham, AL	99	97	-2.0%
Buffalo-Niagara Falls, NY	105	104	-1.0%
Canton-Massillon, OH	99	95	-4.0%
Charleston, WV	95	93	-2.1%
Charlotte-Gastonia-Rock Hill, NC-SC	99	94	-5.1%
Chattanooga, TN	99	97	-2.0%
Clarksville-Hopkinsville, TN-KY	77	76	-1.3%
Columbia, SC	83	81	-2.4%
Columbus, GA-AL	100	98	-2.0%
Columbus, OH	96	92	-4.2%
Dayton-Springfield, OH	88	83	-5.7%
Dover, DE	83	80	-3.6%
Erie, PA	88	86	-2.3%
Evansville-Henderson, IN-KY	90	89	-1.1%
Fayetteville, NC	72	68	-5.6%

Fort Wayne, IN	76	73	-3.9%
Grand Rapids-Muskegon-Holland, MI	128	123	-3.9%
Greensboro-Winston Salem, NC	81	79	-2.5%
Greenville-Spartanburg, SC	83	79	-4.8%
Harrisburg-Lebanon-Carlisle, PA	94	91	-3.2%
Hartford, CT	127	123	-3.1%
Hickory-Morganton, NC	81	79	-2.5%
Huntington-Ashland, WV-KY-OH	98	97	-1.0%
Huntsville, AL	80	78	-2.5%
Indianapolis, IN	93	89	-4.3%
Jamestown, NY	88	85	-3.4%
Janesville-Beloit, WI	88	86	-2.3%
Johnson City, TN	75	73	-2.7%
Johnstown, PA	83	81	-2.4%
Knoxville, TN	76	74	-2.6%
Lake Charles, LA	107	106	-0.9%
Lancaster, PA	91	88	-3.3%
Lima, OH	80	77	-3.8%
Little Rock, AR	89	87	-2.2%
Longview-Marshall, TX	87	86	-1.1%
Louisville, KY-IN	113	111	-1.8%
Macon, GA	130	128	-1.5%
Memphis, TN-AR-MS	111	109	-1.8%
Montgomery, AL	84	83	-1.2%
Nashville, TN	100	98	-2.0%
New Haven-Bridgeport-Stamford, CT	128	125	-2.3%
New London - Norwich CT	122	116	-4.9%
New Orleans, LA	125	124	-0.8%
Norfolk-Virginia Beach-Newport News	92	89	-3.3%
Parkersburg-Marietta, WV	90	87	-3.3%
Pensacola, FL	93	92	-1.1%
Pittsburgh, PA	98	96	-2.0%
Providence, RI	114	108	-5.3%
Raleigh-Durham, NC	80	77	-3.8%
Reading, PA	93	90	-3.2%
Richmond-Petersburg, VA	109	106	-2.8%
Roanoke, VA	63	60	-4.8%
Rocky Mount, NC	72	69	-4.2%
St. Louis, MO-IL	111	109	-1.8%
Sarasota-Bradenton, FL	97	92	-5.2%
Scranton-Wilkes Barre, PA	92	88	-4.3%
Sharon, PA	79	76	-3.8%
Sheboygan, WI	92	89	-3.3%
Shreveport, LA	93	92	-1.1%
Springfield, MA	92	88	-4.3%
Toledo, OH	92	90	-2.2%
Tulsa, OK	85	84	-1.2%
York, PA	87	83	-4.6%
Youngstown-Warren, OH	91	89	-2.2%

Table C-2. Number of cells in which 8-hour average ozone >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2020.

Count of cells >= 85 ppb	2020 Base	2020 Control	Percent Difference
Total	**7056**	**6087**	**-13.7%**
Boston	42	25	-40.5%
Chicago	458	419	-8.5%
Cincinnati	146	103	-29.5%
Cleveland	70	39	-44.3%
Dallas	4	1	-75.0%
Detroit	193	163	-15.5%
Houston	540	483	-10.6%
Milwaukee	57	44	-22.8%
New York City	490	457	-6.7%
Philadelphia	214	172	-19.6%
Washington-Baltimore	248	159	-35.9%
Allentown-Bethlehem-Easton, PA	10	3	-70.0%
Atlanta, GA	684	627	-8.3%
Augusta-Aiken, GA-SC	5	3	-40.0%
Austin-San Marcos, TX	0	0	
Barnstable-Yarmouth, MA	28	25	-10.7%
Baton Rouge, LA	354	343	-3.1%
Beaumont-Port Arthur, TX	242	226	-6.6%
Benton Harbor, MI	59	55	-6.8%
Biloxi-Gulfport-Pascagoula, MS	333	307	-7.8%
Birmingham, AL	56	34	-39.3%
Buffalo-Niagara Falls, NY	17	16	-5.9%
Canton-Massillon, OH	20	9	-55.0%
Charleston, WV	3	2	-33.3%
Charlotte-Gastonia-Rock Hill, NC-SC	19	7	-63.2%
Chattanooga, TN	22	15	-31.8%
Clarksville-Hopkinsville, TN-KY	0	0	
Columbia, SC	0	0	
Columbus, GA-AL	32	27	-15.6%
Columbus, OH	29	18	-37.9%
Dayton-Springfield, OH	9	0	-100.0%
Dover, DE	0	0	
Erie, PA	10	2	-80.0%
Evansville-Henderson, IN-KY	11	8	-27.3%
Fayetteville, NC	0	0	
Fort Wayne, IN	0	0	
Grand Rapids-Muskegon-Holland, MI	143	123	-14.0%
Greensboro-Winston Salem, NC	0	0	
Greenville-Spartanburg, SC	0	0	
Harrisburg-Lebanon-Carlisle, PA	43	37	-14.0%
Hartford, CT	42	33	-21.4%
Hickory-Morganton, NC	0	0	

Huntington-Ashland, WV-KY-OH	25	20	-20.0%
Huntsville, AL	0	0	
Indianapolis, IN	15	3	-80.0%
Jamestown, NY	6	2	-66.7%
Janesville-Beloit, WI	11	3	-72.7%
Johnson City, TN	0	0	
Johnstown, PA	0	0	
Knoxville, TN	0	0	
Lake Charles, LA	169	161	-4.7%
Lancaster, PA	4	3	-25.0%
Lima, OH	0	0	
Little Rock, AR	3	1	-66.7%
Longview-Marshall, TX	4	1	-75.0%
Louisville, KY-IN	159	138	-13.2%
Macon, GA	171	152	-11.1%
Memphis, TN-AR-MS	133	110	-17.3%
Montgomery, AL	0	0	
Nashville, TN	49	31	-36.7%
New Haven-Bridgeport-Stamford, CT	51	48	-5.9%
New London - Norwich CT	32	29	-9.4%
New Orleans, LA	1091	1065	-2.4%
Norfolk-Virginia Beach-Newport News	10	5	-50.0%
Parkersburg-Marietta, WV	4	1	-75.0%
Pensacola, FL	66	52	-21.2%
Pittsburgh, PA	88	58	-34.1%
Providence, RI	56	42	-25.0%
Raleigh-Durham, NC	0	0	
Reading, PA	25	15	-40.0%
Richmond-Petersburg, VA	28	23	-17.9%
Roanoke, VA	0	0	
Rocky Mount, NC	0	0	
St. Louis, MO-IL	119	85	-28.6%
Sarasota-Bradenton, FL	11	5	-54.5%
Scranton-Wilkes Barre, PA	26	8	-69.2%
Sharon, PA	0	0	
Sheboygan, WI	8	5	-37.5%
Shreveport, LA	30	22	-26.7%
Springfield, MA	14	6	-57.1%
Toledo, OH	4	3	-25.0%
Tulsa, OK	1	0	-100.0%
York, PA	2	0	-100.0%
Youngstown-Warren, OH	8	5	-37.5%

Table C-3. Number of days (out of 30 possible per subregion) in which peak 8-hour average ozone >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2020.

Number of Days w/ 8-Hour Averages >= 85 ppb	2020 Base	2020 Control	Percent Difference
Total	**427**	**370**	**-13.3%**
Boston	4	3	-25.0%
Chicago	21	19	-9.5%
Cincinnati	12	8	-33.3%
Cleveland	7	5	-28.6%
Dallas	2	1	-50.0%
Detroit	11	11	0.0%
Houston	13	11	-15.4%
Milwaukee	9	9	0.0%
New York City	12	13	8.3%
Philadelphia	11	9	-18.2%
Washington-Baltimore	14	14	0.0%
Allentown-Bethlehem-Easton, PA	3	1	-66.7%
Atlanta, GA	21	21	0.0%
Augusta-Aiken, GA-SC	1	1	0.0%
Austin-San Marcos, TX	0	0	
Barnstable-Yarmouth, MA	3	3	0.0%
Baton Rouge, LA	17	16	-5.9%
Beaumont-Port Arthur, TX	14	14	0.0%
Benton Harbor, MI	9	9	0.0%
Biloxi-Gulfport-Pascagoula, MS	14	13	-7.1%
Birmingham, AL	6	4	-33.3%
Buffalo-Niagara Falls, NY	1	1	0.0%
Canton-Massillon, OH	3	2	-33.3%
Charleston, WV	1	1	0.0%
Charlotte-Gastonia-Rock Hill, NC-SC	4	2	-50.0%
Chattanooga, TN	4	3	-25.0%
Clarksville-Hopkinsville, TN-KY	0	0	
Columbia, SC	0	0	
Columbus, GA-AL	3	3	0.0%
Columbus, OH	2	2	0.0%
Dayton-Springfield, OH	3	0	-100.0%
Dover, DE	0	0	
Erie, PA	2	1	-50.0%
Evansville-Henderson, IN-KY	2	1	-50.0%
Fayetteville, NC	0	0	
Fort Wayne, IN	0	0	
Grand Rapids-Muskegon-Holland, MI	9	8	-11.1%
Greensboro-Winston Salem, NC	0	0	
Greenville-Spartanburg, SC	0	0	
Harrisburg-Lebanon-Carlisle, PA	1	1	0.0%
Hartford, CT	7	5	-28.6%
Hickory-Morganton, NC	0	0	

Huntington-Ashland, WV-KY-OH	5	4	-20.0%
Huntsville, AL	0	0	
Indianapolis, IN	5	1	-80.0%
Jamestown, NY	1	1	0.0%
Janesville-Beloit, WI	3	2	-33.3%
Johnson City, TN	0	0	
Johnstown, PA	0	0	
Knoxville, TN	0	0	
Lake Charles, LA	13	13	0.0%
Lancaster, PA	2	1	-50.0%
Lima, OH	0	0	
Little Rock, AR	1	1	0.0%
Longview-Marshall, TX	1	1	0.0%
Louisville, KY-IN	18	14	-22.2%
Macon, GA	13	13	0.0%
Memphis, TN-AR-MS	17	17	0.0%
Montgomery, AL	0	0	
Nashville, TN	8	6	-25.0%
New Haven-Bridgeport-Stamford, CT	9	8	-11.1%
New London - Norwich CT	5	4	-20.0%
New Orleans, LA	18	18	0.0%
Norfolk-Virginia Beach-Newport News	3	3	0.0%
Parkersburg-Marietta, WV	2	1	-50.0%
Pensacola, FL	8	8	0.0%
Pittsburgh, PA	8	6	-25.0%
Providence, RI	5	5	0.0%
Raleigh-Durham, NC	0	0	
Reading, PA	2	2	0.0%
Richmond-Petersburg, VA	2	2	0.0%
Roanoke, VA	0	0	
Rocky Mount, NC	0	0	
St. Louis, MO-IL	13	11	-15.4%
Sarasota-Bradenton, FL	3	1	-66.7%
Scranton-Wilkes Barre, PA	2	1	-50.0%
Sharon, PA	0	0	
Sheboygan, WI	2	2	0.0%
Shreveport, LA	4	4	0.0%
Springfield, MA	1	1	0.0%
Toledo, OH	3	2	-33.3%
Tulsa, OK	1	0	-100.0%
York, PA	1	0	-100.0%
Youngstown-Warren, OH	2	2	0.0%

Table C-4. Total sum of daily maximum 8-hour ozone averages >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2020.

Total PPB Sum >= 85 ppb	2020 Base	2020 Control	Percent Difference
Total	**73442.4**	**62084.6**	**-15.5%**
Boston	299.3	150.5	-49.7%
Chicago	4944.9	4341.2	-12.2%
Cincinnati	947.4	572.3	-39.6%
Cleveland	325	161.3	-50.4%
Dallas	4.3	0.5	-88.4%
Detroit	1448.4	1154.1	-20.3%
Houston	3654.5	3141.8	-14.0%
Milwaukee	469	351.6	-25.0%
New York City	6264.5	5396.7	-13.9%
Philadelphia	1806.6	1345.3	-25.5%
Washington-Baltimore	1821.7	1061.4	-41.7%
Allentown-Bethlehem-Easton, PA	21.4	6	-72.0%
Atlanta, GA	9815.1	8102.4	-17.4%
Augusta-Aiken, GA-SC	15.1	8.5	-43.7%
Austin-San Marcos, TX	0	0	
Barnstable-Yarmouth, MA	175.6	83.1	-52.7%
Baton Rouge, LA	5606.4	5164.1	-7.9%
Beaumont-Port Arthur, TX	1701.8	1513	-11.1%
Benton Harbor, MI	927.1	790.1	-14.8%
Biloxi-Gulfport-Pascagoula, MS	3002.9	2690.1	-10.4%
Birmingham, AL	244.3	154.9	-36.6%
Buffalo-Niagara Falls, NY	167.6	154.7	-7.7%
Canton-Massillon, OH	80.5	42.7	-47.0%
Charleston, WV	18.3	14.3	-21.9%
Charlotte-Gastonia-Rock Hill, NC-SC	68.9	26.3	-61.8%
Chattanooga, TN	105.7	79.7	-24.6%
Clarksville-Hopkinsville, TN-KY	0	0	
Columbia, SC	0	0	
Columbus, GA-AL	215.4	161.3	-25.1%
Columbus, OH	120.3	49.8	-58.6%
Dayton-Springfield, OH	12.2	0	-100.0%
Dover, DE	0	0	
Erie, PA	15.6	2.1	-86.5%
Evansville-Henderson, IN-KY	34.4	14.1	-59.0%
Fayetteville, NC	0	0	
Fort Wayne, IN	0	0	
Grand Rapids-Muskegon-Holland, MI	2016.2	1593.7	-21.0%
Greensboro-Winston Salem, NC	0	0	
Greenville-Spartanburg, SC	0	0	
Harrisburg-Lebanon-Carlisle, PA	274.6	135.4	-50.7%
Hartford, CT	586.5	460.3	-21.5%

Hickory-Morganton, NC	0	0	
Huntington-Ashland, WV-KY-OH	137.9	102.6	-25.6%
Huntsville, AL	0	0	
Indianapolis, IN	35.9	9.5	-73.5%
Jamestown, NY	13.9	1.4	-89.9%
Janesville-Beloit, WI	19.2	2	-89.6%
Johnson City, TN	0	0	
Johnstown, PA	0	0	
Knoxville, TN	0	0	
Lake Charles, LA	1392.3	1268.1	-8.9%
Lancaster, PA	13.3	6.1	-54.1%
Lima, OH	0	0	
Little Rock, AR	5.7	2.3	-59.6%
Longview-Marshall, TX	4.4	1.4	-68.2%
Louisville, KY-IN	1360.5	1086.6	-20.1%
Macon, GA	2151.4	1894.9	-11.9%
Memphis, TN-AR-MS	840.1	640	-23.8%
Montgomery, AL	0	0	
Nashville, TN	235	130	-44.7%
New Haven-Bridgeport-Stamford, CT	657.9	609.6	-7.3%
New London - Norwich CT	510.3	393.4	-22.9%
New Orleans, LA	16153.7	15314.1	-5.2%
Norfolk-Virginia Beach-Newport News	28.9	11.2	-61.2%
Parkersburg-Marietta, WV	7.7	2.8	-63.6%
Pensacola, FL	208.6	140.3	-32.7%
Pittsburgh, PA	395.6	235.4	-40.5%
Providence, RI	557.9	360.2	-35.4%
Raleigh-Durham, NC	0	0	
Reading, PA	80.4	35.2	-56.2%
Richmond-Petersburg, VA	261.7	199.3	-23.8%
Roanoke, VA	0	0	
Rocky Mount, NC	0	0	
St. Louis, MO-IL	816.7	581.4	-28.8%
Sarasota-Bradenton, FL	48.3	20.6	-57.3%
Scranton-Wilkes Barre, PA	73	13.1	-82.1%
Sharon, PA	0	0	
Sheboygan, WI	31.4	15.5	-50.6%
Shreveport, LA	87.3	53	-39.3%
Springfield, MA	55.3	10.3	-81.4%
Toledo, OH	19.6	11.4	-41.8%
Tulsa, OK	0.5	0	-100.0%
York, PA	3.9	0	-100.0%
Youngstown-Warren, OH	22.6	9.1	-59.7%

Table C-5. Population-weighted (using 2000 population), total sum of all 8-hour ozone averages >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2020.

Population-Weighted Total PPB Sum >= 85 ppb	2020 Base	2020 Control	Percent Difference
Total	**38173.3**	**34257.8**	**-10.3%**
Boston	116.9	57.6	-50.7%
Chicago	3259	3343.9	2.6%
Cincinnati	772.5	522.1	-32.4%
Cleveland	205.4	136.8	-33.4%
Dallas	14.6	2	-86.3%
Detroit	879.9	795.1	-9.6%
Houston	3060.8	2717.3	-11.2%
Milwaukee	303	246	-18.8%
New York City	9611.2	9940	3.4%
Philadelphia	2028.9	1657.5	-18.3%
Washington-Baltimore	1851.3	1248.7	-32.6%
Allentown-Bethlehem-Easton, PA	7.7	2.7	-64.9%
Atlanta, GA	6583.3	5485.4	-16.7%
Augusta-Aiken, GA-SC	5.1	2.9	-43.1%
Austin-San Marcos, TX	0	0	
Barnstable-Yarmouth, MA	19.9	8.9	-55.3%
Baton Rouge, LA	1143.3	1051.5	-8.0%
Beaumont-Port Arthur, TX	318.1	289.7	-8.9%
Benton Harbor, MI	45	37.3	-17.1%
Biloxi-Gulfport-Pascagoula, MS	322.4	289.5	-10.2%
Birmingham, AL	138.9	94.1	-32.3%
Buffalo-Niagara Falls, NY	58.7	52.4	-10.7%
Canton-Massillon, OH	28.4	13.9	-51.1%
Charleston, WV	5.6	4.4	-21.4%
Charlotte-Gastonia-Rock Hill, NC-SC	44.6	18.7	-58.1%
Chattanooga, TN	6	4.3	-28.3%
Clarksville-Hopkinsville, TN-KY	0	0	
Columbia, SC	0	0	
Columbus, GA-AL	18.8	11.4	-39.4%
Columbus, OH	52	21.3	-59.0%
Dayton-Springfield, OH	14.5	0	-100.0%
Dover, DE	0	0	
Erie, PA	1.8	0.2	-88.9%
Evansville-Henderson, IN-KY	10.2	4.5	-55.9%
Fayetteville, NC	0	0	
Fort Wayne, IN	0	0	
Grand Rapids-Muskegon-Holland, MI	290.9	231.4	-20.5%
Greensboro-Winston Salem, NC	0	0	
Greenville-Spartanburg, SC	0	0	
Harrisburg-Lebanon-Carlisle, PA	41.4	21.3	-48.6%
Hartford, CT	158.5	116.9	-26.2%
Hickory-Morganton, NC	0	0	

Huntington-Ashland, WV-KY-OH	25.2	19.1	-24.2%
Huntsville, AL	0	0	
Indianapolis, IN	35.3	13.6	-61.5%
Jamestown, NY	0.7	0	-100.0%
Janesville-Beloit, WI	1.8	0.2	-88.9%
Johnson City, TN	0	0	
Johnstown, PA	0	0	
Knoxville, TN	0	0	
Lake Charles, LA	171.9	159.1	-7.4%
Lancaster, PA	4.2	1.9	-54.8%
Lima, OH	0	0	
Little Rock, AR	0.4	0.1	-75.0%
Longview-Marshall, TX	0.2	0.1	-50.0%
Louisville, KY-IN	729.1	625.7	-14.2%
Macon, GA	298.7	262.4	-12.2%
Memphis, TN-AR-MS	234.5	166.7	-28.9%
Montgomery, AL	0	0	
Nashville, TN	192.7	123.7	-35.8%
New Haven-Bridgeport-Stamford, CT	574.8	542.4	-5.6%
New London - Norwich CT	117.8	91.1	-22.7%
New Orleans, LA	2888.3	2766	-4.2%
Norfolk-Virginia Beach-Newport News	3.6	0.7	-80.6%
Parkersburg-Marietta, WV	0.1	0	-100.0%
Pensacola, FL	90.5	66.3	-26.7%
Pittsburgh, PA	302.8	202.5	-33.1%
Providence, RI	187.4	124.1	-33.8%
Raleigh-Durham, NC	0	0	
Reading, PA	22	10.6	-51.8%
Richmond-Petersburg, VA	176.1	137.1	-22.1%
Roanoke, VA	0	0	
Rocky Mount, NC	0	0	
St. Louis, MO-IL	585.2	460.5	-21.3%
Sarasota-Bradenton, FL	13	4.3	-66.9%
Scranton-Wilkes Barre, PA	9.7	2.1	-78.4%
Sharon, PA	0	0	
Sheboygan, WI	5.2	2.2	-57.7%
Shreveport, LA	53.7	39.7	-26.1%
Springfield, MA	25.7	4.1	-84.0%
Toledo, OH	1.9	1.3	-31.6%
Tulsa, OK	0.1	0	-100.0%
York, PA	0.7	0	-100.0%
Youngstown-Warren, OH	1.7	0.6	-64.7%

Appendix D
Effect of Proposed Nonroad Controls on 8-Hour Ozone in 2030 for Selected Eastern U.S. CMSA/MSAs

Table D-1. Modeled episodic peak 8-hour average ozone, before and after the proposed Nonroad emissions reductions in 2030.

Episodic 8-hour Maximum Ozone	2030 Base	2030 Control	Percent Difference
Total	**150**	**143**	**-4.7%**
Boston	105	97	-7.6%
Chicago	139	136	-2.2%
Cincinnati	106	101	-4.7%
Cleveland	103	98	-4.9%
Dallas	88	84	-4.5%
Detroit	122	121	-0.8%
Houston	112	111	-0.9%
Milwaukee	114	110	-3.5%
New York City	130	126	-3.1%
Philadelphia	112	108	-3.6%
Washington-Baltimore	114	109	-4.4%
Allentown-Bethlehem-Easton, PA	90	86	-4.4%
Atlanta, GA	150	143	-4.7%
Augusta-Aiken, GA-SC	91	89	-2.2%
Austin-San Marcos, TX	73	71	-2.7%
Barnstable-Yarmouth, MA	98	93	-5.1%
Baton Rouge, LA	123	121	-1.6%
Beaumont-Port Arthur, TX	110	108	-1.8%
Benton Harbor, MI	147	143	-2.7%
Biloxi-Gulfport-Pascagoula, MS	113	111	-1.8%
Birmingham, AL	99	95	-4.0%
Buffalo-Niagara Falls, NY	105	104	-1.0%
Canton-Massillon, OH	101	95	-5.9%
Charleston, WV	94	92	-2.1%
Charlotte-Gastonia-Rock Hill, NC-SC	100	92	-8.0%
Chattanooga, TN	99	97	-2.0%
Clarksville-Hopkinsville, TN-KY	77	75	-2.6%
Columbia, SC	83	80	-3.6%
Columbus, GA-AL	99	97	-2.0%
Columbus, OH	97	92	-5.2%
Dayton-Springfield, OH	88	81	-8.0%
Dover, DE	83	79	-4.8%
Erie, PA	89	85	-4.5%
Evansville-Henderson, IN-KY	91	87	-4.4%

Fayetteville, NC	72	66	-8.3%
Fort Wayne, IN	77	72	-6.5%
Grand Rapids-Muskegon-Holland, MI	130	122	-6.2%
Greensboro-Winston Salem, NC	81	78	-3.7%
Greenville-Spartanburg, SC	83	78	-6.0%
Harrisburg-Lebanon-Carlisle, PA	95	90	-5.3%
Hartford, CT	129	122	-5.4%
Hickory-Morganton, NC	81	78	-3.7%
Huntington-Ashland, WV-KY-OH	99	97	-2.0%
Huntsville, AL	80	77	-3.8%
Indianapolis, IN	94	87	-7.4%
Jamestown, NY	89	85	-4.5%
Janesville-Beloit, WI	89	85	-4.5%
Johnson City, TN	75	73	-2.7%
Johnstown, PA	83	79	-4.8%
Knoxville, TN	75	72	-4.0%
Lake Charles, LA	109	108	-0.9%
Lancaster, PA	92	88	-4.3%
Lima, OH	81	77	-4.9%
Little Rock, AR	89	86	-3.4%
Longview-Marshall, TX	88	86	-2.3%
Louisville, KY-IN	113	110	-2.7%
Macon, GA	130	127	-2.3%
Memphis, TN-AR-MS	112	108	-3.6%
Montgomery, AL	84	83	-1.2%
Nashville, TN	101	98	-3.0%
New Haven-Bridgeport-Stamford, CT	130	124	-4.6%
New London - Norwich CT	124	115	-7.3%
New Orleans, LA	127	125	-1.6%
Norfolk-Virginia Beach-Newport News	93	88	-5.4%
Parkersburg-Marietta, WV	90	86	-4.4%
Pensacola, FL	94	92	-2.1%
Pittsburgh, PA	99	96	-3.0%
Providence, RI	115	106	-7.8%
Raleigh-Durham, NC	80	76	-5.0%
Reading, PA	94	89	-5.3%
Richmond-Petersburg, VA	109	106	-2.8%
Roanoke, VA	63	59	-6.3%
Rocky Mount, NC	72	67	-6.9%
St. Louis, MO-IL	113	109	-3.5%
Sarasota-Bradenton, FL	96	90	-6.3%
Scranton-Wilkes Barre, PA	93	87	-6.5%
Sharon, PA	80	75	-6.3%
Sheboygan, WI	94	89	-5.3%
Shreveport, LA	94	91	-3.2%
Springfield, MA	93	87	-6.5%
Toledo, OH	93	90	-3.2%
Tulsa, OK	86	84	-2.3%
York, PA	87	81	-6.9%
Youngstown-Warren, OH	91	88	-3.3%

Table D-2. Number of cells in which 8-hour average ozone >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2030.

Count of cells >= 85 ppb	2030 Base	2030 Control	Percent Difference
Total	**7506**	**5968**	**-20.5%**
Boston	46	24	-47.8%
Chicago	509	442	-13.2%
Cincinnati	159	89	-44.0%
Cleveland	81	34	-58.0%
Dallas	5	0	-100.0%
Detroit	208	163	-21.6%
Houston	600	519	-13.5%
Milwaukee	62	41	-33.9%
New York City	527	456	-13.5%
Philadelphia	225	161	-28.4%
Washington-Baltimore	256	118	-53.9%
Allentown-Bethlehem-Easton, PA	15	3	-80.0%
Atlanta, GA	683	574	-16.0%
Augusta-Aiken, GA-SC	5	3	-40.0%
Austin-San Marcos, TX	0	0	
Barnstable-Yarmouth, MA	30	22	-26.7%
Baton Rouge, LA	366	348	-4.9%
Beaumont-Port Arthur, TX	266	243	-8.6%
Benton Harbor, MI	62	55	-11.3%
Biloxi-Gulfport-Pascagoula, MS	340	310	-8.8%
Birmingham, AL	53	27	-49.1%
Buffalo-Niagara Falls, NY	18	16	-11.1%
Canton-Massillon, OH	21	9	-57.1%
Charleston, WV	3	2	-33.3%
Charlotte-Gastonia-Rock Hill, NC-SC	21	6	-71.4%
Chattanooga, TN	21	15	-28.6%
Clarksville-Hopkinsville, TN-KY	0	0	
Columbia, SC	0	0	
Columbus, GA-AL	30	22	-26.7%
Columbus, OH	34	12	-64.7%
Dayton-Springfield, OH	10	0	-100.0%
Dover, DE	0	0	
Erie, PA	11	2	-81.8%
Evansville-Henderson, IN-KY	11	5	-54.5%
Fayetteville, NC	0	0	
Fort Wayne, IN	0	0	
Grand Rapids-Muskegon-Holland, MI	155	118	-23.9%
Greensboro-Winston Salem, NC	0	0	
Greenville-Spartanburg, SC	0	0	
Harrisburg-Lebanon-Carlisle, PA	43	31	-27.9%
Hartford, CT	48	32	-33.3%
Hickory-Morganton, NC	0	0	
Huntington-Ashland, WV-KY-OH	29	19	-34.5%

Huntsville, AL	0	0	
Indianapolis, IN	16	2	-87.5%
Jamestown, NY	6	1	-83.3%
Janesville-Beloit, WI	13	2	-84.6%
Johnson City, TN	0	0	
Johnstown, PA	0	0	
Knoxville, TN	0	0	
Lake Charles, LA	182	168	-7.7%
Lancaster, PA	6	3	-50.0%
Lima, OH	0	0	
Little Rock, AR	3	1	-66.7%
Longview-Marshall, TX	5	1	-80.0%
Louisville, KY-IN	166	126	-24.1%
Macon, GA	170	143	-15.9%
Memphis, TN-AR-MS	141	104	-26.2%
Montgomery, AL	0	0	
Nashville, TN	52	21	-59.6%
New Haven-Bridgeport-Stamford, CT	65	55	-15.4%
New London - Norwich CT	36	28	-22.2%
New Orleans, LA	1142	1090	-4.6%
Norfolk-Virginia Beach-Newport News	13	5	-61.5%
Parkersburg-Marietta, WV	4	1	-75.0%
Pensacola, FL	72	53	-26.4%
Pittsburgh, PA	94	48	-48.9%
Providence, RI	57	40	-29.8%
Raleigh-Durham, NC	0	0	
Reading, PA	28	14	-50.0%
Richmond-Petersburg, VA	30	21	-30.0%
Roanoke, VA	0	0	
Rocky Mount, NC	0	0	
St. Louis, MO-IL	138	77	-44.2%
Sarasota-Bradenton, FL	12	3	-75.0%
Scranton-Wilkes Barre, PA	27	5	-81.5%
Sharon, PA	0	0	
Sheboygan, WI	8	5	-37.5%
Shreveport, LA	33	21	-36.4%
Springfield, MA	14	4	-71.4%
Toledo, OH	6	3	-50.0%
Tulsa, OK	2	0	-100.0%
York, PA	3	0	-100.0%
Youngstown-Warren, OH	9	2	-77.8%

Table D-3. Number of days (out of 30 possible per subregion) in which peak 8-hour average ozone >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2030.

Number of Days w/ 8-Hour Averages >= 85 ppb	2030 Base	2030 Control	Percent Difference
Total	450	370	**-17.8%**
Boston	4	3	-25.0%
Chicago	22	21	-4.5%
Cincinnati	13	8	-38.5%
Cleveland	7	5	-28.6%
Dallas	2	0	-100.0%
Detroit	11	11	0.0%
Houston	13	12	-7.7%
Milwaukee	11	9	-18.2%
New York City	14	13	-7.1%
Philadelphia	12	10	-16.7%
Washington-Baltimore	16	12	-25.0%
Allentown-Bethlehem-Easton, PA	3	1	-66.7%
Atlanta, GA	21	21	0.0%
Augusta-Aiken, GA-SC	1	1	0.0%
Austin-San Marcos, TX	0	0	
Barnstable-Yarmouth, MA	4	3	-25.0%
Baton Rouge, LA	17	17	0.0%
Beaumont-Port Arthur, TX	14	14	0.0%
Benton Harbor, MI	10	9	-10.0%
Biloxi-Gulfport-Pascagoula, MS	14	13	-7.1%
Birmingham, AL	6	4	-33.3%
Buffalo-Niagara Falls, NY	1	1	0.0%
Canton-Massillon, OH	3	2	-33.3%
Charleston, WV	1	1	0.0%
Charlotte-Gastonia-Rock Hill, NC-SC	5	2	-60.0%
Chattanooga, TN	4	3	-25.0%
Clarksville-Hopkinsville, TN-KY	0	0	
Columbia, SC	0	0	
Columbus, GA-AL	3	3	0.0%
Columbus, OH	5	2	-60.0%
Dayton-Springfield, OH	3	0	-100.0%
Dover, DE	0	0	
Erie, PA	2	1	-50.0%
Evansville-Henderson, IN-KY	2	1	-50.0%
Fayetteville, NC	0	0	
Fort Wayne, IN	0	0	
Grand Rapids-Muskegon-Holland, MI	9	8	-11.1%
Greensboro-Winston Salem, NC	0	0	
Greenville-Spartanburg, SC	0	0	
Harrisburg-Lebanon-Carlisle, PA	1	1	0.0%
Hartford, CT	8	5	-37.5%
Hickory-Morganton, NC	0	0	

Huntington-Ashland, WV-KY-OH	5	4	-20.0%
Huntsville, AL	0	0	
Indianapolis, IN	5	1	-80.0%
Jamestown, NY	1	1	0.0%
Janesville-Beloit, WI	3	2	-33.3%
Johnson City, TN	0	0	
Johnstown, PA	0	0	
Knoxville, TN	0	0	
Lake Charles, LA	13	13	0.0%
Lancaster, PA	3	1	-66.7%
Lima, OH	0	0	
Little Rock, AR	1	1	0.0%
Longview-Marshall, TX	1	1	0.0%
Louisville, KY-IN	18	14	-22.2%
Macon, GA	13	13	0.0%
Memphis, TN-AR-MS	17	17	0.0%
Montgomery, AL	0	0	
Nashville, TN	8	5	-37.5%
New Haven-Bridgeport-Stamford, CT	9	9	0.0%
New London - Norwich CT	5	3	-40.0%
New Orleans, LA	18	18	0.0%
Norfolk-Virginia Beach-Newport News	4	3	-25.0%
Parkersburg-Marietta, WV	2	1	-50.0%
Pensacola, FL	8	8	0.0%
Pittsburgh, PA	8	6	-25.0%
Providence, RI	5	5	0.0%
Raleigh-Durham, NC	0	0	
Reading, PA	2	2	0.0%
Richmond-Petersburg, VA	2	2	0.0%
Roanoke, VA	0	0	
Rocky Mount, NC	0	0	
St. Louis, MO-IL	14	11	-21.4%
Sarasota-Bradenton, FL	3	1	-66.7%
Scranton-Wilkes Barre, PA	2	1	-50.0%
Sharon, PA	0	0	
Sheboygan, WI	2	2	0.0%
Shreveport, LA	4	4	0.0%
Springfield, MA	1	1	0.0%
Toledo, OH	4	2	-50.0%
Tulsa, OK	2	0	-100.0%
York, PA	2	0	-100.0%
Youngstown-Warren, OH	3	1	-66.7%

Table D-4. Total sum of daily maximum 8-hour ozone averages >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2030.

Total PPB Sum >= 85 ppb	2030 Base	2030 Control	Percent Difference
Total	80019.1	62480.3	**-21.9%**
Boston	344.6	118.6	-65.6%
Chicago	5683.5	4616.2	-18.8%
Cincinnati	1021.4	450.7	-55.9%
Cleveland	398.2	142.4	-64.2%
Dallas	7	0	-100.0%
Detroit	1720.9	1221.7	-29.0%
Houston	4395.1	3560.3	-19.0%
Milwaukee	537.8	339.9	-36.8%
New York City	6767.3	5350.7	-20.9%
Philadelphia	1948.2	1243.4	-36.2%
Washington-Baltimore	1895.9	813.4	-57.1%
Allentown-Bethlehem-Easton, PA	29.6	3.2	-89.2%
Atlanta, GA	9749.8	7233.7	-25.8%
Augusta-Aiken, GA-SC	18.5	8.8	-52.4%
Austin-San Marcos, TX	0	0	
Barnstable-Yarmouth, MA	211.9	66.9	-68.4%
Baton Rouge, LA	6099	5439.6	-10.8%
Beaumont-Port Arthur, TX	2081.4	1780.6	-14.5%
Benton Harbor, MI	981.7	763.8	-22.2%
Biloxi-Gulfport-Pascagoula, MS	3292.3	2823.4	-14.2%
Birmingham, AL	227.3	113.2	-50.2%
Buffalo-Niagara Falls, NY	175.3	153.5	-12.4%
Canton-Massillon, OH	92.4	35.2	-61.9%
Charleston, WV	17.6	12.2	-30.7%
Charlotte-Gastonia-Rock Hill, NC-SC	77.6	16.3	-79.0%
Chattanooga, TN	104.2	68.2	-34.5%
Clarksville-Hopkinsville, TN-KY	0	0	
Columbia, SC	0	0	
Columbus, GA-AL	208.6	134.5	-35.5%
Columbus, OH	145.5	33.4	-77.0%
Dayton-Springfield, OH	16.8	0	-100.0%
Dover, DE	0	0	
Erie, PA	21.1	0.2	-99.1%
Evansville-Henderson, IN-KY	36	8	-77.8%
Fayetteville, NC	0	0	
Fort Wayne, IN	0	0	
Grand Rapids-Muskegon-Holland, MI	2182.6	1512.9	-30.7%
Greensboro-Winston Salem, NC	0	0	
Greenville-Spartanburg, SC	0	0	
Harrisburg-Lebanon-Carlisle, PA	301	99.1	-67.1%
Hartford, CT	651.6	438.1	-32.8%
Hickory-Morganton, NC	0	0	
Huntington-Ashland, WV-KY-OH	153.2	99.2	-35.2%

Huntsville, AL	0	0	
Indianapolis, IN	41.6	4.3	-89.7%
Jamestown, NY	18	0.1	-99.4%
Janesville-Beloit, WI	27.2	0.7	-97.4%
Johnson City, TN	0	0	
Johnstown, PA	0	0	
Knoxville, TN	0	0	
Lake Charles, LA	1667.2	1471.1	-11.8%
Lancaster, PA	17.1	5.4	-68.4%
Lima, OH	0	0	
Little Rock, AR	6.2	1.5	-75.8%
Longview-Marshall, TX	6.9	1.4	-79.7%
Louisville, KY-IN	1396.5	971.6	-30.4%
Macon, GA	2135	1766.6	-17.3%
Memphis, TN-AR-MS	928	613.4	-33.9%
Montgomery, AL	0	0	
Nashville, TN	252	108.3	-57.0%
New Haven-Bridgeport-Stamford, CT	750.8	632.2	-15.8%
New London - Norwich CT	561.2	367.1	-34.6%
New Orleans, LA	17536.8	16290.3	-7.1%
Norfolk-Virginia Beach-Newport News	37.9	9	-76.3%
Parkersburg-Marietta, WV	8.3	1.6	-80.7%
Pensacola, FL	246.2	143.3	-41.8%
Pittsburgh, PA	440.6	201.6	-54.2%
Providence, RI	628.3	320.3	-49.0%
Raleigh-Durham, NC	0	0	
Reading, PA	105.9	30.2	-71.5%
Richmond-Petersburg, VA	278	185.5	-33.3%
Roanoke, VA	0	0	
Rocky Mount, NC	0	0	
St. Louis, MO-IL	927.6	553	-40.4%
Sarasota-Bradenton, FL	47.6	10.3	-78.4%
Scranton-Wilkes Barre, PA	91.6	6.2	-93.2%
Sharon, PA	0	0	
Sheboygan, WI	40.3	13.5	-66.5%
Shreveport, LA	101.7	49.1	-51.7%
Springfield, MA	70.9	5.3	-92.5%
Toledo, OH	25.1	10.6	-57.8%
Tulsa, OK	1.4	0	-100.0%
York, PA	4.5	0	-100.0%
Youngstown-Warren, OH	24	5.7	-76.3%

Table D-5. Population-weighted (2000 population), total sum of all 8-hour ozone averages >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2030.

Population-Weighted Total PPB Sum >= 85 ppb	2030 Base	2030 Control	Percent Difference
Total	41501	35162.4	**-15.3%**
Boston	134.6	44.2	-67.2%
Chicago	3914	4026.5	2.9%
Cincinnati	838.6	443.8	-47.1%
Cleveland	244.1	131	-46.3%
Dallas	23.2	0	-100.0%
Detroit	1086.1	914.8	-15.8%
Houston	3552.5	3014	-15.2%
Milwaukee	345.6	245.6	-28.9%
New York City	10233.9	10521.3	2.8%
Philadelphia	2208.3	1618.2	-26.7%
Washington-Baltimore	1959.5	1045.2	-46.7%
Allentown-Bethlehem-Easton, PA	9.6	1.4	-85.4%
Atlanta, GA	6616.6	4971.1	-24.9%
Augusta-Aiken, GA-SC	6.1	2.9	-52.5%
Austin-San Marcos, TX	0	0	
Barnstable-Yarmouth, MA	24.5	7.2	-70.6%
Baton Rouge, LA	1239.8	1103.3	-11.0%
Beaumont-Port Arthur, TX	379.3	334.6	-11.8%
Benton Harbor, MI	47.8	35.6	-25.5%
Biloxi-Gulfport-Pascagoula, MS	351.6	301.6	-14.2%
Birmingham, AL	130.1	70.3	-46.0%
Buffalo-Niagara Falls, NY	63.8	52.7	-17.4%
Canton-Massillon, OH	32.8	10.9	-66.8%
Charleston, WV	5.3	3.6	-32.1%
Charlotte-Gastonia-Rock Hill, NC-SC	51.4	12.2	-76.3%
Chattanooga, TN	5.8	3.6	-37.9%
Clarksville-Hopkinsville, TN-KY	0	0	
Columbia, SC	0	0	
Columbus, GA-AL	18.2	8.8	-51.6%
Columbus, OH	68.6	13.8	-79.9%
Dayton-Springfield, OH	19.4	0	-100.0%
Dover, DE	0	0	
Erie, PA	2.5	0	-100.0%
Evansville-Henderson, IN-KY	10.9	2.7	-75.2%
Fayetteville, NC	0	0	
Fort Wayne, IN	0	0	
Grand Rapids-Muskegon-Holland, MI	315.4	220.3	-30.2%
Greensboro-Winston Salem, NC	0	0	
Greenville-Spartanburg, SC	0	0	
Harrisburg-Lebanon-Carlisle, PA	46.7	16.9	-63.8%
Hartford, CT	180.1	109.5	-39.2%
Hickory-Morganton, NC	0	0	

Huntington-Ashland, WV-KY-OH	27.9	18.7	-33.0%
Huntsville, AL	0	0	
Indianapolis, IN	38.1	6.7	-82.4%
Jamestown, NY	1	0	-100.0%
Janesville-Beloit, WI	2.6	0	-100.0%
Johnson City, TN	0	0	
Johnstown, PA	0	0	
Knoxville, TN	0	0	
Lake Charles, LA	201.2	181.4	-9.8%
Lancaster, PA	5.8	1.7	-70.7%
Lima, OH	0	0	
Little Rock, AR	0.4	0.1	-75.0%
Longview-Marshall, TX	0.3	0.1	-66.7%
Louisville, KY-IN	764.9	598.7	-21.7%
Macon, GA	297	243.6	-18.0%
Memphis, TN-AR-MS	266.2	161	-39.5%
Montgomery, AL	0	0	
Nashville, TN	206.5	108.1	-47.7%
New Haven-Bridgeport-Stamford, CT	660.9	571.8	-13.5%
New London - Norwich CT	130	85.3	-34.4%
New Orleans, LA	3097.7	2918.9	-5.8%
Norfolk-Virginia Beach-Newport News	5.8	0.6	-89.7%
Parkersburg-Marietta, WV	0.1	0	-100.0%
Pensacola, FL	102.4	65.4	-36.1%
Pittsburgh, PA	342	185.3	-45.8%
Providence, RI	206.8	107.7	-47.9%
Raleigh-Durham, NC	0	0	
Reading, PA	28.9	9.3	-67.8%
Richmond-Petersburg, VA	183.6	126.8	-30.9%
Roanoke, VA	0	0	
Rocky Mount, NC	0	0	
St. Louis, MO-IL	635.3	439.5	-30.8%
Sarasota-Bradenton, FL	12.4	0.9	-92.7%
Scranton-Wilkes Barre, PA	12.7	1.1	-91.3%
Sharon, PA	0	0	
Sheboygan, WI	6.1	1.3	-78.7%
Shreveport, LA	59.1	37.9	-35.9%
Springfield, MA	32.6	1.2	-96.3%
Toledo, OH	2.4	1.3	-45.8%
Tulsa, OK	0.4	0	-100.0%
York, PA	0.8	0	-100.0%
Youngstown-Warren, OH	2.4	0.3	-87.5%

Appendix E
Effect of Proposed Nonroad Controls on 8-Hour Ozone in 2020 forSelected Western U.S. CMSA/MSAs

Table E-1. Modeled episodic peak 8-hour average ozone, before and after the proposed Nonroad emissions reductions in 2020.

Episodic 8-Hour Maximum Ozone	2020 Base	2020 Control	Percent Difference
Total	**135**	**132**	**-2.2%**
Bakersfield, CA	103	101	-1.9%
Fresno, CA	77	76	-1.3%
Los Angeles	135	132	-2.2%
Merced, CA	72	68	-5.6%
Modesto, CA	73	71	-2.7%
Phoenix-Mesa, AZ	96	94	-2.1%
Sacramento	67	65	-3.0%
San Diego, CA	88	86	-2.3%
San Francisco	78	77	-1.3%
Visalia-Tulare, CA	76	74	-2.6%

Table E-2. Number of cells in which 8-hour average ozone >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2020.

Episodic 8-Hour Maximum Ozone	2020 Base	2020 Control	Percent Difference
Total	**711**	**652**	**-8.3%**
Bakersfield, CA	14	11	-21.4
Fresno, CA	0	0	
Los Angeles	647	605	-6.5%
Merced, CA	0	0	
Modesto, CA	0	0	
Phoenix-Mesa, AZ	46	35	-23.9%
Sacramento	0	0	
San Diego, CA	4	1	-75.0%
San Francisco	0	0	
Visalia-Tulare, CA	0	0	

Table E-3. Number of days (out of 26 possible per subregion) in which peak 8-hour average ozone >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2020.

Episodic 8-Hour Maximum Ozone	2020 Base	2020 Control	Percent Difference
Total	**25**	**23**	**-8.0%**
Bakersfield, CA	1	1	0.0%
Fresno, CA	0	0	
Los Angeles	16	15	-6.3%
Merced, CA	0	0	
Modesto, CA	0	0	
Phoenix-Mesa, AZ	6	6	0.0%
Sacramento	0	0	
San Diego, CA	2	1	-50.0%
San Francisco	0	0	
Visalia-Tulare, CA	0	0	

Table E-4. Total sum of daily maximum 8-hour ozone average >=85 ppb, before and after the proposed Nonroad emissions reductions in 2020.

Episodic 8-Hour Maximum Ozone	2020 Base	2020 Control	Percent Difference
Total	**8571.5**	**7656.9**	**-10.7%**
Bakersfield, CA	99.4	78.5	-21.0%
Fresno, CA	0	0	
Los Angeles	8260.7	7452.2	-9.8%
Merced, CA	0	0	
Modesto, CA	0	0	
Phoenix-Mesa, AZ	201.6	124.9	-38.0%
Sacramento	0	0	
San Diego, CA	9.7	1.2	-87.6%
San Francisco	0	0	
Visalia-Tulare, CA	0	0	

Table E-5. Population-weighted (2000 population), total sum of all 8-hour ozone averages >=85 ppb, before and after the proposed Nonroad emissions reductions in 2020.

Episodic 8-Hour Maximum Ozone	2020 Base	2020 Control	Percent Difference
Total	**3774.9**	**3699.0**	**-2.0%**
Bakersfield, CA	1.8	1.3	-27.8%
Fresno, CA	0	0	
Los Angeles	3576.4	3544.2	-0.9%
Merced, CA	0	0	
Modesto, CA	0	0	
Phoenix-Mesa, AZ	196.5	153.4	-21.9%
Sacramento	0	0	
San Diego, CA	0.3	0.1	-66.7%
San Francisco	0	0	
Visalia-Tulare, CA	0	0	

Appendix F
Effect of Proposed Nonroad Controls on 8-Hour Ozone in 2030 for Selected Western U.S. CMSA/MSAs

Table F-1. Modeled episodic peak 8-hour average ozone, before and after the proposed Nonroad emissions reductions in 2030.

Episodic 8-Hour Maximum Ozone	2030 Base	2030 Control	Percent Difference
Total	**136**	**131**	**-3.7%**
Bakersfield, CA	104	100	-3.8%
Fresno, CA	78	75	-3.8%
Los Angeles	136	131	-3.7%
Merced, CA	72	68	-5.6%
Modesto, CA	73	70	-4.1%
Phoenix-Mesa, AZ	97	95	-2.1%
Sacramento	67	65	-3.0%
San Diego, CA	88	85	-3.4%
San Francisco	79	77	-2.5%
Visalia-Tulare, CA	76	73	-3.9%

Table F-2. Number of cells in which 8-hour average ozone >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2030.

Episodic 8-Hour Maximum Ozone	2030 Base	2030 Control	Percent Difference
Total	**757**	**656**	**-13.3%**
Bakersfield, CA	16	11	-31.3%
Fresno, CA	0	0	
Los Angeles	677	605	-10.6%
Merced, CA	0	0	
Modesto, CA	0	0	
Phoenix-Mesa, AZ	60	39	-35.0%
Sacramento	0	0	
San Diego, CA	4	1	-75.0%
San Francisco	0	0	
Visalia-Tulare, CA	0	0	

Table F-3. Number of days (out of 26 possible per subregion) in which peak 8-hour average ozone >= 85 ppb, before and after the proposed Nonroad emissions reductions in 2030.

Episodic 8-Hour Maximum Ozone	2030 Base	2030 Control	Percent Difference
Total	**26**	**23**	**-11.5%**
Bakersfield, CA	1	1	0.0%
Fresno, CA	0	0	
Los Angeles	16	15	-6.3%
Merced, CA	0	0	
Modesto, CA	0	0	
Phoenix-Mesa, AZ	7	6	-14.3%
Sacramento	0	0	
San Diego, CA	2	1	-50.0%
San Francisco	0	0	
Visalia-Tulare, CA	0	0	

Table F-4. Total sum of daily maximum 8-hour ozone average >=85 ppb, before and after the proposed Nonroad emissions reductions in 2030.

Episodic 8-Hour Maximum Ozone	2030 Base	2030 Control	Percent Difference
Total	**9301.8**	**7743.5**	**-16.8%**
Bakersfield, CA	108.2	74.3	-31.3%
Fresno, CA	0	0	
Los Angeles	8910.5	7528.2	-15.5%
Merced, CA	0	0	
Modesto, CA	0	0	
Phoenix-Mesa, AZ	273.2	140.9	-48.4%
Sacramento	0	0	
San Diego, CA	9.9	0	-100.0%
San Francisco	0	0	
Visalia-Tulare, CA	0	0	

Table F-5. Population-weighted (2000 population), total sum of all 8-hour ozone averages >=85 ppb, before and after the proposed Nonroad emissions reductions in 2030.

Episodic 8-Hour Maximum Ozone	2030 Base	2030 Control	Percent Difference
Total	**4265.0**	**4067.6**	**-4.6%**
Bakersfield, CA	1.9	1.2	-36.8%
Fresno, CA	0	0	
Los Angeles	3995.6	3877.3	-3.0%
Merced, CA	0	0	
Modesto, CA	0	0	
Phoenix-Mesa, AZ	267.2	189.0	-29.3%
Sacramento	0	0	
San Diego, CA	0.3	0	-100.0%
San Francisco	0	0	
Visalia-Tulare, CA	0	0	

Appendix G
IMPROVE Monitoring Sites used in the REMSAD Model Performance Evaluation

IMPROVE Site Code	Site Name	State
ACAD1	Acadia National Park	Maine
BADL1	Badlands National Park	South Dakota
BAND1	Bandelier National Monument	New Mexico
BIBE1	Big Bend National Park	Texas
BLIS1	Bliss State Park(TRPA)	California
BOWA1	Boundary Waters Canoe Area	Minnesota
BRCA1	Bryce Canyon National Park	Colorado
BRID1	Bridger Wilderness	Wyoming
BRIG1	Brigantine National Wildlife Refu	New Jersey
BRLA1	Brooklyn Lake	Wyoming
CANY1	Canyonlands National Park	Utah
CHAS1	Chassahowitzka National Wildlife	Florida
CHIR1	Chiricahua National Monument	Arizona
CORI1	Columbia River Gorge	Washington
CRLA1	Crater Lake National Park	Oregon
CRMO1	Craters of the Moon NM(US DOE)	Idaho
DEVA1	Death Valley Monument	California
DOLA1	Dome Lands Wilderness	California
DOSO1	Dolly Sods /Otter Creek Wildernes	West Virginia
EVER1	Everglades National Park	Florida
GICL1	Gila Wilderness	New Mexico
GLAC1	Glacier National Park	Montana
GRBA1	Great Basin National Park	Nevada
GRCA1	Grand Canyon NP- Hopi Point	Arizona
GRSA1	Great Sand Dunes National Monument	Colorado
GRSM1	Great Smoky Mountains National Park	Tennessee
GUMO1	Guadalupe Mountains National Park	Texas
JARB1	Jarbidge Wilderness	Nevada
JEFF1	Jefferson/James River Face Wildern	Virginia
LAVO1	Lassen Volcanic National Park	California
LOPE1	Lone Peak Wilderness	Utah
LYBR1	Lye Brook Wilderness	Vermont
MACA1	Mammoth Cave National Park	Kentucky
MEVE1	Mesa Verde National Park	Colorado
MOOS1	Moosehorn NWR	Maine
MORA1	Mount Rainier National Park	Washington
MOZI1	Mount Zirkel Wilderness	Colorado
OKEF1	Okefenokee National Wildlife Refu	Georgia
PEFO1	Petrified Forest National Park	Arizona
PINN1	Pinnacles National Monument	California
PORE1	Point Reyes National Seashore	California

IMPROVE Site Code	Site Name	State
PUSO1	Puget Sound	Washington
REDW1	Redwood National Park	California
ROMA1	Cape Romain National Wildlife Ref	South Carolina
ROMO2	Rocky Mountain National Park	Colorado
SAGO1	San Gorgonio Wilderness	California
SALM1	Salmon National Forest	Idaho
SAWT1	Sawtooth National Forest	Idaho
SCOV1	Scoville (US DOE)	Idaho
SEQU1	Sequoia National Park	California
SHEN1	Shenandoah National Park	Virginia
SHRO1	Shining Rock Wilderness	North Carolina
SIPS1	Sipsy Wilderness	Alabama
SNPA1	Snoqualamie Pass, Snoqualamie N.F	Washington
SOLA1	South Lake Tahoe (TRPA)	California
SULA1	Sula (Selway Bitteroot Wilderness)	Montana
THSI1	Three Sisters Wilderness	Idaho
TONT1	Tonto National Monument	Arizona
UPBU1	Upper Buffalo Wilderness	Arkansas
WASH1	Washington D.C.	Washington D.C.

Appendix H

Annual PM2.5 Design Values for 1999-2001 and 2020 and 2030 Base Case and Control Case Scenarios.

		Nonroad Proposal PM2.5 County Design Values and Population									
		[Based on REMSAD v7.01 Modeling]									
FIPS State	**FIPS Cnty**	**State**	**County**	**1999 - 2001**	**2020 Base**	**2020 Control**	**2030 Base**	**2030 Control**	**2000 Pop**	**2020 Pop**	**2030 Pop**
1	27	Alabama	Clay	15.5	14.1	13.82	14.65	14.26	14,254	15,600	16,298
1	33	Alabama	Colbert	15.3	12.34	12.03	12.79	12.36	54,984	57,232	58,485
1	49	Alabama	De Kalb	16.8	14.96	14.61	15.59	15.09	64,452	77,672	84,590
1	69	Alabama	Houston	16.3	15.28	15.02	15.85	15.49	88,787	106,041	115,148
1	73	Alabama	Jefferson	21.6	20.79	20.3	22	21.32	662,047	679,713	690,896
1	89	Alabama	Madison	15.5	13.36	12.99	13.92	13.4	276,700	343,075	378,069
1	97	Alabama	Mobile	15.3	14.94	14.69	15.73	15.39	399,843	440,944	463,124
1	101	Alabama	Montgomery	16.8	15.82	15.54	16.49	16.1	223,510	257,634	275,746
1	103	Alabama	Morgan	19.1	16.93	16.54	17.64	17.1	111,064	133,015	144,685
1	113	Alabama	Russell	18.4	17.61	17.21	18.33	17.78	49,756	56,127	59,536
1	117	Alabama	Shelby	17.2	15.95	15.63	16.69	16.24	143,293	259,341	320,220
1	121	Alabama	Talladega	17.8	16.57	16.28	17.29	16.89	80,321	87,739	91,815
4	5	Arizona	Coconino	7.5	7.22	7.13	7.38	7.25	116,320	147,562	164,495
4	7	Arizona	Gila	9.6	9.39	9.2	9.74	9.48	51,335	86,549	104,850
4	13	Arizona	Maricopa	11.2	11.83	10.97	13	11.83	3,072,149	4,513,344	5,266,724
4	21	Arizona	Pinal	8.6	8.93	8.7	9.59	9.28	179,727	298,094	359,616
4	23	Arizona	Santa Cruz	12.1	12.45	12.18	13.19	12.82	38,381	49,022	54,635
5	35	Arkansas	Crittenden	15.3	14.23	13.61	14.98	14.16	50,866	54,912	57,013
5	119	Arkansas	Pulaski	15.9	14.41	14.01	15.03	14.47	361,474	382,366	393,433
6	1	California	Alameda	12.2	11.2	10.6	12.06	11.17	1,443,741	1,684,320	1,812,462
6	7	California	Butte	15.4	13.54	13.32	14.01	13.69	203,171	253,550	279,642
6	9	California	Calaveras	9.4	7.94	7.76	8.19	7.92	40,554	56,980	65,483
6	11	California	Colusa	10.3	9.38	9.25	9.6	9.39	18,804	24,342	27,300
6	17	California	El Dorado	8.1	7.1	6.95	7.42	7.21	156,299	235,742	277,664
6	19	California	Fresno	24	21.28	20.56	22.55	21.5	799,407	1,010,798	1,121,458
6	23	California	Humboldt	9.2	9.04	8.94	9.2	9.08	126,518	140,881	148,723
6	25	California	Imperial	15.7	14.54	14.09	15.18	14.52	142,361	183,499	204,781
6	29	California	Kern	23.7	20.52	19.89	21.3	20.36	661,645	851,039	949,174
6	31	California	Kings	16.6	13.82	13.38	14.29	13.62	129,461	171,603	193,641
6	37	California	Los Angeles	25.9	24.04	23.06	26.03	24.61	9,519,338	10,068,317	10,397,571

6	45	California	Mendocino	8	6.76	6.66	6.91	6.77	86,265	99,671	106,876
6	47	California	Merced	18.9	15.66	15.16	16.23	15.49	210,554	261,895	288,668
6	49	California	Modoc	8	7.1	7	7.17	7.04	9,449	9,859	10,033
6	59	California	Orange	22.4	22.01	21.01	23.89	22.41	2,846,289	3,681,637	4,114,415
6	61	California	Placer	12.5	10.75	10.45	11.23	10.79	248,399	449,083	555,897
6	65	California	Riverside	29.8	29.69	28.5	32.21	30.39	1,545,387	2,176,313	2,500,652
6	71	California	San Bernardino	25.8	25.7	24.68	27.88	26.31	1,709,434	2,298,311	2,602,018
6	73	California	San Diego	17.1	17.57	16.85	19.4	18.27	2,813,833	3,720,010	4,194,289
6	77	California	San Joaquin	16.4	14.3	13.79	15.05	14.29	563,598	711,131	788,116
6	79	California	San Luis Obispo	10	10.2	9.99	10.63	10.32	246,681	320,613	358,966
6	89	California	Shasta	10.4	8.92	8.82	9.12	8.99	163,256	200,480	219,953
6	97	California	Sonoma	11.1	9.45	9.23	9.89	9.58	458,614	592,845	662,549
6	99	California	Stanislaus	19.7	16.49	15.95	17.12	16.32	446,997	576,927	644,333
6	101	California	Sutter	12.9	11.7	11.51	11.96	11.68	78,930	106,062	120,252
6	107	California	Tulare	24.7	21.83	21.29	22.77	21.96	368,021	461,550	510,533
6	111	California	Ventura	14.5	14.03	13.69	15.01	14.52	753,197	974,455	1,089,111
8	13	Colorado	Boulder	9.2	9.38	9.04	9.94	9.52	291,288	384,637	433,584
8	77	Colorado	Mesa	7.3	6.82	6.66	7.13	6.92	116,255	160,627	183,761
9	1	Connecticut	Fairfield	13.6	12.97	12.47	13.67	12.97	882,567	902,450	915,655
9	9	Connecticut	New Haven	16.8	15.88	15.36	16.71	15.98	824,008	835,856	844,674
10	1	Delaware	Kent	12.9	11.84	11.53	12.38	11.92	126,697	152,443	166,217
10	3	Delaware	New Castle	16.6	15.72	15.28	16.52	15.9	500,265	567,457	603,839
10	5	Delaware	Sussex	14.5	13.38	13.05	14.01	13.52	156,638	207,387	233,829
11	1	D.C.	Washington	16.6	15.56	15.05	16.39	15.66	572,059	544,554	532,846
12	1	Florida	Alachua	10.9	10.03	9.85	10.39	10.15	217,955	264,811	289,558
12	11	Florida	Broward	9	9.25	8.88	9.89	9.38	1,623,018	2,132,443	2,399,060
12	17	Florida	Citrus	10.5	9.12	8.94	9.43	9.2	118,085	148,847	164,729
12	25	Florida	Dade	8.5	8.12	7.98	8.55	8.36	2,253,362	**2,253,362**	**2,253,362**
12	33	Florida	Escambia	13.4	11.82	11.57	12.26	11.91	294,410	341,459	367,084
12	57	Florida	Hillsborough	12.6	11.49	11.1	12.22	11.69	998,948	1,263,223	1,400,587
12	71	Florida	Lee	9.6	8.94	8.64	9.39	8.98	440,888	628,905	727,235
12	73	Florida	Leon	13.4	12.4	12.14	12.87	12.52	239,452	315,384	355,230
12	95	Florida	Orange	11.4	11.13	10.7	11.8	11.19	896,344	1,227,393	1,400,894
12	103	Florida	Pinellas	11.8	10.76	10.39	11.45	10.94	921,482	1,027,556	1,088,025
12	111	Florida	St Lucie	9.6	8.76	8.53	9.1	8.8	192,695	257,927	291,959
12	115	Florida	Sarasota	10.5	9.21	8.98	9.6	9.29	325,957	400,330	439,136
12	117	Florida	Seminole	10.5	9.63	9.34	10.11	9.71	365,196	569,587	677,953
12	127	Florida	Volusia	10.6	9.83	9.58	10.25	9.91	443,343	563,819	626,353
13	21	Georgia	Bibb	17.6	17.73	17.39	18.56	18.09	153,887	163,780	169,321

13	51	Georgia	Chatham	16.5	17.08	16.84	17.84	17.51	232,048	252,931	264,176
13	59	Georgia	Clarke	18.6	17.17	16.73	17.92	17.29	101,489	112,738	118,720
13	63	Georgia	Clayton	19.2	19.08	18.55	20.19	19.44	236,517	296,995	328,695
13	67	Georgia	Cobb	18.6	17.78	17.35	18.6	17.99	607,751	878,010	1,019,356
13	89	Georgia	De Kalb	19.6	20.13	19.36	21.72	20.63	665,865	736,846	774,881
13	95	Georgia	Dougherty	16.6	16.64	16.4	17.3	16.95	96,065	102,414	105,869
13	115	Georgia	Floyd	18.5	17.56	17.18	18.44	17.91	90,565	100,842	106,408
13	121	Georgia	Fulton	21.2	21.77	20.94	23.49	22.31	816,006	899,328	944,173
13	139	Georgia	Hall	17.2	15.36	14.97	15.98	15.42	139,277	175,978	195,214
13	215	Georgia	Muscogee	18	17.22	16.84	17.93	17.4	186,291	203,643	213,076
13	223	Georgia	Paulding	16.8	15.89	15.53	16.64	16.13	81,678	128,988	153,773
13	245	Georgia	Richmond	17.4	16.2	15.83	16.88	16.36	199,775	216,710	225,937
13	303	Georgia	Washington	16.5	15.88	15.64	16.45	16.13	21,176	23,302	24,439
13	319	Georgia	Wilkinson	18.1	17.95	17.7	18.8	18.46	10,220	11,450	12,105
16	1	Idaho	Ada	9.5	8.01	7.77	8.22	7.9	300,904	430,613	498,386
16	5	Idaho	Bannock	10	9.1	8.9	9.58	9.3	75,565	92,988	102,241
16	27	Idaho	Canyon	10.2	8.61	8.49	8.66	8.49	131,441	161,808	177,844
16	83	Idaho	Twin Falls	3.2	2.97	2.91	3.02	2.95	64,284	81,940	91,186
17	19	Illinois	Champaign	13.8	12.5	12.13	12.98	12.44	179,669	190,977	197,308
17	31	Illinois	Cook	18.8	18.6	17.88	19.86	18.89	5,376,741	5,389,403	5,415,053
17	43	Illinois	Du Page	15.4	14.96	14.37	15.8	14.98	904,161	1,126,926	1,243,827
17	115	Illinois	Macon	15.4	13.96	13.59	14.54	14.01	114,706	112,528	111,690
17	119	Illinois	Madison	17.3	16.26	15.79	17.18	16.53	258,941	277,485	287,588
17	157	Illinois	Randolph	13.9	11.98	11.68	12.46	12.02	33,893	36,184	37,390
17	163	Illinois	St Clair	17.4	16.45	16	17.4	16.76	256,082	251,771	249,705
17	167	Illinois	Sangamon	14.2	12.39	12.02	12.85	12.32	188,951	203,496	211,534
17	197	Illinois	Will	15.9	15.42	14.97	16.22	15.59	502,266	676,751	768,045
18	19	Indiana	Clark	17.3	15.81	15.33	16.67	16	96,472	117,704	129,061
18	39	Indiana	Elkhart	15.1	13.63	13.22	14.15	13.56	182,791	209,889	224,577
18	43	Indiana	Floyd	15.6	14.25	13.82	15.03	14.43	70,823	85,015	92,614
18	67	Indiana	Howard	15.4	13.71	13.24	14.23	13.55	84,964	88,876	90,901
18	89	Indiana	Lake	16.3	15.57	15.11	16.36	15.71	484,564	492,963	498,991
18	97	Indiana	Marion	17	15.64	15.01	16.45	15.56	860,454	907,240	932,219
18	127	Indiana	Porter	13.9	13.27	12.88	13.95	13.4	146,798	184,172	203,679
18	157	Indiana	Tippecanoe	15.4	13.71	13.27	14.22	13.58	148,955	178,981	194,850
18	163	Indiana	Vanderburgh	16.9	14.75	14.31	15.37	14.75	171,922	180,244	185,028
18	167	Indiana	Vigo	15.4	12.96	12.54	13.43	12.81	105,848	105,837	105,963
19	13	Iowa	Black Hawk	11.7	10.21	9.84	10.5	9.96	128,012	131,365	133,578
19	45	Iowa	Clinton	12.4	10.99	10.64	11.35	10.83	50,149	49,104	48,749

19	103	Iowa	Johnson	11.6	10.16	9.8	10.45	9.93	111,006	142,696	159,465
19	113	Iowa	Linn	11.4	10.04	9.71	10.35	9.88	191,701	223,880	240,980
19	153	Iowa	Polk	10.9	9.63	9.22	9.95	9.35	374,601	456,867	500,239
19	163	Iowa	Scott	13	11.76	11.34	12.18	11.58	158,668	175,894	185,378
19	193	Iowa	Woodbury	10	8.84	8.47	9.07	8.52	103,877	117,766	125,197
20	91	Kansas	Johnson	11.8	10.62	10.19	11.02	10.42	451,086	625,281	716,948
20	107	Kansas	Linn	11.2	9.72	9.42	9.98	9.55	9,570	9,998	10,395
20	173	Kansas	Sedgwick	11.8	10.68	10.32	11	10.5	452,869	528,750	568,900
20	177	Kansas	Shawnee	11.3	10.11	9.77	10.41	9.93	169,871	181,292	187,649
21	13	Kentucky	Bell	16.8	14.19	13.87	14.71	14.27	30,060	33,087	34,721
21	19	Kentucky	Boyd	15.5	13.97	13.65	14.67	14.23	49,752	48,055	47,412
21	29	Kentucky	Bullitt	16	13.44	13.09	13.96	13.47	61,236	81,834	92,881
21	37	Kentucky	Campbell	15.5	13.88	13.41	14.55	13.9	88,616	95,627	99,377
21	43	Kentucky	Carter	12.9	11.3	11.05	11.76	11.41	26,889	31,905	34,505
21	59	Kentucky	Daviess	15.8	13.67	13.3	14.24	13.71	91,545	102,223	108,122
21	67	Kentucky	Fayette	16.8	14.23	13.84	14.83	14.27	260,512	326,968	362,189
21	73	Kentucky	Franklin	14.5	12.28	11.94	12.8	12.31	47,687	58,066	63,579
21	111	Kentucky	Jefferson	17.1	15.63	15.15	16.48	15.81	693,604	725,700	743,029
21	117	Kentucky	Kenton	15.9	14.34	13.86	15.06	14.38	151,464	171,352	181,909
21	145	Kentucky	McCracken	15.1	13.01	12.66	13.52	13.03	65,514	74,308	78,993
21	195	Kentucky	Pike	16.1	14.44	14.16	15.03	14.64	68,736	77,184	81,653
21	227	Kentucky	Warren	15.4	12.52	12.17	12.93	12.44	92,522	113,224	124,048
22	17	Louisiana	Caddo	13.7	13.51	13.17	14.11	13.64	252,161	267,902	276,688
22	19	Louisiana	Calcasieu	12.7	12.92	12.66	13.79	13.43	183,577	215,763	232,906
22	33	Louisiana	East Baton Rouge	14.6	15.03	14.73	15.95	15.55	412,852	518,879	574,689
22	47	Louisiana	Iberville	13.9	13.72	13.49	14.39	14.08	33,320	33,003	33,048
22	51	Louisiana	Jefferson	13.6	13.4	12.95	14.23	13.65	455,466	532,172	572,938
22	55	Louisiana	Lafayette	12.4	11.87	11.57	12.4	12	190,503	233,196	255,915
22	71	Louisiana	Orleans	14.1	13.89	13.42	14.76	14.16	484,674	430,421	404,817
22	73	Louisiana	Ouachita	13	12.42	12.17	12.98	12.63	147,250	163,820	172,805
22	79	Louisiana	Rapides	13.3	12.8	12.55	13.34	12.99	126,337	134,449	138,921
22	105	Louisiana	Tangipahoa	13.5	12.77	12.46	13.41	13	100,588	123,191	135,181
22	121	Louisiana	West Baton Rouge	14.1	14.52	14.23	15.4	15.01	21,601	23,842	25,065
23	1	Maine	Androscoggin	10.3	9.29	9.07	9.63	9.33	103,793	112,835	117,751
23	3	Maine	Aroostook	10.8	10.15	10.03	10.29	10.14	73,938	69,371	67,299
23	5	Maine	Cumberland	11.7	10.81	10.51	11.24	10.83	265,612	308,231	330,836
23	9	Maine	Hancock	6	5.42	5.31	5.59	5.43	51,791	56,083	58,499
23	11	Maine	Kennebec	10	8.92	8.72	9.23	8.95	117,114	123,081	126,672
23	17	Maine	Oxford	10.4	9.6	9.41	9.87	9.61	54,755	60,048	62,916

23	19	Maine	Penobscot	9.4	8.37	8.18	8.62	8.37	144,919	154,987	160,631
24	5	Maryland	Baltimore	16	14.67	14.29	15.36	14.82	754,292	831,729	873,717
24	33	Maryland	Prince Georges	17.3	16.22	15.69	17.08	16.32	801,515	884,449	929,496
24	510	Maryland	Baltimore City	17.8	16.55	15.99	17.43	16.64	651,154	575,980	540,899
25	13	Massachusetts	Hampden	14.1	13.4	13.01	14.06	13.51	456,228	450,007	448,459
25	15	Massachusetts	Hampshire	9	8.5	8.24	8.89	8.53	152,251	164,397	171,127
25	25	Massachusetts	Suffolk	16.1	15.59	14.31	16.59	14.8	689,807	659,760	646,962
25	27	Massachusetts	Worcester	12.7	11.75	11.31	12.3	11.68	750,963	812,259	846,065
26	5	Michigan	Allegan	12.2	11.28	10.96	11.73	11.28	105,665	137,366	153,990
26	21	Michigan	Berrien	12.5	11.37	11.05	11.81	11.35	162,453	167,167	169,909
26	49	Michigan	Genesee	12.7	11.62	11.3	12.06	11.62	436,141	446,891	453,670
26	65	Michigan	Ingham	13.1	11.78	11.43	12.21	11.72	279,320	290,827	297,581
26	77	Michigan	Kalamazoo	15	13.6	13.19	14.13	13.55	238,603	262,738	275,735
26	81	Michigan	Kent	14.1	12.85	12.42	13.41	12.79	574,335	684,461	742,687
26	99	Michigan	Macomb	13.2	12.18	11.88	12.6	12.18	788,149	890,585	946,209
26	121	Michigan	Muskegon	12.2	11.4	11.11	11.87	11.46	170,200	181,910	188,401
26	139	Michigan	Ottawa	13.3	12.12	11.71	12.64	12.07	238,314	316,914	358,079
26	147	Michigan	St Clair	13.8	12.55	12.3	12.87	12.52	164,235	193,051	208,573
26	163	Michigan	Wayne	18.9	17.75	17.27	18.53	17.85	2,061,162	1,897,446	1,818,661
28	33	Mississippi	De Soto	14	12.23	11.91	12.67	12.22	107,199	173,599	210,077
28	35	Mississippi	Forrest	15.2	14.22	14	14.66	14.37	72,604	83,371	89,113
28	45	Mississippi	Hancock	12.2	11.7	11.42	12.36	12	42,967	61,659	71,279
28	49	Mississippi	Hinds	15.1	13.66	13.31	14.28	13.79	250,800	268,318	278,025
28	59	Mississippi	Jackson	13.8	13.45	13.2	14.02	13.69	131,420	153,814	165,743
28	67	Mississippi	Jones	16.6	15.07	14.81	15.54	15.18	64,958	73,388	77,897
28	75	Mississippi	Lauderdale	15.3	13.96	13.69	14.45	14.08	78,161	84,485	87,885
28	81	Mississippi	Lee	14.2	12.34	12.03	12.8	12.37	75,755	95,564	105,932
28	87	Mississippi	Lowndes	15.1	13.01	12.74	13.51	13.14	61,586	65,500	67,716
29	21	Missouri	Buchanan	12.4	11.04	10.68	11.39	10.87	85,998	84,393	83,729
29	39	Missouri	Cedar	11.5	9.79	9.5	10.03	9.62	13,733	14,933	15,530
29	47	Missouri	Clay	12.8	11.95	11.49	12.5	11.86	184,006	243,759	275,253
29	77	Missouri	Greene	12.2	10.48	10.18	10.77	10.35	240,391	287,457	312,253
29	95	Missouri	Jackson	13.9	12.97	12.47	13.57	12.88	654,880	660,463	665,053
29	97	Missouri	Jasper	13.7	11.45	11.12	11.77	11.29	104,686	128,109	140,409
29	99	Missouri	Jefferson	15	14.18	13.79	15	14.45	198,099	264,327	300,317
29	137	Missouri	Monroe	11	9.5	9.22	9.78	9.39	9,311	9,177	9,142
29	183	Missouri	St Charles	14.6	13.72	13.33	14.5	13.95	283,883	402,014	466,353
29	186	Missouri	Ste Genevieve	14.2	12.25	11.92	12.68	12.21	17,842	20,974	22,653
29	189	Missouri	St Louis	14.1	13.25	12.87	14	13.47	1,016,315	1,033,549	1,043,340

29	510	Missouri	St Louis City	16.3	15.41	14.99	16.3	15.7	348,189	301,448	277,083
30	49	Montana	Lewis And Clark	8.5	8.64	8.55	8.96	8.84	55,716	73,082	82,209
30	53	Montana	Lincoln	16.4	15.22	15.07	15.35	15.14	18,837	19,735	20,307
30	63	Montana	Missoula	11.8	11.04	10.87	11.22	10.98	95,802	126,218	142,114
30	111	Montana	Yellowstone	8	7.95	7.81	8.23	8.03	129,352	157,282	171,961
31	109	Nebraska	Lancaster	10.5	9.41	9.01	9.66	9.09	250,291	319,321	355,359
32	3	Nevada	Clark	11	11.57	10.16	12.69	10.73	1,375,765	2,287,193	2,763,400
32	31	Nevada	Washoe	9.7	8.97	8.68	9.51	9.11	339,486	435,434	486,504
34	17	New Jersey	Hudson	17.5	15.87	15.2	16.81	15.88	608,975	606,667	607,696
34	21	New Jersey	Mercer	14.3	13.76	13.38	14.49	13.95	350,761	369,672	380,558
34	39	New Jersey	Union	16.3	15	14.52	15.87	15.21	522,541	532,182	539,007
35	13	New Mexico	Dona Ana	10.9	10.47	10.17	10.84	10.44	174,682	235,150	266,803
35	17	New Mexico	Grant	5.7	5.66	5.6	5.87	5.79	31,002	43,675	50,353
35	25	New Mexico	Lea	6.9	6.59	6.45	6.75	6.56	55,511	61,522	64,859
35	43	New Mexico	Sandoval	5	5.14	5	5.48	5.29	89,908	156,855	191,838
35	49	New Mexico	Santa Fe	4.8	4.46	4.39	4.57	4.47	129,292	200,022	237,288
36	5	New York	Bronx	16.4	15.49	14.63	16.34	15.14	1,332,650	1,273,213	1,247,937
36	61	New York	New York	17.8	16.81	15.88	17.74	16.43	1,537,195	1,549,867	1,561,676
37	1	North Carolina	Alamance	15.3	14.04	13.7	14.68	14.21	130,800	163,548	180,531
37	25	North Carolina	Cabarrus	15.7	14.1	13.72	14.79	14.24	131,063	194,287	227,392
37	35	North Carolina	Catawba	17.1	15.06	14.7	15.75	15.25	141,685	169,675	184,315
37	37	North Carolina	Chatham	13.4	12.39	12.07	12.99	12.53	49,329	61,495	67,885
37	51	North Carolina	Cumberland	15.4	13.64	13.27	14.2	13.67	302,963	341,187	361,645
37	57	North Carolina	Davidson	17.3	15.8	15.42	16.62	16.07	147,246	183,125	201,995
37	61	North Carolina	Duplin	12.6	11.06	10.8	11.44	11.07	49,063	53,223	55,448
37	63	North Carolina	Durham	15.3	14.75	14.22	15.63	14.87	223,314	281,262	311,720
37	67	North Carolina	Forsyth	16.2	14.95	14.58	15.71	15.17	306,067	366,864	398,805
37	71	North Carolina	Gaston	15.3	14.37	14.03	15.13	14.64	190,365	220,661	236,720
37	81	North Carolina	Guilford	16.3	15.19	14.75	16	15.37	421,048	497,827	538,355
37	87	North Carolina	Haywood	15.4	13.62	13.33	14.24	13.84	54,033	63,759	68,965
37	111	North Carolina	McDowell	16.2	14.63	14.34	15.35	14.95	42,151	48,933	52,572
37	119	North Carolina	Mecklenburg	16.8	15.85	15.27	16.77	15.95	695,454	941,939	1,070,973
37	121	North Carolina	Mitchell	15.5	13.71	13.44	14.29	13.92	15,687	16,288	16,644
37	129	North Carolina	New Hanover	12.2	11.72	11.5	12.27	11.97	160,307	233,447	271,367
37	133	North Carolina	Onslow	12.1	11.08	10.83	11.5	11.16	150,355	162,645	169,450
37	135	North Carolina	Orange	14.3	13.23	12.88	13.86	13.37	118,227	157,410	177,913
37	173	North Carolina	Swain	14.1	12.42	12.18	12.9	12.57	12,968	15,962	17,531

37	183	North Carolina	Wake	15.3	14.75	14.22	15.63	14.87	627,846	948,294	1,115,401
37	191	North Carolina	Wayne	15.3	13.32	13	13.78	13.33	113,329	128,949	137,243
38	17	North Dakota	Cass	8.6	7.82	7.48	8.06	7.56	123,138	159,734	179,181
38	57	North Dakota	Mercer	6.3	5.71	5.53	5.78	5.5	8,644	9,840	10,629
38	91	North Dakota	Steele	6.9	6.17	5.9	6.28	5.87	2,258	2,143	2,105
39	17	Ohio	Butler	17.4	15.53	15.02	16.26	15.55	332,807	438,817	495,203
39	35	Ohio	Cuyahoga	20.3	19.17	18.5	20.17	19.22	1,393,978	1,314,252	1,277,539
39	49	Ohio	Franklin	18.1	16.2	15.64	16.93	16.17	1,068,978	1,221,199	1,301,984
39	61	Ohio	Hamilton	19.3	17.28	16.7	18.12	17.3	845,303	844,891	845,159
39	81	Ohio	Jefferson	18.9	17.4	17.06	18.11	17.66	73,894	67,057	63,997
39	85	Ohio	Lake	14	12.94	12.56	13.52	13.02	227,511	247,357	258,390
39	87	Ohio	Lawrence	17.4	15.68	15.32	16.47	15.98	62,319	63,291	63,930
39	93	Ohio	Lorain	15.1	13.87	13.48	14.44	13.91	284,664	299,991	308,902
39	95	Ohio	Lucas	16.7	15.66	15.18	16.41	15.75	455,054	439,718	433,056
39	99	Ohio	Mahoning	16.4	14.85	14.43	15.5	14.92	257,555	247,426	243,143
39	113	Ohio	Montgomery	17.6	16.02	15.49	16.8	16.04	559,062	547,126	543,119
39	133	Ohio	Portage	15.3	14.06	13.66	14.71	14.15	152,061	173,779	185,622
39	145	Ohio	Scioto	20	17.44	17.06	18.19	17.65	79,195	81,119	82,336
39	151	Ohio	Stark	18.3	16.4	15.95	17.09	16.45	378,098	386,771	392,398
39	153	Ohio	Summit	17.3	15.9	15.45	16.63	16	542,899	566,693	580,778
39	155	Ohio	Trumbull	16.2	14.67	14.26	15.31	14.74	225,116	227,563	229,495
41	3	Oregon	Benton	7.4	6.8	6.73	6.85	6.76	78,153	100,204	111,826
41	9	Oregon	Columbia	6.6	5.92	5.78	6.12	5.93	43,560	53,045	57,963
41	29	Oregon	Jackson	11.3	9.8	9.68	9.85	9.68	181,269	274,059	322,247
41	35	Oregon	Klamath	9.7	8.88	8.81	8.9	8.81	63,775	71,177	75,195
41	37	Oregon	Lake	7.6	7.05	6.98	7.09	7	7,422	8,309	8,760
41	39	Oregon	Lane	13.2	12.14	11.9	12.23	11.93	322,959	409,094	454,385
41	47	Oregon	Marion	8.2	7.29	7.18	7.36	7.23	284,834	353,405	389,154
41	51	Oregon	Multnomah	9.1	8.45	8.18	8.9	8.53	660,486	732,692	770,078
41	59	Oregon	Umatilla	8.8	9.12	8.94	9.21	8.95	70,548	90,312	100,659
41	67	Oregon	Washington	7.8	7.24	7.01	7.63	7.31	445,342	707,747	846,117

42	3	Pennsylvania	Allegheny	21	17.17	16.7	17.83	17.17	1,281,666	1,242,514	1,227,036
42	11	Pennsylvania	Berks	15.6	14.23	13.84	14.88	14.32	373,638	405,375	422,931
42	21	Pennsylvania	Cambria	15.3	13.19	12.9	13.67	13.27	152,598	141,356	136,383
42	43	Pennsylvania	Dauphin	15.5	13.56	13.15	14.15	13.56	251,798	278,696	293,157
42	45	Pennsylvania	Delaware	15	14.48	14.07	15.32	14.75	550,864	543,058	540,509
42	71	Pennsylvania	Lancaster	16.9	14.2	13.76	14.74	14.1	470,658	554,898	600,235
42	101	Pennsylvania	Philadelphia	16.6	16.03	15.57	16.95	16.33	1,517,550	1,323,566	1,228,773
42	125	Pennsylvania	Washington	15.5	13.14	12.8	13.66	13.19	202,897	207,824	211,081
42	129	Pennsylvania	Westmoreland	15.6	12.75	12.41	13.24	12.75	369,993	376,604	381,310
42	133	Pennsylvania	York	16.3	14.57	14.16	15.21	14.63	381,751	426,517	450,509
45	19	South Carolina	Charleston	12.6	12.26	12.03	12.83	12.51	309,969	413,794	468,239
45	43	South Carolina	Georgetown	13.9	13.2	12.97	13.76	13.46	55,797	68,463	75,143
45	45	South Carolina	Greenville	17	15.55	15.15	16.2	15.64	379,616	468,167	514,778
45	63	South Carolina	Lexington	15.6	14.71	14.41	15.33	14.9	216,014	328,789	387,567
45	73	South Carolina	Oconee	12.3	11.09	10.86	11.53	11.21	66,215	75,582	80,607
45	79	South Carolina	Richland	15.4	14.42	14.13	14.95	14.55	320,677	379,594	410,744
45	83	South Carolina	Spartanburg	15.4	14.09	13.73	14.68	14.17	253,791	296,784	319,577
46	99	South Dakota	Minnehaha	10.4	9.3	8.9	9.57	8.97	148,281	197,855	223,297
47	37	Tennessee	Davidson	17	15	14.5	15.79	15.09	569,891	614,007	638,965
47	65	Tennessee	Hamilton	18.9	16.75	16.38	17.44	16.91	307,896	347,332	368,296
47	93	Tennessee	Knox	20.4	17.61	17.19	18.42	17.84	382,032	473,001	520,715
47	145	Tennessee	Roane	17	14.33	14.03	14.88	14.46	51,910	57,776	60,862
47	157	Tennessee	Shelby	15.6	14.51	13.87	15.28	14.44	897,472	1,021,255	1,086,498
47	163	Tennessee	Sullivan	17	14.67	14.4	15.36	14.98	153,048	166,896	174,404
47	165	Tennessee	Sumner	15.7	13.85	13.39	14.58	13.93	130,449	179,345	204,820
48	113	Texas	Dallas	14.4	14.85	14.2	15.9	15.01	2,218,899	2,554,577	2,737,690
48	201	Texas	Harris	15.1	16.25	15.72	17.61	16.91	3,400,578	4,151,794	4,549,359
49	11	Utah	Davis	9	9.79	8.85	10.75	9.47	238,994	380,216	453,302
49	35	Utah	Salt Lake	13.6	14.79	13.38	16.24	14.32	898,387	1,213,017	1,378,102
49	45	Utah	Tooele	7.2	7.99	7.67	8.69	8.25	40,735	55,270	62,805
49	49	Utah	Utah	10.4	10.85	10.31	11.68	10.95	368,536	550,933	645,756
49	57	Utah	Weber	8.8	9.28	8.75	10.1	9.37	196,533	242,468	267,013
50	3	Vermont	Bennington	9.9	9.14	8.92	9.49	9.19	36,994	39,841	41,416
50	7	Vermont	Chittenden	6.8	6.17	6.06	6.33	6.18	146,571	173,091	187,081
50	21	Vermont	Rutland	11.3	10.22	9.99	10.54	10.23	63,400	65,527	66,875
50	23	Vermont	Washington	10.5	9.42	9.24	9.68	9.43	58,039	60,941	62,628

51	520	Virginia	Bristol City	16	13.43	13.15	13.95	13.55	17,367	18,209	18,678
51	760	Virginia	Richmond City	14.9	14.52	14.15	15.34	14.83	197,790	175,431	164,515
51	700	Virginia	Newport News City	12.7	12.27	11.98	12.95	12.55	180,150	195,895	204,594
51	770	Virginia	Roanoke City	15.2	13.33	12.99	13.86	13.39	94,911	93,712	93,612
51	810	Virginia	Virginia Beach Cit	13.2	12.96	12.6	13.72	13.22	425,257	549,024	613,524
53	33	Washington	King	11.9	11.41	10.84	12.25	11.5	1,737,034	2,107,326	2,301,410
53	53	Washington	Pierce	11.7	11.05	10.61	11.72	11.13	700,820	944,042	1,071,521
53	61	Washington	Snohomish	11.4	10.29	10	10.83	10.43	606,024	845,477	970,992
53	63	Washington	Spokane	10.4	9.3	9.11	9.51	9.24	417,939	509,105	557,164
53	67	Washington	Thurston	9.7	8.4	8.16	8.77	8.45	207,355	280,103	318,265
53	73	Washington	Whatcom	7.9	7.33	7.17	7.68	7.46	166,814	226,580	257,874
54	3	West Virginia	Berkeley	16	13.93	13.58	14.47	13.98	75,905	107,760	124,408
54	9	West Virginia	Brooke	17.4	16.01	15.71	16.67	16.26	25,447	24,298	23,878
54	11	West Virginia	Cabell	17.8	15.77	15.36	16.47	15.92	96,784	91,739	89,564
54	29	West Virginia	Hancock	17.4	16.01	15.71	16.67	16.26	32,667	30,659	29,778
54	33	West Virginia	Harrison	14.8	12.81	12.54	13.27	12.91	68,652	71,377	72,950
54	39	West Virginia	Kanawha	18.4	16.55	16.09	17.27	16.67	200,073	197,841	197,586
54	51	West Virginia	Marshall	16.5	14.42	14.12	14.94	14.53	35,519	31,563	29,729
54	61	West Virginia	Monongalia	15	12.84	12.57	13.31	12.94	81,866	88,976	93,035
54	69	West Virginia	Ohio	15.7	13.55	13.23	14.06	13.62	47,427	46,546	46,276
54	81	West Virginia	Raleigh	14	12.27	12.02	12.72	12.38	79,220	81,108	82,355
54	89	West Virginia	Summers	10.9	9.49	9.3	9.82	9.57	12,999	12,851	12,861
54	107	West Virginia	Wood	17.6	15.28	14.9	15.87	15.36	87,986	87,471	87,560
55	9	Wisconsin	Brown	11.4	10.3	10.01	10.69	10.28	226,778	270,348	293,548
55	25	Wisconsin	Dane	13.2	12.03	11.63	12.53	11.95	426,526	538,843	597,808
55	27	Wisconsin	Dodge	11.8	10.54	10.22	10.89	10.43	85,897	101,526	109,834
55	29	Wisconsin	Door	8	7.44	7.27	7.69	7.47	27,961	33,124	35,898
55	31	Wisconsin	Douglas	8.3	8.58	8.43	9.16	8.95	43,287	45,371	46,594
55	43	Wisconsin	Grant	12.3	10.7	10.35	11	10.49	49,597	50,281	50,845
55	55	Wisconsin	Jefferson	12.5	11.29	10.95	11.71	11.21	74,021	79,638	82,748
55	59	Wisconsin	Kenosha	12.1	11.66	11.31	12.25	11.76	149,577	183,393	201,186
55	71	Wisconsin	Manitowoc	10.3	9.39	9.13	9.76	9.4	82,887	84,259	85,140
55	79	Wisconsin	Milwaukee	14.5	14.4	13.95	15.26	14.62	940,164	906,519	891,733
55	87	Wisconsin	Outagamie	11.3	10.4	10.1	10.85	10.43	160,971	202,072	223,681
55	125	Wisconsin	Vilas	6.4	5.89	5.76	6.08	5.89	21,033	29,797	34,546
55	133	Wisconsin	Waukesha	14.1	13.39	12.96	14.06	13.47	360,767	466,063	521,974

55	139	Wisconsin	Winnebago	11.2	10.17	9.88	10.55	10.13	156,763	183,637	197,968
55	141	Wisconsin	Wood	10.6	9.37	9.13	9.69	9.34	75,555	88,639	95,597
56	21	Wyoming	Laramie	5.4	5.64	5.51	5.97	5.8	81,607	93,096	99,109
56	33	Wyoming	Sheridan	10.9	10.33	10.14	10.52	10.26	26,560	29,543	31,126
		# Nonattainment Cntys		**149**	**79**	**67**	**107**	**84**			