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Health and Welfare Benefits Analyses to Support the Second Section 812 Benefit-Cost Analysis of the Clean Air Act

Final Report | February 2011

prepared for:

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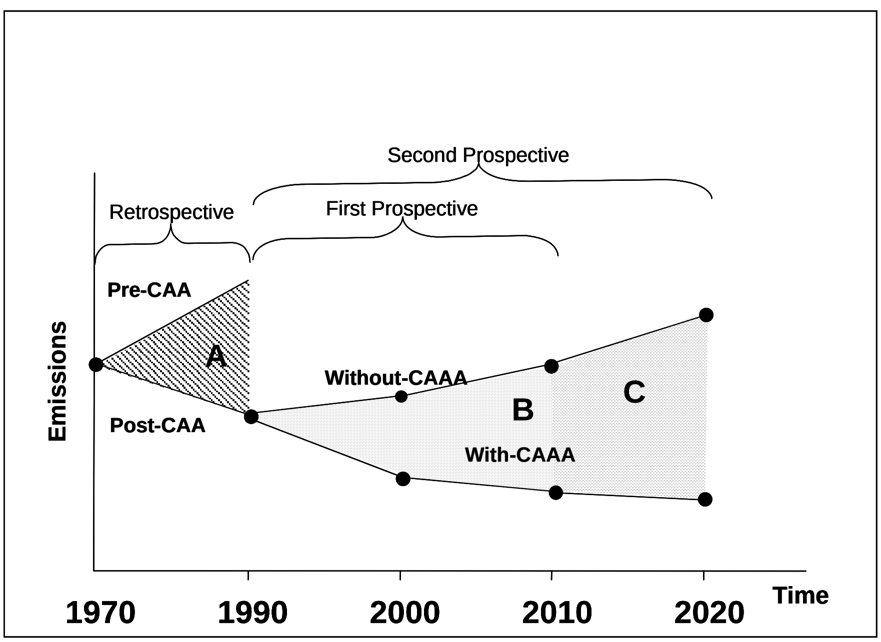
CHAPTER 1 | INTRODUCTION

Section 812 of the Clean Air Act Amendments of 1990 (CAAA) required the U.S. Environmental Protection Agency (EPA) to perform periodic, comprehensive analyses of the total costs and total benefits of programs implemented pursuant to the Clean Air Act (CAA). The first analysis conducted was a retrospective analysis, addressing the original CAA and covering the period 1970 to 1990. The Retrospective was completed in 1997. Section 812 also required performance of prospective cost-benefit analyses, the first of which was completed in 1999. The prospective analyses address the incremental costs and benefits of the CAAA. The First Prospective covered implementation of the CAAA over the period 1990 to 2010.

EPA's Office of Air and Radiation (OAR) began work on the Second Prospective with the drafting of an analytical plan for the study. This analytical plan was reviewed by a statutorily-mandated outside peer review group, the Science Advisory Board's Advisory Council for Clean Air Compliance Analysis (Council), and the Council provided comments, which have been incorporated into the technical analysis planning. This report describes the development of quantified and monetized primary benefits associated with emissions reductions estimated for the second prospective section 812 analysis. Exhibit 1-1 below outlines the relationship among the section 812 Retrospective, the First Prospective, and the Second Prospective.

EXHIBIT 1-1. 812 SCENARIOS: CONCEPTUAL SCHEMATIC



The scope of this analysis is to estimate the benefits of reducing emissions of criteria pollutants under two scenarios, depicted in schematic form in Exhibit 1-1 above:

1. An historical, "*with-CAAA*" scenario control case that reflects expected or likely future measures implemented since 1990 to comply with rules promulgated through September 2005[1]; and
2. A counterfactual "*without CAAA*" scenario baseline case that freezes the scope and stringency of emissions controls at their 1990 levels, while allowing for changes in population and economic activity and, therefore, in emissions attributable to economic and population growth.

Criteria pollutant emissions reductions addressed in this analysis include: volatile organic compounds (VOCs), oxides of nitrogen (NO_x), sulfur dioxide (SO_2), particulate matter of 10 microns or less (PM_{10}), and particulate matter with an aerodynamic diameter of 2.5 microns or less ($PM_{2.5}$). Benefits estimates, however, focus not on the emissions but on the ambient air concentration outcomes that result from emissions changes attributed to implementation of the Clean Air Act Amendments. The two major ambient pollutants for which benefits estimates are readily available are fine particulate matter and tropospheric ozone. Air quality changes associated with changes in emissions of lead, the remaining criteria pollutant under the Clean Air Act, are not addressed in this report, and were not addressed in the first prospective analysis, because of the relatively modest impact of CAAA regulations in place by 2005 on lead emissions.[2]

This report presents the results of EPA's analysis of the future effects of implementation of the CAAA's programs on air emissions from the following emission sectors: electricity generating units (EGUs), non-electricity generating unit point sources, nonroad engines/vehicles, on-road vehicles, and nonpoint sources. The study years for the analysis are 1990, 2000, 2010, and 2020. Because the CAAA was signed into law in 1990, emissions and air quality changes attributed to its implementation were not realized until after that point. As a result, benefits are estimated only for the target years 2000, 2010, and 2020.

The purpose of this report is to present the methods used to generate estimates of physical and economic benefits that result from the CAAA, and to present the results of our analyses for each target year. The scope of the benefits analyses conducted to support the second prospective analysis includes the following:

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[1] The lone exception is the Coke Ovens Residual Risk rulemaking, promulgated under Title III of the Act in March 2005. We omitted this rule because it has a very small impact on criteria pollutant emissions (less than 10 tons per year VOCs) relative to the with-CAAA scenario. The primary MACT rule for coke oven emissions, however, involves much larger reductions and therefore is included in the with-CAAA scenario.

[2] Lead emissions were effectively controlled under regulations authorized by the original Clean Air Act. As a result, analysis of lead emissions is a major focus of the section 812 retrospective study. Recently finalized revisions to the lead NAAQS could have significant effects on emissions for some localities, but those changes were first proposed on May 1, 2008 and were therefore not included in the scope of this analysis.

- ***Health Benefits***: These include avoided premature mortality and avoided morbidity associated with reduced human exposures to air pollutants.
- ***Visibility Benefits***: Reductions in air pollutants, particularly fine particulate matter, improve visibility, leading to physical and economic benefits in both recreational and residential settings.
- ***Agricultural and Forest Productivity Benefits***: Tropospheric ozone inhibits plant growth; as a result, reduction in ozone concentrations yield physical and economic benefits in the form of enhanced agricultural and forest productivity.
- ***Materials Damage Benefits***: Some materials are susceptible to accelerated deterioration when exposed to air pollution; as a result, reduction in air pollution can extend the life of these materials, yielding physical and economic benefits.
- ***Ecological Benefits***: A wide range of ecological resources are susceptible to damage when exposed to ambient air pollution or deposition of pollutants to terrestrial or aquatic environments. For a small portion of these effects, it is possible to quantify and estimate the economic value of avoided pollutant exposure. As outlined below, quantified and monetized ecological benefits of the CAAA are included in our summary of the benefits of CAAA programs presented later in this chapter. The methods and data used to generate these estimates are not described in this report, but in an accompanying EPA report prepared to support the second prospective analysis.

RELATIONSHIP OF THIS REPORT TO OTHER SECOND PROSPECTIVE ANALYSES

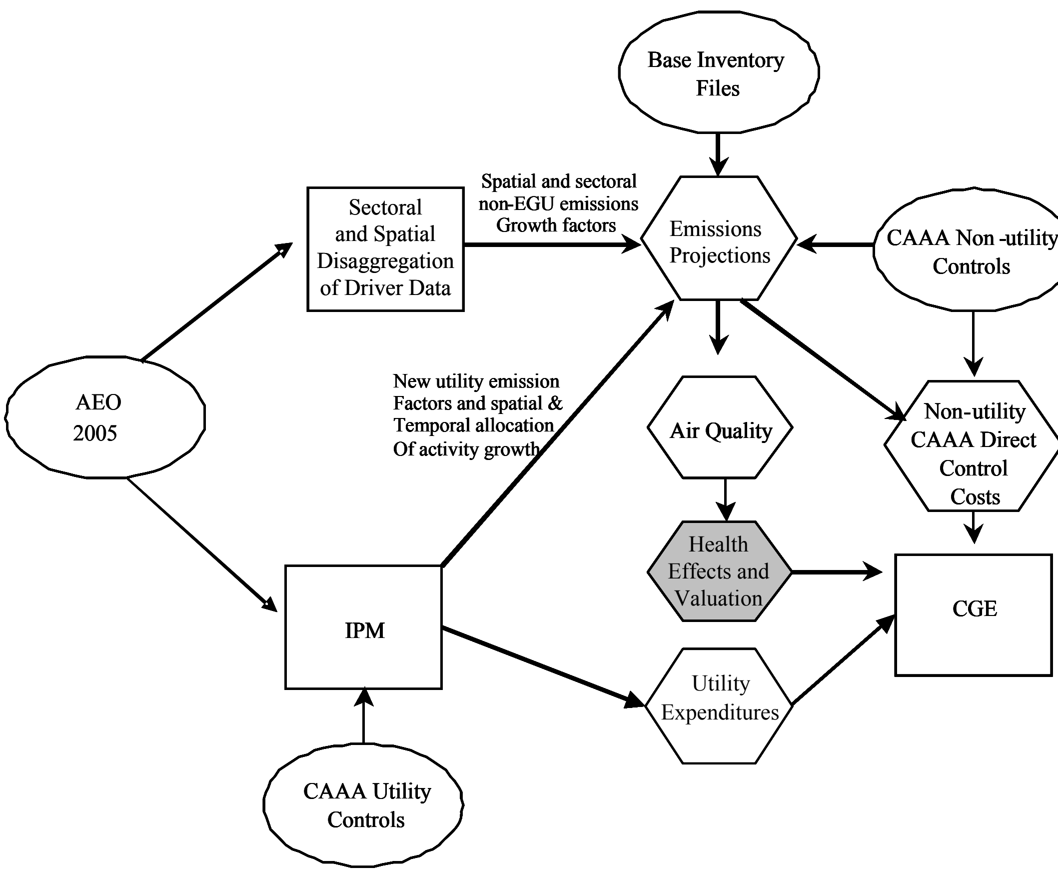
The benefits estimates presented in this report rely on results generated in prior analytic components of the overall second prospective effort. As illustrated in Exhibit 1-2, EPA conducted both emissions estimation and air quality modeling analyses to generate data that underlies the benefits estimation approaches. EPA plans to make full reports on each of these major analytic steps available to the public online at the project website, www.epa.gov/oar/sect812. Details on the use of air quality inputs in the health, visibility, agricultural, forestry, and materials damage analyses are provided in the subsequent chapters of this report. In almost all cases, some post-processing of air quality data is involved to estimate pollutant exposures appropriate to the specific benefits analysis.

This report focuses on presentation of the primary benefits estimates. The primary benefits estimates are based on EPA's preferred set of analytic assumptions, models, and data sources, many of which have been explicitly reviewed by EPA Science Advisory Board over the course of many years and have been embodied in standard benefits estimation practice as carried out by EPA's Office of Air and Radiation in Regulatory Impact Analyses (RIAs). As an integral part of preparing the primary benefits results, EPA also conducted a series of analyses to estimate uncertainty in the primary results. The methods and results of these uncertainty and sensitivity analyses are described in a separate report, *Uncertainty Analyses to Support the Second Section 812 Prospective Benefit-Cost Analysis of the Clean Air Act*.

In addition, as noted above, estimation of the ecological benefits of the CAAA are described in detail in a separate report, *Ecological Benefits Analyses to Support the Second Section 812 Prospective Benefit-Cost Analysis of the Clean Air Act*. The ecological benefits report addresses the estimation of quantified ecological benefits, including estimates of the value of reduced lake acidification in the Adirondacks region of New York State, but also characterizes a range of unquantifiable ecological impacts through an exhaustive literature review and presentation of maps showing the relation between prevented air pollutant exposure and selected sensitive ecological receptors.

Within each of the following chapters, there is a brief discussion of the scope of quantified and monetized benefits. In addition, we include a brief discussion of other, unquantified benefits of the Clean Air Act. With the completion and review of the benefits analyses, the Agency will prepare an integrated report for the entire project. The integrated report will address each of these major analytic components, and present comparisons of benefits and costs for each of the target years, as well as uncertainty analyses that characterize confidence in these results.

EXHIBIT 1-2. MAY 2003 ANALYTICAL PLAN - SCHEMATIC FLOW CHART



OVERVIEW OF METHODS

The methods applied in this report generally follow approaches developed by EPA over many years to support Regulatory Impact Analyses for major Office of Air and Radiation rulemakings, prior Section 812 analyses, and other Agency economic analyses. In a few cases, summarized below, this Second Prospective reflects methodologies, data, or benefits categories that are new to Agency analysis. In general, the primary benefits results presented here reflect methods, data, and benefits that have been vetted through Council review, as well as internal EPA review by OAR economists and benefits analysts.

The general method we apply to quantify and monetize benefits involves four basic steps:

1. ***Access the relevant air quality results from the suite of Second Prospective CMAQ runs***. The Community Multiscale Air Quality (CMAQ) data include estimates of ambient air quality measured as concentrations of particulate matter and ozone, estimates of visibility expressed in deciviews, and estimates of deposition measured as a deposition flux per unit area.
2. ***Estimate exposure for each scenario***. Exposure analyses can vary by endpoint – for example, most health endpoints use an 8-hour maximum measure, while the agricultural analyses use a cumulative measure of ozone exposure over a growing season.
3. ***Estimate changes in physical effects.*** Physical effects are quantified benefits (e.g., cases of chronic bronchitis) attributable to CAAA regulations, and are generated based on differences in exposure between scenarios. A few effects, such as visibility, are estimated for both scenarios, rather than based on differences in exposure.
4. ***Value changes in effects***. In most cases, this step involves application of a unit economic value. The unit values reflect willingness to pay to avoid a small risk of incidence of a health effect; they are not values to avoid a certain health effect. In a few cases, valuation is directly estimated from air quality outcomes, applies avoided cost methods rather than willingness to pay, or is combined with step 3 in an integrated approach or model.

Exhibit 1-3 summarizes our approach to steps 2 through 4 above for each major category of benefits. Detailed descriptions of these approaches are provided in the subsequent chapters.

SUMMARY OF RESULTS

Exhibit 1-4 below provides a summary of the economic benefits results generated for the categories of benefits addressed in this report.

EXHIBIT 1-3. SUMMARY OF ESTIMATION APPROACH FOR MAJOR BENEFITS CATEGORIES

BENEFIT CATEGORY	EXPOSURE ESTIMATION	PHYSICAL EFFECTS ESTIMATION	ECONOMIC VALUE ESTIMATION
Health Effects	Model Attainment Test Software (MATS) for PM; Enhanced Voronoi Neighbor Averaging (eVNA) for ozone	Benefits Mapping and Analysis Program (BenMAP)	
Visibility	CMAQ-derived deciview estimates		Custom benefits transfer models
Agriculture and Forest Productivity	eVNA extrapolation , BenMAP procedure, and offline GIS analysis	NCLAN-based concentration-response functions	Forest and Agricultural Sector Optimization Model (FASOM)
Materials Damage	Air Pollution Emissions Experiments and Policy (APEEP) model		
Lake Acidification	CMAQ deposition outputs	Model of Acidification of Groundwater in Catchments (MAGIC)	Custom random-utility model for Adirondack lakes
Note: Models and approaches are described in detail in Chapters 2 through 5 of this report.			

EXHIBIT 1-4. SUMMARY OF MEAN PRIMARY BENEFITS RESULTS

BENEFIT CATEGORY	MONETIZED BENEFITS (MILLION 2006$) BY TARGET YEAR			NOTES
	2000	2010	2020	
Health Effects				
PM Mortality PM Morbidity Ozone Mortality Ozone Morbidity	$710,000 $27,000 $10,000 $420	$1,200,000 $46,000 $33,000 $1,300	$1,700,000 $68,000 $55,000 $2,100	- PM mortality estimates based on Weibull distribution derived from Pope et. al (2002) and Laden et al., 2006. - Ozone mortality estimates based on pooled function
Subtotal Health Effects	$750,000	$1,300,000	$1,900,000	
Visibility				
Recreational Residential	$3,300 $11,000	$8,600 $25,000	$19,000 $48,000	Recreational visibility only includes benefits in the regions analyzed in Chestnut and Rowe, 1990 (i.e., California, the Southwest, and the Southeast).
Subtotal Visibility	$14,000	$34,000	$67,000	
Agricultural and Forest Productivity	$1,000	$5,500	$11,000	
Materials Damage	$58	$93	$110	
Ecological	$6.9	$7.5	$8.2	Reduced lake acidification benefits to recreational fishing assuming effect threshold of 50 microequivalents per liter.
Total: all categories	$770,000	$1,300,000	$2,000,000	
Note: See Chapters 2 through 5 of this report for detailed results summaries. Values presented are means from results reported as distributions. Additional, alternative estimates are provided in the separate companion report on uncertainty. Estimates presented with two significant figures.				

The health effects estimates for the second prospective are much larger than the estimates EPA developed for the first prospective. The 2020 estimates are new to the second prospective, but the comparable mean estimate of health benefits in 2000 and 2010 for the first prospective were $71 billion in 2000 and $110 billion in 2010, in 1990$[3] - if updated to 2006$, these estimates would be $110 billion in 2000 and $170 billion in 2010. There are six key reasons we have identified for the increase in benefits:

1. ***Scenario differences:*** The *with-CAAA* scenario, especially for the 2010 target year, includes new rules with substantial additional pollutant reductions that were not

[3] See The Benefits and Costs of the Clean Air Act 1990 to 2010, USEPA Office of Air and Radiation and Office of Policy, EPA-410-R-99-001, November 1999.

included in the comparable first prospective scenario, such as the Clean Air Interstate Rule (CAIR).

2. ***Improved air quality models*:** The first prospective relied on the Regional Acid Deposition Model/Regional Particulate Model (RADM/RPM) for PM and deposition estimates in the eastern U.S., the Regulatory Modeling System for Aerosols and Acid Deposition (REMSAD) for PM estimates in the western U.S., and the Urban Airshed Model (versions V and IV) at various regional and urban scales to generate ozone estimates. The second prospective relies on the integrated CMAQ modeling tool, which reflects substantial improvements in air quality modeling, provides more comprehensive spatial coverage, and achieves improved model performance.

3. ***Better, more comprehensive exposure estimates*:** The first prospective relied on first generation exposure extrapolation tools to generate monitor-adjusted exposure estimates away from monitors. Since then, the monitor network, availability of speciated data, and the performance of speciated exposure estimation tools have improved substantially.

4. ***Updated dose-response estimates***: Since 1999, some concentration response functions have been updated, most notably the PM-premature mortality C/R function, whose central estimate of the mortality impact of fine PM has nearly doubled. In addition, health effects research has addressed endpoints that were not covered in the first prospective, including premature mortality associated with ozone exposure.

Although the Agency has not yet conducted a rigorous quantitative analysis to assess the impact of these methodology and data improvements, the impact of most of these factors is to increase the estimates of benefits.

ORGANIZATION OF THIS REPORT

The remainder of this report is organized as follows. First, we present methods, data, and results for health effects and their valuation. As noted above, the health benefits constitute the majority of the monetized benefits in our analysis. Second, we present benefits associated with changes in visibility in both recreational and residential settings. Third, we present benefits associated with changes in productivity of agricultural crops and commercial forests. Fourth, we present benefits associated with reduced materials damage, including such resources as bridges, architectural coatings, and other materials that can be damaged by air pollution. The report concludes with aggregation and summary of all four of these categories of primary benefits.

CHAPTER 2 | ESTIMATION OF HUMAN HEALTH EFFECTS AND ECONOMIC BENEFITS

OVERVIEW OF APPROACH

This chapter addresses the economic valuation of human health effects realized as a result of the CAAA. The reduced incidence of physical effects is a valuable measure of health benefits for individual endpoints. To compare or aggregate benefits across endpoints, the benefits must be monetized. Assigning a dollar value to avoided incidences of each effect permits us to sum monetized benefits realized as a result of the CAAA, and compare them with the associated costs.

In the second prospective section 812 analysis, we have two broad categories of benefits: health and welfare benefits. Human health effects include mortality and morbidity endpoints, which are presented in this chapter. Welfare effects include visibility, agricultural and ecological benefits, and materials damage, which are covered in Chapters 3 through 5. We obtain valuation estimates from the economic literature and report them in "dollars per case reduced" for health effects. Similar to estimates of physical effects provided by health studies, we report each of the monetary values of benefits applied in this analysis in terms of a central estimate and a probability distribution around that value. The statistical form of the probability distribution varies by endpoint. For example, we use a log-normal distribution to describe the estimated dollar value of an avoided premature mortality, while we assume the estimate for the value of a reduced case of acute bronchitis is uniformly distributed between a minimum and maximum value.

Human health benefits of the 1990 Amendments are attributed to reduced emissions of criteria pollutants (Titles I through V) and reduced emission of ozone depleting substances (Title VI). This chapter focuses on the valuation of human health effects attributed to the reduction criteria pollutant emissions.[4] Our analysis indicates that the benefit of avoided premature mortality risk reduction dominates the overall net benefit estimate. This is, in part, due to the high monetary value assigned to the avoidance of premature mortality relative to the unit value of other health endpoints. As described in detail in this chapter, there are also significant reductions in short term and chronic health

[4] OAR's First Prospective analysis of the Costs and Benefits of the Clean Air Act Amendments included a detailed analysis of the health and welfare benefits of Title VI provisions. That analysis concluded that the benefits of the Title VI stratospheric ozone protection programs were very large compared to the costs. For the Second Prospective analysis, EPA has decided that updating the prior analysis likely would provide little in the way of additional insights. As a result, the Second Prospective analysis focuses on benefits and costs of criteria pollutant programs.

effects and a substantial number of health benefits that we could not quantify or monetize.

Similar to the first section 812 prospective analysis, the study design adopted for this analysis uses a sequence of linked analytical models to estimate benefits. The first step is an analysis of the likely implementation activities undertaken in response to the CAAA. These forecasted activities provided a basis for modeling criteria pollutant emissions under the two scenarios considered (the *with-CAAA* scenario and the *without-CAAA* scenario), as documented in the Emissions Projections for the Clean Air Act Second Section 812 Prospective Analysis.[5] The emissions estimates were input into the Community Multiscale Air Quality (CMAQ) model and, in turn, ambient pollutant concentrations estimated by CMAQ were input into the Environmental Benefits Mapping and Analysis Program (BenMAP).

BenMAP is a tool developed by the U.S. Environmental Protection Agency (EPA) for estimating the human health effects and economic benefits associated with changes in ambient air pollution.[6] BenMAP relies on three inputs: 1) forecasted changes in air quality between a baseline and control scenario; 2) health impact functions that quantify the relationship between the forecasted changes in exposure and expected changes in specific health effects; and 3) health valuation functions that assign a monetary value to changes in specific health effects. From these inputs, BenMAP compares changes in pollutant exposure between two scenarios and produces results in terms of avoided health effects and monetary valuation of the willingness to pay to avoid those effects. This chapter begins by discussing methods used to quantify changes in air quality and how that is interpreted for human exposure to specific pollutants, goes on to describe the health impact functions used, and then details the health valuation functions applied. The chapter concludes with a presentation and discussion of the results.

QUANTIFYING CHANGES IN AIR QUALITY

This analysis is the first Section 812 prospective analysis to use an integrated modeling system, the Community Multiscale Air Quality (CMAQ) model, to simulate changes in national and regional-scale pollutant concentrations and deposition. CMAQ has previously been deployed in several EPA economic analyses including the 2008 Ozone National Ambient Air Quality Standards (NAAQS) Regulatory Impact Analysis (RIA) (EPA, 2008) and the 2006 PM NAAQS RIA (EPA, 2006b). The CMAQ model (Byun and Ching, 1999) is a state-of-the-science, regional air quality modeling system that is designed to simulate the physical and chemical processes that govern the formation,

[5] See EH Pechan and Industrial Economics, *Emission Projections for the Clean Air Act Second Section 812 Prospective Analysis: Revised Draft Report*, March 2009, available at www.epa.gov/oar/sect 812.

[6] This analysis uses BenMAP Version 3.0.16. The current version of BenMAP can be downloaded from http://www.epa.gov/air/benmap/

transport, and deposition of gaseous and particulate species in the atmosphere. The latest version of CMAQ (Version 4.6) was employed for this analysis.

The CMAQ model was applied for seven core CAAA scenarios that include four different years that span a 30-year period – 1990, 2000, 2010 and 2020. Scenarios that incorporate the emission reductions associated with the CAA are referred to as *with-CAAA* while those that do not are referred to as *without-CAAA*. The scenarios include:

Retrospective Base-Year Scenario

1990 without-CAAA

Base and Projected Year Scenarios without 1990 CAAA Controls

2000 without-CAAA

2010 without-CAAA

2020 without-CAAA

Base and Projected Year Scenarios with 1990 CAAA Controls

2000 with-CAAA

2010 with-CAAA

2020 with-CAAA

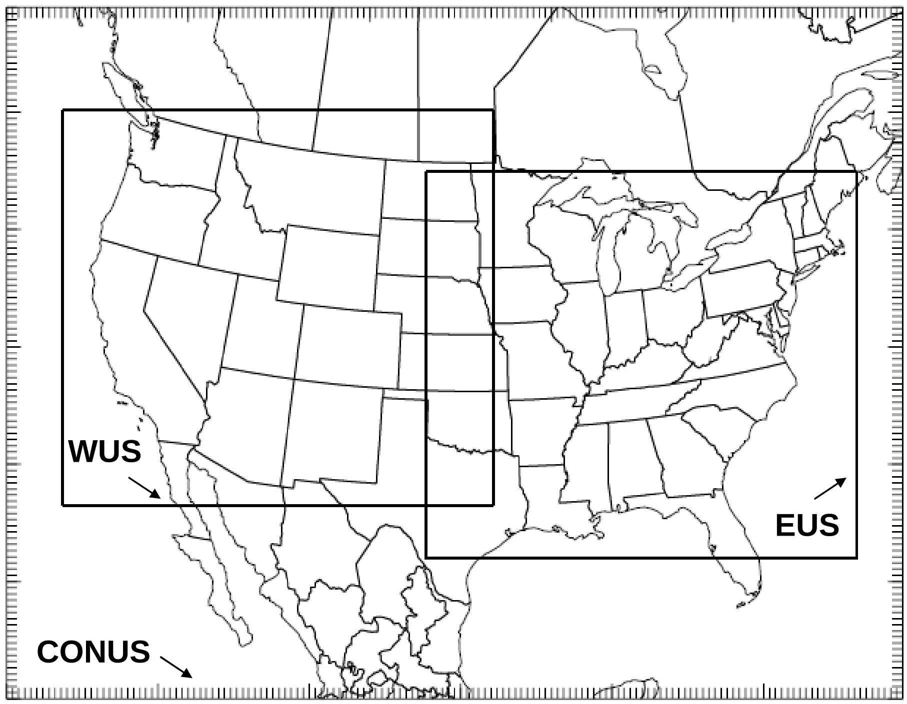
An integral component of the modeling analysis is the estimation of future-year emissions for the seven core scenarios – these are described in detail in companion reports available at EPA's Section 812 study website.[7] Emissions for the historical years (1990 and 2000) were based on the best available emission inventories for these years. Projection to the future years was based on economic growth projections, future-year control requirements (for attainment of NAAQS), and control efficiencies. Different assumptions were applied for the *with-* and *without-CAAA* scenarios resulting in a different future-year emissions pathway for each scenario. The emissions data were processed for input to the CMAQ modeling using the Sparse-Matrix Operator Kernel Emissions (SMOKE) emissions processing system.

The model-ready emission inventories for each scenario and year were then used to obtain base- and future-year estimates of the key criteria pollutants, as well as many other species. The air quality modeling analysis was designed to make use of tools and databases that have recently been developed and evaluated by EPA for other national- and regional-scale air quality modeling studies. In particular, model-ready meteorological input files for 2002 were provided by EPA for use in this study. For fine particulate matter ($PM_{2.5}$) and related species, the CMAQ model was applied for an annual simulation period (January through December). A 36-km resolution modeling domain that encompasses the contiguous 48 states was used for the annual modeling (see

[7] See www.epa.gov/oar/sect812

Exhibit 2-1). For ozone and related species, the CMAQ model was applied for a five-month simulation period that captures the key ozone-season months of May through September. Two 12-km resolution modeling domains (that when combined cover the contiguous 48 U.S. states) were used for the ozone-season modeling (see Exhibit 2-1). Altogether, model-ready emission inventories were prepared and the CMAQ model was applied for a total of 21 simulations (comprising seven core scenarios and three modeling domains).[8]

EXHIBIT 2-1. MAP OF THE CMAQ MODELING DOMAINS USED FOR SECOND SECTION 812 PROSPECTIVE ANALYSIS



Legend:

CONUS: Continental U.S. 36 km grid, PM2.5 and deposition estimates
EUS: Eastern U.S. 12 km grid, ozone estimates
WUS: Western U.S. 12 km grid, ozone estimates

[8] A detailed report on the air quality modeling analyses was prepared for EPA. This description is based on the September 2008 draft report, Second Prospective Analysis of Air Quality in the U.S.: Air Quality Modeling, prepared for James DeMocker of the EPA Office of Policy Analysis and Review by Sharon G. Douglas, Jay L. Haney, A. Belle Hudischewskyj, Thomas C. Myers, and Y. Wei of ICF International.

$PM_{2.5}$ and ozone outputs from CMAQ provide the basis of the air quality inputs needed for BenMAP. The raw CMAQ output is adjusted to take into account monitor data. The $PM_{2.5}$ output is adjusted using the Modeled Attainment Test Software (MATS, Version 2.1.1, Build 807) procedure and the ozone output is adjusted using the enhanced Voronoi Neighbor Averaging (eVNA) routine in BenMAP.

MATS estimates quarterly mean $PM_{2.5}$ chemical component concentrations at monitor locations (point estimates) by conducting a Speciated Modeled Attainment Test (SMAT) analysis. MATS can also estimate quarterly mean concentration estimates for each $PM_{2.5}$ chemical component concentrations at all grid cells in an Eulerian grid model such as CMAQ using a spatial field gradient interpolation procedure. All $PM_{2.5}$ concentration estimates for this analysis were prepared using the spatial and temporal relative adjustment method in MATS. $PM_{2.5}$ concentration estimates in CMAQ grid cells without a monitor were interpolated from nearby monitors using the inverse distance squared weighting option in the Voronoi Neighbor Averaging (VNA) procedure in MATS. The MATS analysis conducted for the $PM_{2.5}$ used the following input information:

- Observed $PM_{2.5}$ data from 1,336 Federal Reference Method (FRM) monitors with sufficient data in at least one year from 2002 to 2004 (as provided with the MATS Version 2.1.1 installation package);
- Observed chemically speciated fine particle mass data from both the $PM_{2.5}$ Speciated Trends Network (STN) and the Interagency Monitoring of Protected Visual Environments (IMPROVE) network, a total of 420 monitors with sufficient data in as least one year from 2002 to 2004 (as provided with the MATS Version 2.1.1 installation package);
- Speciated CMAQ estimates for 6 $PM_{2.5}$ species (SO_4, NO_3, elemental carbon, organic carbon, NH_4, and crustal material) at the 36 kilometer PM CMAQ grid cell level for each of the scenarios (from CMAQ speciated output data files provided by ICF/SAI).

Additional detail on the MATS procedure is available in the MATS User Manual (Abt Associates, 2009). MATS produced estimated average quarterly concentrations for each of the CMAQ 36 km grid cells. These estimates were subsequently rewritten to the format required for inputting daily $PM_{2.5}$ data into EPA's BenMAP software.

The daily ozone concentration estimates used in this analysis were prepared using a monitor and model relative adjustment procedure, combining the hourly CMAQ estimates with observed ozone monitor data. The monitor and model relative adjustment procedure was conducted using the extended VNA procedure (eVNA) with both spatial and temporal scaling in EPA's BenMAP software. The 1,162 ozone monitors used in the eVNA procedure were the 2002 ozone monitors contained in the BenMAP (ver. 3.0.15) US Setup installation file. The 2002 monitor data was selected because the base case CMAQ analysis ("2000 with Clean Air Act") used a 2002 emission inventory. The

CMAQ ozone estimates were prepared for the two separate eastern and western United States domains shown in Exhibit 2-1, each with a 12 kilometer by 12 kilometer grid.

HEALTH IMPACT FUNCTIONS[9]

Health impact functions measure the change in a health endpoint of interest, such as hospital admissions, for a given change in ambient ozone or $PM_{2.5}$ concentration. There are several types of data that can support the development of health impact functions relating air pollutant exposure or ambient concentrations to incidence of health outcomes. These sources of data include toxicological studies (including animal and cellular studies), human clinical trials, observational epidemiology studies, and meta-analyses of multiple epidemiology studies. All of these data sources provide important contributions to the weight of evidence surrounding a particular health impact, however, only epidemiology studies provide direct concentration-response (C-R) relationships which can be used to evaluate population-level impacts of reductions in ambient pollution levels.

However, standard environmental epidemiology studies provide only a limited representation of the uncertainty associated with a specific health impact function, measuring only the statistical error in the estimates, and usually relating more to the power of the underlying study (driven largely by population size and the frequency of the outcome measure). There are many other sources of uncertainty in the relationships between ambient pollution and population level health outcomes, including many sources of model uncertainty, such as model specification, potential confounding between factors that are both correlated with the health outcome and each other, and many other factors. As such, in recent years, EPA has begun investigating how expert elicitation methods can be used to integrate across various sources of data in developing health impact functions for regulatory benefits analyses.

Expert elicitation is useful in integrating the many sources of information about uncertainty in the health impact function, because it allows experts to synthesize these data sources using their own mental models, and provide a probabilistic representation of their synthesis of the data in the form of a probability distribution of the health impact function. EPA has used expert elicitation to inform the regulatory process in the past (see for example the staff paper for the lead NAAQS (EPA, 1990) and the PM NAAQS RIA (EPA, 2006b)). In the current analysis, we have used expert elicitation to characterize one representation of the health impact function for the relationship between $PM_{2.5}$ and premature mortality. However, similar methods could be used to characterize health impact functions for other health outcomes.

A standard health impact function has four components: 1) an effect estimate from a particular study; 2) a baseline incidence rate for the health effect (obtained from either the epidemiology study or a source of public health statistics such as the Centers for Disease

[9] Portions of this section were derived from the PM NAAQS RIA (EPA, 2006b) and the Ozone NAAQS RIA (EPA, 2008).

Control); 3) the size of the potentially affected population; and 4) the estimated change in the relevant ozone or PM summary measures.

A typical health impact function might be of the following generic form:

$$\Delta y = y_0 \cdot \left(e^{\beta \cdot \Delta x} - 1\right),$$

where y_0 is the baseline incidence (the product of the baseline incidence rate times the potentially affected population), β is the effect estimate, and Δx is the estimated change in the summary ozone or $PM_{2.5}$measure. There are other functional forms, but the basic elements remain the same. The ozone and PM air quality inputs to the health impact functions are described in the section above. The following subsections describe the sources for each of the other elements: size of potentially affected populations; effect estimates; and baseline incidence rates.

POTENTIALLY AFFECTED POPULATIONS

The starting point for estimating the size of potentially affected populations is the 2000 U.S. Census block level dataset (Geolytics 2002). BenMAP incorporates 250 age/gender/race categories to match specific populations potentially affected by ozone and $PM_{2.5}$. The software constructs specific populations matching the populations in each epidemiological study by accessing the appropriate age-specific populations from the overall population database. To estimate population levels for the years after 2000, BenMAP scales the 2000 Census-based population estimate with the ratio of the county-level forecast for the future year of interest over the 2000 county-level population level. Woods & Poole (2007) provides the county-level population forecasts used to calculate the scaling ratios.

HEALTH EFFECT ESTIMATE SOURCES

The most significant monetized benefits of reducing ambient concentrations of ozone and PM are attributable to reductions in human health risks. EPA's Ozone and PM Criteria Documents outline numerous health effects known or suspected to be linked to exposure to ambient ozone and PM (EPA, 2006; Anderson et al., 2004). EPA recently evaluated the ozone and PM literature for use in the benefits analyses for the Ozone NAAQS RIA (EPA, 2008) and PM NAAQS RIA (EPA, 2006b), respectively. The discussion of individual effect estimates presented in this section relies heavily on the research done for these RIAs.

Exhibit 2-2 lists the human health effects of ozone and $PM_{2.5}$. Exhibit 2-3 and 2-4 lists the health endpoints associated with ozone and $PM_{2.5}$, respectively, included in this analysis. A number of endpoints that are not health-related may also contribute significant monetized benefits. Welfare benefits such as increased recreational and residential visibility, increased recreational fishing opportunities, increased commercial forest and agriculture productivity, and decreased building materials damage are discussed in Chapters 3 through 5.

EXHIBIT 2-2. HUMAN HEALTH EFFECTS OF OZONE AND $PM_{2.5}$

POLLUTANT/EFFECT	QUANTIFIED AND MONETIZED IN BASE ESTIMATES[a]	UNQUANTIFIED EFFECTS[g,h]—CHANGES IN:
PM/Health[b]	Premature mortality based on both cohort study estimates and on expert elicitation[c,d] Bronchitis: chronic and acute Hospital admissions: respiratory and cardiovascular Emergency room visits for asthma Nonfatal heart attacks (myocardial infarction) Lower respiratory symptoms Minor restricted-activity days Work loss days Asthma exacerbations (asthmatic population) Upper Respiratory symptoms (asthmatic population) Infant mortality	Subchronic bronchitis cases Low birth weight Pulmonary function Chronic respiratory diseases other than chronic bronchitis Morphological changes Altered host defense mechanisms Cancer Non-asthma respiratory emergency room Visits UVb exposure (+/-)e Stroke/cerebrovascular disease
Ozone/Health[f]	Premature mortality: short-term exposures Hospital admissions: respiratory Emergency room visits for asthma Minor restricted-activity days School loss days Outdoor worker productivity	Cardiovascular emergency room visits Asthma attacks Respiratory symptoms Chronic respiratory damage Increased responsiveness to stimuli Inflammation in the lung Premature aging of the lungs Acute inflammation and respiratory cell damage Increased susceptibility to respiratory infection Non-asthma respiratory emergency room Visits UVb exposure (+/-)e

[a] Primary quantified and monetized effects are those included when determining the primary estimate of total monetized benefits of the alternative standards.
[b] In addition to primary economic endpoints, there are a number of biological responses that have been associated with PM health effects including morphological changes and altered host defense mechanisms. The public health impact of these biological responses may be partly represented by our quantified endpoints.
[c] Cohort estimates are designed to examine the effects of long-term exposures to ambient pollution, but relative risk estimates may also incorporate some effects due to shorter term exposures (see Kunzli (2001) for a discussion of this issue).
[d] While some of the effects of short-term exposure are likely to be captured by the cohort estimates, there may be additional premature mortality from short-term PM exposure not captured in the cohort estimates included in the primary analysis.
[e] May result in benefits or dis-benefits.
[f] In addition to primary economic endpoints, there are a number of biological responses that have been associated with ozone health including increased airway responsiveness to stimuli, inflammation in the lung, acute inflammation and respiratory cell damage, and increased susceptibility to respiratory infection. The public health impact of these biological responses may be partly represented by our quantified endpoints.
[g] The categorization of un-quantified health effects is not exhaustive.
[h] Health endpoints in the un-quantified benefits column include both a) those for which there is not consensus on causality and b) those for which causality has been determined but empirical data are not available to allow calculation of benefits.

EXHIBIT 2-3. OZONE RELATED HEALTH ENDPOINTS BASIS FOR THE HEALTH IMPACT FUNCTION ASSOCIATED WITH THAT ENDPOINT, AND SUB-POPULATIONS FOR WHICH THEY WERE COMPUTED

ENDPOINT	POLLUTANT	STUDY	STUDY POPULATION
Premature Mortality			
Premature mortality—all cause	O3 (8-hour max)	Equal weight pooling of: Ito et al. (2005) Schwartz (2005) Bell et al. (2004) Bell et al. (2005) Levy et al. (2005) Huang et al. (2005)	All ages
Hospital Admissions			
Respiratory	O3 (8-hour max)	Pooled estimate: Schwartz (1995)—ICD 460-519 (all respiratory) Schwartz (1994a; 1994b)—ICD 480-486 (pneumonia) Moolgavkar et al. (1997)—ICD 480-487, 490-496 (pneumonia, COPD) Schwartz (1994b)—ICD 491-492, 494-496 (COPD)	>64 years
Respiratory	O3 (8-hour max)	Burnett et al. (2001)	<2 years
Asthma-related ER visits	O3 (8-hour max)	Pooled estimate: Jaffe et al (2003) Peel et al (2005) Wilson et al (2005)	 5-34 years All ages All ages
Other Health Endpoints			
Minor restricted-activity days	O3 (24-hour avg)	Ostro and Rothschild (1989)	18-64 years
School loss days	 O3 (8-hour avg) O3 (1-hour max)	Pooled estimate: Gilliland et al. (2001) Chen et al. (2000)	5-17 years[a]
Outdoor worker productivity	O3 (8-hour max)	Crocker and Horst (1981)	18-64 years

a Gilliland et al. (2001) studied children aged 9 and 10. Chen et al. (2000) studied children 6 to 11. Based on recent advice from the National Research Council and the EPA Council's Health Effects Subcommittee (HES), we have calculated reductions in school absences for all school-aged children based on the biological similarity between children aged 5 to 17.

EXHIBIT 2-4. PM RELATED HEALTH ENDPOINTS BASIS FOR THE HEALTH IMPACT FUNCTION ASSOCIATED WITH THAT ENDPOINT, AND SUB-POPULATIONS FOR WHICH THEY WERE COMPUTED

ENDPOINT	POLLUTANT	STUDY	STUDY POPULATION
Premature Mortality			
Premature mortality—all-cause[a]	$PM_{2.5}$ (annual avg)	Weibull distribution of C-R coefficients[a]	>24 years
Infant mortality—all-cause	$PM_{2.5}$ (annual avg)	Woodruff et al. (1997)	Infant (<1 year)
Chronic Illness			
Chronic bronchitis	$PM_{2.5}$ (annual avg)	Abbey et al. (1995)	>26 years
Nonfatal myocardial infarction	$PM_{2.5}$ (24-hour avg)	Peters et al. (2001)	Adults (>18 years)
Hospital Admissions			
Respiratory	$PM_{2.5}$ (24-hour avg)	Pooled estimate: Moolgavkar (2003)—ICD 490-496 (COPD) Ito (2003)—ICD 490-496, 480-487 (COPD, pneumonia)	>64 years
Respiratory	$PM_{2.5}$ (24-hour avg)	Moolgavkar (2000a)—ICD 490-492, 494-496 (COPD, less asthma)	20-64 years
Respiratory	$PM_{2.5}$ (24-hour avg)	Sheppard (2003)—ICD 493 (asthma)	<65 years
Cardiovascular	$PM_{2.5}$ (24-hour avg)	Pooled estimate: Moolgavkar (2003)—ICD 390-429 (all cardiovascular) Ito (2003)—ICD 411-414, 429, 428 (ischemic heart disease, dysrhythmia, heart failure)	>64 years
Cardiovascular	$PM_{2.5}$ (24-hour avg)	Moolgavkar (2000b)—ICD 390-429 (all cardiovascular)	20-64 years
Asthma-related ER visits	$PM_{2.5}$ (24-hour avg)	Norris et al. (1999)	<18 years
Other Health Endpoints			
Acute bronchitis	$PM_{2.5}$ (annual avg)	Dockery et al. (1996)	8-12 years
Lower respiratory symptoms	$PM_{2.5}$ (24-hour avg)	Schwartz and Neas (2000)	7-14 years
Upper respiratory symptoms	$PM_{2.5}$ (24-hour avg)	Pope et al. (1991)	9-11 years

ENDPOINT	POLLUTANT	STUDY	STUDY POPULATION
Asthma exacerbation	$PM_{2.5}$ (24-hour avg)	Pooled estimate: Ostro et al. (2001) (cough, wheeze, shortness of breath) Vedal et al. (1998) (cough)	6-18 years[b]
Minor restricted-activity days	$PM_{2.5}$ (24-hour avg)	Ostro and Rothschild (1989)	18-64 years
Work loss days	$PM_{2.5}$ (24-hour avg)	Ostro (1987)	18-64 years

a This distribution of coefficients for the PM mortality function is based on recommendations made by the HES; it features a Weibull distribution with a mean value of 1.06 that is approximately the average of coefficients derived from Pope et al. (2002) and Laden et al. (2006). The Pope and Laden coefficients fall roughly at the 25th and 75th percentiles of the Weibull distribution.

b The original study populations were 8 to 13 for the Ostro et al. (2001) study and 6 to 13 for the Vedal et al. (1998) study. Based on advice from the HES, we extended the applied population to 6 to 18, reflecting the common biological basis for the effect in children in the broader age group. See: U.S. Science Advisory Board. 2004. Advisory Plans for Health Effects Analysis in the Analytical Plan for EPA's Second Prospective Analysis - Benefits and Costs of the Clean Air Act, 1990—2020. EPA-SAB-COUNCIL-ADV-04-004. See also National Research Council (NRC). 2002. Estimating the Public Health Benefits of Proposed Air Pollution Regulations. Washington, DC: The National Academies Press.

LITERATURE SOURCES FOR OZONE HEALTH EFFECTS FUNCTIONS

PREMATURE MORTALITY

While PM is the criteria pollutant most clearly associated with premature mortality, recent research suggests that short-term repeated ozone exposure also likely contributes to premature death. The 2006 Ozone Criteria Document states, "Consistent with observed ozone-related increases in respiratory- and cardiovascular-related morbidity, several newer multi-city studies, single-city studies, and several meta-analyses of these studies have provided relatively strong epidemiologic evidence for associations between short-term ozone exposure and all-cause mortality, even after adjustment for the influence of season and PM" (EPA, 2006a: 8-78). The epidemiologic data are also supported by recent experimental data from both animal and human studies, which provide evidence suggestive of plausible pathways by which risk of respiratory or cardiovascular morbidity and mortality could be increased by ambient ozone. With respect to short-term exposure, the Ozone Criteria Document concludes, "This overall body of evidence is highly suggestive that ozone directly or indirectly contributes to non-accidental and cardiopulmonary-related mortality, but additional research is needed to more fully establish underlying mechanisms by which such effects occur" (p. 8-78).

With respect to the time-series studies, the conclusion regarding the relationship between short-term exposure and premature mortality is based, in part, upon recent city-specific time-series studies such as the Schwartz (2005) analysis in Houston and the Huang et al.

(2005) analysis in Los Angeles.[10] This conclusion is also based on recent meta-analyses by Bell et al. (2005), Ito et al. (2005), and Levy et al. (2005) and on analyses of the National Morbidity, Mortality, and Air Pollution Study (NMMAPS) data set by Bell et al. (2004), Schwartz (2005), and Huang et al. (2005). Consistent with the methodology used in the Ozone NAAQS RIA (2008), and with more recent advice in NAS (2008), we included ozone mortality in the primary health effects analysis, with the recognition that the exact magnitude of the effects estimate is subject to continuing uncertainty. In this chapter we present estimates derived from an equal-weight pooling of the six studies listed above. The Uncertainty Analysis to Support the Second Section 812 Benefit-Cost analysis of the Clean Air Act (Uncertainty Analysis) includes estimates from all six studies separately. Use of these six studies represents a slight change from the Ozone NAAQS RIA (2008); two NMMAPS-based studies (Schwartz (2005) and Huang et al. (2005)) have been added based on guidance from the National Academy of Sciences (NAS) (2008).

Ozone Exposure Metric. Both the NMMAPS analyses and the individual time series studies upon which the meta-analyses were based use the 24-hour average or 1-hour maximum ozone levels as exposure metrics. The 24-hour average is not the most relevant ozone exposure metric to characterize population-level exposure. Given that the majority of the people tend to be outdoors during the daylight hours and concentrations are highest during the daylight hours, the 24-hour average metric is not appropriate. Moreover, the 1-hour maximum metric uses an exposure window different than that used for the current ozone NAAQS. Together, this means that the most biologically relevant metric, and the one used in the ozone NAAQS since 1997, is the 8-hour maximum standard. Thus, for this analysis, we have converted ozone mortality health impact functions that use a 24-hour average or 1-hour maximum ozone metric to maximum 8-hour average ozone concentration using a procedure described in the BenMAP user's manual (see Abt Associates, 2008). A similar method was used for the final Ozone NAAQS RIA (2008).

RESPIRATORY HOSPITAL ADMISSIONS

Detailed hospital admission and discharge records provide data for an extensive body of literature examining the relationship between hospital admissions and air pollution. This is especially true for the portion of the population aged 65 and older, because of the availability of detailed Medicare records. In addition, there is one study (Burnett et al., 2001) providing an effect estimate for respiratory hospital admissions in children less than two years of age.

[10] For an exhaustive review of the city-specific time-series studies considered in the ozone staff paper, see: U.S. Environmental Protection Agency, 2007. Review of the National Ambient Air Quality Standards for Ozone: Policy Assessment of Scientific and Technical Information. Prepared by the Office of Air and Radiation. Available at http://www.epa.gov/ttn/naaqs/standards/ozone/data/2007_01_ozone_staff_paper.pdf. pp. 5-36.

Because the number of hospital admission studies we considered is so large, we used results from a number of studies to pool some hospital admission endpoints. Pooling is the process by which multiple study results may be combined in order to produce better estimates of the effect estimate, or β.[11] To estimate total respiratory hospital admissions associated with changes in ambient ozone concentrations for adults over 65, we first estimated the change in hospital admissions for each of the different effects categories that each study provided for each city. These cities included Minneapolis, Detroit, Tacoma and New Haven. To estimate total respiratory hospital admissions for Detroit, we added the pneumonia and chronic obstructive pulmonary disease (COPD) estimates, based on the effect estimates in the Schwartz study (1994b). Similarly, we summed the estimated hospital admissions based on the effect estimates the Moolgavkar study reported for Minneapolis (Moolgavkar et al., 1997). To estimate total respiratory hospital admissions for Minneapolis using the Schwartz study (1994a), we simply estimated pneumonia hospital admissions based on the effect estimate. Making this assumption that pneumonia admissions represent the total impact of ozone on hospital admissions in this city will give some weight to the possibility that there is no relationship between ozone and COPD, reflecting the equivocal evidence represented by the different studies. We then used a fixed-effects pooling procedure to combine the two total respiratory hospital admission estimates for Minneapolis. Finally, we used random effects pooling to combine the results for Minneapolis and Detroit with results from studies in Tacoma and New Haven from Schwartz (1995). As noted above, this pooling approach incorporates both the precision of the individual effect estimates and between-study variability characterizing differences across study locations.

ASTHMA-RELATED EMERGENCY ROOM VISITS

We used three studies as the source of the C-R functions we used to estimate the effects of ozone exposure on asthma-related emergency room (ER) visits: Peel et al. (2005); Wilson et al. (2005); and Jaffe et al. (2003). We estimated the change in ER visits using the effect estimate(s) from each study and then pooled the results using the random effects pooling technique (see Abt Associates, 2008). The study by Jaffe et al. (2003) examined the relationship between ER visits and air pollution for populations aged five to 34 in the Ohio cities of Cleveland, Columbus and Cincinnati from 1991 through 1996. In single-pollutant Poisson regression models, ozone was linked to asthma visits. We use the pooled estimate across all three cities as reported in the study. The Peel et al. study (2005) estimated asthma-related ER visits for all ages in Atlanta, using air quality data from 1993 to 2000. Using Poisson generalized estimating equations, the authors found a marginal association between the maximum daily 8-hour average ozone level and ER visits for asthma over a 3-day moving average (lags of 0, 1, and 2 days) in a single pollutant model. Wilson et al. (2005) examined the relationship between ER visits for respiratory illnesses and asthma and air pollution for all people residing in Portland,

[11] For a complete discussion of the pooling process see Abt Associates, 2008.

Maine from 1998–2000 and Manchester, New Hampshire from 1996–2000. For all models used in the analysis, the authors restricted the ozone data incorporated into the model to the months ozone levels are usually measured, the spring-summer months (April through September). Using the generalized additive model, Wilson et al. (2005) found a significant association between the maximum daily 8-hour average ozone level and ER visits for asthma in Portland, but found no significant association for Manchester. Similar to the approach used to generate effect estimates for hospital admissions, we used random effects pooling to combine the results across the individual study estimates for ER visits for asthma. The Peel et al. (2005) and Wilson et al. (2005) Manchester estimates were not significant at the 95 percent level, and thus, the confidence interval for the pooled incidence estimate based on these studies includes negative values. This is an artifact of the statistical power of the studies, and the negative values in the tails of the estimated effect distributions do not represent improvements in health as ozone concentrations are increased. Instead, these should be viewed as a measure of uncertainty due to limitations in the statistical power of the study. We included both hospital admissions and ER visits as separate endpoints associated with ozone exposure because our estimates of hospital admission costs do not include the costs of ER visits and most asthma ER visits do not result in a hospital admission.

MINOR RESTRICTED-ACTIVITY DAYS

Minor restricted-activity days (MRADs) occur when individuals reduce most usual daily activities and replace them with less-strenuous activities or rest, but do not miss work or school. We estimated the effect of ozone exposure on MRADs using a concentration-response function derived from Ostro and Rothschild (1989). These researchers estimated the impact of ozone and $PM_{2.5}$ on MRAD incidence in a national sample of the adult working population (ages 18 to 64) living in metropolitan areas. We developed separate coefficients for each year of the Ostro and Rothschild analysis (1976–1981), which we then combined for use in EPA's analysis. The effect estimate used in the impact function is a weighted average of the coefficients in Ostro and Rothschild (1989, Table 4), using the inverse of the variance as the weight.

SCHOOL LOSS DAYS

Children may be absent from school due to respiratory or other acute diseases caused, or aggravated by, exposure to air pollution. Several studies have found a significant association between ozone levels and school absence rates. We use two studies (Gilliland et al., 2001; Chen et al., 2000) to estimate changes in school absences resulting from changes in ozone levels. The Gilliland et al. study estimated the incidence of new periods of absence, while the Chen et al. study examined daily absence rates. We converted the Gilliland et al. estimate to days of absence by multiplying the absence periods by the average duration of an absence. We estimated 1.6 days as the average duration of a school absence, the result of dividing the average daily school absence rate from Chen et al. (2000) and Ransom and Pope (1992) by the episodic absence duration from Gilliland et al. (2001). Thus, each Gilliland et al. period of absence is converted into 1.6 absence days.

Following advice from the National Research Council (2002), we calculated reductions in school absences for the full population of school age children, ages five to 17. We estimated the change in school absences using both Chen et al. (2000) and Gilliland et al. (2001) and then, similar to hospital admissions and ER visits, pooled the results using the random effects pooling procedure.

OUTDOOR WORKER PRODUCTIVITY

To monetize benefits associated with increased outdoor worker productivity resulting from improved ozone air quality, we used information reported in Crocker and Horst (1981). Crocker and Horst examined the impacts of ozone exposure on the productivity of outdoor citrus workers. The study measured productivity impacts. Worker productivity is measuring the value of the loss in productivity for a worker who is at work on a particular day, but due to ozone, cannot work as hard. It only applies to outdoor workers, like fruit and vegetable pickers, or construction workers. Here, productivity impacts are measured as the change in income associated with a change in ozone exposure, given as the elasticity of income with respect to ozone concentration. The reported elasticity translates a ten percent reduction in ozone to a 1.4 percent increase in income. Given the national median daily income for outdoor workers engaged in strenuous activity reported by the U.S. Census Bureau (2002), $68 per day (2000$), a ten percent reduction in ozone yields about $0.97 in increased daily wages. We adjust the national median daily income estimate to reflect regional variations in income using a factor based on the ratio of county median household income to national median household income. No information was available for quantifying the uncertainty associated with the central valuation estimate. Therefore, no uncertainty analysis was conducted for this endpoint.

LITERATURE SOURCES FOR PM HEALTH EFFECTS FUNCTIONS

ADULT PREMATURE MORTALITY

The estimated relationship between particulate matter exposure and premature mortality is one of the most important parameters in the overall quantified and monetized benefit estimate for this study. An extensive base of literature exists to support development of the C-R function linking fine particulate matter exposure with premature mortality. Our knowledge of both the potential biological mechanisms linking $PM_{2.5}$ exposure with mortality and the potential magnitude of this effect has grown since the First Prospective was completed as the result of continued research and follow-up of existing study populations. Both short-term and long-term epidemiological studies have been conducted to examine the PM/mortality relationship. Short-term exposure studies attempt to relate short-term (often day-to-day) changes in PM concentrations and changes in daily mortality rates up to several days after a period of elevated PM concentrations. Long-term exposure studies examine the potential relationship between longer-term (e.g., annual) changes in exposure and annual mortality rates. Although positive, significant results have been reported using both of these study types, we rely exclusively on long-term studies to quantify PM mortality effects. This is because cohort studies are able to discern changes in mortality rates due to long-term exposure to elevated air pollution concentrations, which more closely matches the benefits of air pollution control programs under the CAAA, which are themselves focused on reducing long-term exposure. These effect estimates may also include some of the mortality changes due to short-term peak exposures.[12] Therefore, the use of C-R functions from long-term studies is likely to yield a more complete assessment of the effect of PM on mortality risk.

Among long-term PM studies, we prefer those using a prospective cohort design to those using an ecologic or population-level design. Prospective cohort studies follow individuals forward in time for a specified period, periodically evaluating each individual's exposure and health status. Population-level ecological studies assess the relationship between population-wide health information (such as counts of daily mortality) and ambient levels of air pollution. Prospective cohort studies are preferred because they are better at controlling a source of uncertainty known as "confounding." Confounding is the mis-estimation of an association that results if a study does not control for factors that are correlated with both the outcome of interest (e.g., mortality) and the exposure of interest (e.g., PM exposure). For example, smoking is associated with mortality. If populations in high PM areas tend to smoke more than populations in low PM areas, and a PM exposure study does not include smoking as a factor in its model, then the mortality effects of smoking may be erroneously attributed to PM, leading to an overestimate of the risk from PM. Prospective cohort studies are better at controlling for confounding than ecologic studies because the former follow a group of individuals forward in time and can gather individual-specific information on important risk factors such as smoking.

Two major prospective cohort studies have been conducted in the U.S.: the American Cancer Society (ACS) study and the Harvard Six Cities study. These two cohorts are large, produce consistent results, provide broad geographic coverage and have been independently reexamined and reanalyzed. Strengths of the ACS study over the Harvard Six Cities study include greater geographic coverage (50 U.S. cities) and larger sample size. However, a key limitation of this study is a recruitment method that led to a study population with higher income, more education, and greater proportion of whites than the general U.S. population. In addition, available monitoring data was often assigned to all of the individuals within a large metropolitan area, potentially allowing for exposure misclassification.[13] Both of these limitations could imply that the ACS results are

[12] See Kunzli et al. (2001) for a discussion of this issue.

[13] Studies have shown that greater spatial resolution of exposures can result in increased effect estimates (Jerrett et al., 2005).

potentially biased low. The Harvard Six Cities study included a more representative sample of subjects within each community and set up monitors purposefully for the study. It was therefore able to assign exposures at a finer geographic scale. However, this study only included six cities and therefore may not be representative of the entire U.S. population, mix of air pollutants, and other potentially important factors.

The extensive epidemiological literature is complemented by EPA's 2006 expert elicitation (EE) study that asked 12 leading experts in PM health effects to integrate this pool of knowledge with the various sources of uncertainty that hinder our ability to precisely identify the true mortality impact of a unit change in annual $PM_{2.5}$ concentration (IEc, 2006). The results of the EE study showed three important findings: first, that advances in the scientific literature led many of the interviewed scientists to espouse greater confidence in the linkage between $PM_{2.5}$ exposure and mortality; second, that many of the experts believed that the central estimate of the mortality effect was considerably higher than the Pope et al., 2002 result used in the first prospective; and third, that most of the experts' uncertainty distributions of the mortality effect reflected a much wider range of possible values, both high and low, than were used in the first prospective study. The EE study does not, however, provide an integrated distribution across all 12 experts of possible values for the PM-mortality C-R function.

Based on consultations with the Council's Health Effects Subcommittee (HES), the 812 Project Team developed a distribution of C-R function coefficients (i.e., the percent change in annual all-cause mortality per one $\mu g/m^3$ change in annual average $PM_{2.5}$) for use in the PM-mortality C-R function for the second prospective study. This distribution is rooted in the epidemiological studies that most inform our understanding of the PM-mortality C-R function, but reflects the broader findings of the EE study. We based the primary C-R coefficient estimate of the second prospective study on a Weibull distribution with a mean of 1.06 percent decrease in annual all-cause mortality per one ug/m3. This mean is roughly equidistant between the results of the two most well-studied PM cohorts, the ACS cohort (0.58, as derived from Pope et al., 2002) and the Six Cities cohort (1.5, as derived from Laden et al., 2006), both of whose results have been robust to continued follow-up and extensive re-analysis. Half of the coefficient values in this distribution fall between these two studies, one-quarter are higher than the Laden mean estimate, and one-quarter are lower than the Pope mean estimate; however all coefficient values are greater than zero. This distribution is consistent with the EE results described above, showing considerable support for higher values based on results from more recent studies (e.g. the Laden et al. 2006 Six Cities follow-up) and concerns cited by the HES that the ACS cohort results may underestimate the true effect. The use of all positive values is consistent with both the increased confidence in a causal link between $PM_{2.5}$ exposure and mortality shown in the EE study and the lack of evidence in general to support a threshold for mortality effects of $PM_{2.5}$ in the U.S. population (EPA SAB, 2010).

INFANT MORTALITY

Recently published studies have strengthened the case for an association between PM exposure and respiratory inflammation and infection leading to premature mortality in children under 5 years of age. With regard to the cohort study conducted by Woodruff et al. (1997), the HES noted several strengths of the study, including the use of a larger cohort drawn from a large number of metropolitan areas and efforts to control for a variety of individual risk factors in infants (e.g., maternal educational level, maternal ethnicity, parental marital status, and maternal smoking status). Based on these findings, the HES recommended that EPA incorporate infant mortality into the primary benefits estimate and that infant mortality be evaluated using an impact function developed from the Woodruff et al. (1997) study (U.S. EPA-SAB, 2004b).[14]

CHRONIC BRONCHITIS

Chronic Bronchitis (CB) is characterized by mucus in the lungs and a persistent wet cough for at least 3 months a year for several years in a row. CB affects an estimated 9.1 million Americans annually (American Lung Association, 2009). A limited number of studies have estimated the impact of air pollution on new incidences of CB. Abbey et al. (1995) provide evidence that long-term $PM_{2.5}$ exposure gives rise to the development of CB in the United States.

NONFATAL MYOCARDIAL INFARCTIONS (HEART ATTACKS)

Nonfatal heart attacks have been linked with short-term exposures to $PM_{2.5}$ in the United States (Peters et al., 2001) and other countries (Poloniecki et al., 1997). Other studies, such as Domenici et al. (2006), Samet et al. (2000), and Moolgavkar (2000b), show a consistent relationship between all cardiovascular hospital admissions, including those for nonfatal heart attacks, and PM. Given the lasting impact of a heart attack on long-term health costs and earnings, we provide a separate estimate for nonfatal heart attacks. The estimate used in this analysis is based on the single available U.S. $PM_{2.5}$ effect estimate from Peters et al. (2001).

RESPIRATORY AND CARDIOVASCULAR HOSPITAL ADMISSIONS

Because of the availability of detailed hospital admission and discharge records, there is an extensive body of literature examining the relationship between hospital admissions and air pollution. Because of this, many of the hospital admission endpoints use pooled impact functions based on the results of a number of studies. The two main groups of hospital admissions estimated in this analysis are respiratory admissions and

[14] A more recent study by Woodruff et al. (2006) continues to find associations between $PM_{2.5}$ and infant mortality. The study also found the most significant relationships with respiratory-related causes of death. We consulted the Council HES about whether they would recommend continued reliance on Woodruff et al. (1997) or recommend that the relationship be characterized by the more recent Woodruff et al. (2006) study. The Council continued to support EPA's decision to include infant mortality in its analysis and recommended that EPA do a "reasoned evaluation of relevant studies and synthesize evidence across the studies" (EPA SAB, 2010). For this report we have continued to rely on Woodruff et al. (1997).

cardiovascular admissions. There is not much evidence linking PM with other types of hospital admissions.

To estimate avoided incidences of $PM_{2.5}$ related cardiovascular hospital admissions in populations aged 65 and older, we use effect estimates from studies by Moolgavkar (2003) and Ito (2003). Moolgavkar (2000a) provides the only separate effect estimate for populations 20 to 64.[15] Total cardiovascular hospital admissions are thus the sum of the pooled estimates from Moolgavkar (2003) and Ito (2003) for populations over 65 and the Moolgavkar (2000a) based impacts for populations aged 20 to 64. Cardiovascular hospital admissions include admissions for myocardial infarctions. To avoid double-counting benefits from reductions in myocardial infarctions when applying the impact function for cardiovascular hospital admissions, we first adjusted the baseline cardiovascular hospital admissions to remove admissions for myocardial infarctions.

To estimate total avoided incidences of respiratory hospital admissions, we used impact functions for several respiratory causes, including COPD, pneumonia, and asthma. Both Moolgavkar (2003) and Ito (2003) provide effect estimates for COPD in populations over 65, allowing us to pool the impact functions for this group. Only Moolgavkar (2000a) provides a separate effect estimate for populations 20 to 64. Total COPD hospital admissions are thus the sum of the pooled estimate for populations over 65 and the single study estimate for populations 20 to 64. In addition, Ito (2003) provides an effect estimate for pneumonia hospital admissions in populations 65 and older and Sheppard (2003) provides an effect estimate for asthma hospital admissions in populations under age 65. The total avoided incidence of respiratory-related hospital admissions is the sum of COPD, pneumonia, and asthma admissions.

ASTHMA-RELATED EMERGENCY ROOM VISITS

Some studies have examined the relationship between air pollution and emergency room visits. Since most emergency room visits do not result in an admission to the hospital (the majority of people going to the emergency room are treated and return home), we treat hospital admissions and emergency room visits separately, taking account of the fraction of emergency room visits that are admitted to the hospital. The only type of emergency room visits that have been consistently linked to PM in the United States are asthma-related visits. To estimate the effects of PM air pollution reductions on asthma-related ER visits, we use the effect estimate from a study of children 18 and under by Norris et al. (1999). We selected the Norris et al. (1999) effect estimate because it focuses on $PM_{2.5}$, as opposed to PM_{10}.

[15] Note that the Moolgavkar (2000) study has not been updated to reflect the more stringent GAM convergence criteria. However, given that no other estimates are available for this age group, we chose to use the existing study. Updates have been provided for the 65 and older population, and showed little difference. Given the very small (<5%) difference in the effect estimates for people 65 and older with cardiovascular hospital admissions between the original and reanalyzed results, we do not expect the difference in the effect estimates for the 20 to 64 population to differ significantly. As such, the choice to use the earlier, uncorrected analysis will likely not introduce much bias.

ACUTE HEALTH EFFECTS

As indicated in Exhibit 2-4, in addition to mortality, chronic illness, and hospital admissions, a number of acute health effects not requiring hospitalization are associated with exposure to ambient levels of PM. The sources for the effect estimates used to quantify these effects are described below.

Around 4 percent of U.S. children between the ages of five and 17 experience episodes of acute bronchitis annually (American Lung Association, 2002c). Acute bronchitis is characterized by coughing, chest discomfort, slight fever, and extreme tiredness, lasting for a number of days. According to the MedlinePlus medical encyclopedia, symptoms usually go away without treatment.[16] Incidence of episodes of acute bronchitis in children between the ages of eight and twelve were estimated using an effect estimate developed from Dockery et al. (1996).

Incidences of lower respiratory symptoms (e.g., wheezing, deep cough) in children aged seven to fourteen were estimated using an effect estimate from Schwartz and Neas (2000).

Because asthmatics have greater sensitivity to stimuli (including air pollution), children with asthma can be more susceptible to a variety of upper respiratory symptoms (e.g., runny or stuffy nose; wet cough; and burning, aching, or red eyes). Research on the effects of air pollution on upper respiratory symptoms has thus focused on effects in asthmatics. Incidences of upper respiratory symptoms in asthmatic children aged nine to eleven are estimated using an effect estimate developed from Pope et al. (1991).[17]

Following recommendations of the HES, to prevent double-counting, we focused on asthma exacerbation occurring in children and excluded adults from the calculation.[18]

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[16] See http://www.nlm.nih.gov/medlineplus/bronchitis.html, accessed October 2009.

[17] Pope et al. (1991) estimates the impact of PM_{10} exposure on the incidence of upper respiratory symptoms. The EPA began applying the C-R function derived from Pope et al. (1991) for PM_{10} to $PM_{2.5}$ air quality estimates in 2005 (EPA, 2005). The implicit assumptions of this action are that a) $PM_{2.5}$ is as toxic as the average of all PM_{10} and b) if a single rule or policy action reduced only precursor pollutants, the change in PM_{10} would equal the change in $PM_{2.5}$.

[18] Estimating asthma exacerbations associated with air pollution exposures is difficult, due to concerns about double-counting of benefits. Concerns over double-counting stem from the fact that studies of the general population also include asthmatics, so estimates based solely on the asthmatic population cannot be directly added to the general population numbers without double-counting. In one specific case (upper respiratory symptoms in children), the only study available is limited to asthmatic children, so this endpoint can be readily included in the calculation of total benefits. However, other endpoints, such as lower respiratory symptoms and MRADs, are estimated for the total population that includes asthmatics. Therefore, to simply add predictions of asthma-related symptoms generated for the population of asthmatics to these total population-based estimates could result in double-counting, especially if they evaluate similar endpoints. The HES, in commenting on the analytical blueprint for the current 812 study, acknowledged these challenges in evaluating asthmatic symptoms and appropriately adding them into the primary analysis (EPA-SAB, 2004b). However, despite these challenges, the HES recommended the addition of asthma-related symptoms (i.e., asthma exacerbations) to the primary analysis, provided that the studies use the panel study approach and that they have comparable design and baseline frequencies in both asthma prevalence and exacerbation rates. Note also, that the HES, while supporting the incorporation of asthma exacerbation estimates, did not believe that the association between ambient air pollution, including ozone and PM, and the new onset of asthma is sufficiently strong to support inclusion of this asthma-related endpoint in the primary estimate.

Asthma exacerbation occurring in adults is assumed to be captured in the general population endpoints such as work loss days and MRADs. Consequently, including an adult-specific asthma exacerbation estimate would likely double-count incidence for this endpoint. However, because the general population endpoints do not cover children (with regard to asthmatic effects), an analysis focused specifically on asthma exacerbation for children (six to eighteen years of age) could be conducted without concern for double-counting.

To characterize asthma exacerbations in children, we selected two studies (Ostro et al., 2001; Vedal et al., 1998) that followed panels of asthmatic children. Ostro et al. (2001) followed a group of 138 African-American children in Los Angeles for 13 weeks, recording daily occurrences of respiratory symptoms associated with asthma exacerbations (e.g., shortness of breath, wheeze, and cough). This study found a statistically significant association between $PM_{2.5}$, measured as a 12-hour average, and the daily prevalence of shortness of breath and wheeze endpoints. Although the association was not statistically significant for cough, the results were still positive and close to significance; consequently, we decided to include this endpoint, along with shortness of breath and wheeze, in generating incidence estimates (see below). Vedal et al. (1998) followed a group of elementary school children, including 74 asthmatics, located on the west coast of Vancouver Island for 18 months including measurements of daily peak expiratory flow (PEF) and the tracking of respiratory symptoms (e.g., cough, phlegm, wheeze, chest tightness) through the use of daily diaries. Because it is difficult to translate PEF measures into clearly defined health endpoints that can be monetized, we only included the cough-related effect estimate from this study in quantifying asthma exacerbations. We employed the following pooling approach in combining estimates generated using effect estimates from the two studies to produce a single asthma exacerbation incidence estimate. First, we pooled the separate incidence estimates for shortness of breath, wheeze, and cough generated using effect estimates from the Ostro et al. study, because each of these endpoints is aimed at capturing the same overall endpoint (asthma exacerbations) and there could be overlap in their predictions. The pooled estimate from the Ostro et al. study is then pooled with the cough-related estimate generated using the Vedal et al. study. The rationale for this second pooling step is similar to the first; both studies are attempting to quantify the same overall endpoint (asthma exacerbations).

Minor Restricted-Activity Days

Exposure to air pollution can result in restrictions in activity levels. These restrictions range from relatively minor changes in daily activities to serious limitations that can result in missed days of work (either from personal symptoms or from caring for a sick family member). We include two types of restricted activity days, MRADs and work loss days (WLDs). MRADs result when individuals reduce most usual daily activities and replace them with less strenuous activities or rest, yet not to the point of missing work or school. The effect of $PM_{2.5}$ on MRADs was estimated using an effect estimate derived from Ostro and Rothschild (1989).

Work Loss Days

WLDs due to $PM_{2.5}$ were estimated using an effect estimate developed from Ostro (1987). Ostro (1987) estimated the impacts of $PM_{2.5}$ on the incidence of WLDs, restricted activity days, and respiratory-related restricted activity days in a national sample of the adult working population, ages 18 to 64.

BASELINE INCIDENCE RATES

Epidemiological studies of the association between pollution levels and adverse health effects generally provide a direct estimate of the relationship of air quality changes to the *relative risk* of a health effect, rather than estimating the absolute number of avoided cases. For example, a typical result might be that a 10 ppb decrease in daily ozone levels might, in turn, decrease hospital admissions by 3 percent. The baseline incidence of the health effect is necessary to convert this relative change into a number of cases. A baseline incidence rate is the estimate of the number of cases of the health effect per year in the assessment location, as it corresponds to baseline pollutant levels in that location. To derive the total baseline incidence per year, this rate must be multiplied by the corresponding population number. For example, if the baseline incidence rate is the number of cases per year per million people, that number must be multiplied by the millions of people in the total population.

Exhibit 2-5 summarizes the sources of baseline incidence rates and provides average incidence rates for the endpoints included in the analysis. For both baseline incidence and prevalence data, we used age-specific rates where available. We applied C-R functions to individual age groups and then summed over the relevant age range to provide an estimate of total population benefits. In most cases, we used a single national incidence rate, due to a lack of more spatially disaggregated data. Whenever possible, the national rates used are national averages, because these data are most applicable to a national assessment of benefits. For some studies, however, the only available incidence information comes from the studies themselves; in these cases, incidence in the study population is assumed to represent typical incidence at the national level. Regional incidence rates are available for hospital admissions, and county-level data are available for premature mortality. We have projected mortality rates such that future mortality rates are consistent with our projections of population growth (Abt Associates, 2005).

EXHIBIT 2-5. BASELINE INCIDENCE/PREVALENCE RATES

		RATE PER 100 PEOPLE PER YEARD BY AGE GROUP									
ENDPOINT	**NOTES/SOURCE**	**<18**	**18-24**	**25-29**	**30-34**	**35-44**	**45-54**	**55-64**	**65-74**	**75-84**	**85+**
Mortality All-cause Non-accidental Cardiopulmonary	CDC Compressed Mortality File, accessed through CDC Wonder (1996-1998)	 0.045 0.025 0.004	 0.093 0.022 0.005	 0.119 0.057 0.013	 0.119 0.057 0.013	 0.211 0.150 0.044	 0.437 0.383 0.143	 1.056 1.006 0.420	 2.518 2.453 1.163	 5.765 5.637 3.179	 15.160 14.859 9.846
Respiratory Hospital Admissions All respiratory Pneumonia Asthma COPD	1999 NHDS[a] public use data files[b]	 1.066 0.308 0.281 0.291	 0.271 0.069 0.081 0.089	 0.318 0.103 0.110 0.124		 0.446 0.155 0.099 0.148	 0.763 0.256 0.144 0.301	 1.632 0.561 0.161 0.711	 5.200 2.355 0.205 1.573		
Cardiovascular Hospital Admissions All cardiovascular Ischemic heart disease Dysrhythmia Heart failure	1999 NHDS public use data files[b]	 0.030 0.004 0.011 0.003	 0.052 0.008 0.017 0.005	 0.146 0.031 0.027 0.011		 0.534 0.231 0.076 0.011	 1.551 0.902 0.158 0.160	 3.385 2.021 0.392 0.469	 8.541 3.708 1.387 2.167		
Asthma ER Visits	2000 NHAMCS public use data files[c]; 1999 NHDS public use data files[b]	1.011	1.087	0.751		0.438	0.352	0.425	0.232		
Chronic Bronchitis	Prevalence 1999 NHIS (American Lung Association, 2002b, Table4)	0.0367					0.0505		0.0587		

		RATE PER 100 PEOPLE PER YEARD BY AGE GROUP									
ENDPOINT	**NOTES/SOURCE**	**<18**	**18-24**	**25-29**	**30-34**	**35-44**	**45-54**	**55-64**	**65-74**	**75-84**	**85+**
	Incidence Abbey et al. (1993, Table 3), for ages 27+	--	--	0.378							
Nonfatal Myocardial Infarction (heart attacks) Northeast Midwest South West	Incidence 1999 NHDS public use data files[b], adjusted by 0.93 for probability of surviving after 29 days (Rosamond et al., 1999)	0.0000 0.0003 0.0006 0.0000	0.2167 0.1772 0.1620 0.1391						1.6359 1.4898 1.1797 1.1971		
Minor Restricted Activity Days	Ostro and Rothschild (1989, p. 243)	--	780						--		
	1996 NIS (Adams et al., 1999, Table 41), U.S. Bureau of Census (1997)	--	197.1	247.5			179.6		--		
School Loss Days—all-cause	National Center for Education Statistics (1996)	990.0	--	--	--	--	--	--	--	--	--

		RATE PER 100 PEOPLE PER YEARD BY AGE GROUP									
ENDPOINT	NOTES/SOURCE	<18	18-24	25-29	30-34	35-44	45-54	55-64	65-74	75-84	85+
Acute Bronchitis	Incidence American Lung Association (2002c, Table 11)	4.3	--	--	--	--	--	--	--	--	--
Lower Respiratory Symptoms	Incidence Schwartz et al. (1994, Table 2)	43.8	--	--	--	--	--	--	--	--	--
Upper Respiratory Symptoms	Incidence among asthmatics Pope et al. (1991, Table 2)	12479	--	--	--	--	--	--	--	--	--
Asthma Exacerbation Shortness of breath Wheeze Cough	Incidence (and prevalence) among asthmatic African Americans Ostro et al. (2001)	1350 (0.074) 2774 (0.173) 2445 (0.145)	--	--	--	--	--	--	--	--	--
Asthma Exacerbation Cough	Incidence among asthmatics Vedal et al. (1998)	3139	--	--	--	--	--	--	--	--	--

a The following abbreviations are used to describe the national surveys conducted by the National Center for Health Statistics: HIS refers to the National Health Interview Survey; NHDS—National Hospital Discharge Survey; NHAMCS—National Hospital Ambulatory Medical Care Survey.
b See ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Datasets/NHDS/
c See ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Datasets/NHAMCS/
d All of the rates reported here are population-weighted. Incidence rates are reported per 100 people per year; prevalence rates are reported as a percentage of the population.
Additional details on the incidence and prevalence rates, as well as the sources for these rates are available upon request.

For the set of endpoints affecting the asthmatic population, in addition to baseline incidence rates, prevalence rates of asthma in the population are needed to define the applicable population. Exhibit 2-5 lists the baseline incidence rates and their sources for asthma symptom endpoints. Exhibit 2-6 lists the prevalence rates used to determine the applicable population for asthma symptom endpoints. Note that these reflect current asthma prevalence and assume no change in prevalence rates in future years. It should be noted that current trends in asthma prevalence do not lead us to expect that asthma prevalence rates will be more than 4 percent overall in 2020, or that large changes will occur in asthma prevalence rates for individual age categories (Mansfield et al., 2005).

EXHIBIT 2-6. ASTHMA PREVALENCE RATES USED TO ESTIMATE ASTHMATIC POPULATIONS IN HEALTH IMPACT FUNCTIONS

POPULATION GROUP	VALUE	SOURCE
All Ages	0.0386	American Lung Association (2002a, Table 7)—based on 1999 HIS
<18	0.0527	American Lung Association (2002a, Table 7)—based on 1999 HIS
5-17	0.0567	American Lung Association (2002a, Table 7)—based on 1999 HIS
18-44	0.0371	American Lung Association (2002a, Table 7)—based on 1999 HIS
45-64	0.0333	American Lung Association (2002a, Table 7)—based on 1999 HIS
65+	0.0221	American Lung Association (2002a, Table 7)—based on 1999 HIS
Male, 27+	0.021	2000 HIS public use data files[a]
African American, 5-17	0.0726	American Lung Association (2002a, Table 7)—based on 1999 HIS
African American, <18	0.0735	American Lung Association (2002a, Table 7)—based on 1999 HIS
a See ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Datasets/NHIS/2000/		

ECONOMIC VALUE FOR HEALTH OUTCOMES

Reductions in ambient concentrations of air pollution generally lower the risk of future adverse health effects for a large population. Therefore, the appropriate economic measure is willingness-to- pay (WTP) for changes in risk of a health effect rather than WTP for a health effect that would occur with certainty (Freeman, 1993). Epidemiological studies generally provide estimates of the relative risks of a particular health effect that is avoided because of a reduction in air pollution. We converted those to units of avoided statistical incidence for ease of presentation. We calculated the value of avoided statistical incidences by dividing individual WTP for a risk reduction by the related observed change in risk. For example, suppose a pollution-reduction regulation is able to reduce the risk of premature mortality from 2 in 10,000 to 1 in 10,000 (a reduction of 1 in 10,000). If individual WTP for this risk reduction is $100, then the WTP for an avoided statistical premature death is $1 million ($100/0.0001 change in risk).

WTP estimates generally are not available for some health effects, such as hospital admissions. In these cases, we used the cost of treating or mitigating the effect as a primary estimate. These cost-of-illness (COI) estimates generally understate the true value of reducing the risk of a health effect, because they reflect the direct expenditures related to treatment, but not the value of avoided pain and suffering (Harrington and

Portney, 1987; Berger, 1987). We provide unit values for health endpoints (along with information on the distribution of the unit value) in Exhibit 2-6. All values are in constant year 2006 dollars, adjusted for growth in real income out to each of the three target years (2000, 2010, and 2020) using the income growth projections contained in BenMAP.[19] Economic theory argues that WTP for most goods, including environmental protection will increase if real income increases. Many of the valuation studies used in this analysis were conducted in the late 1980s and early 1990s. Because real income has grown since the studies were conducted, people's willingness to pay for reductions in the risk of premature death and disease likely has grown as well. We did not adjust cost of illness-based values because they are based on current costs, as parameterized in the BenMAP system. Similarly, we did not adjust the value of school absences, because that value is based on current wage rates. Exhibit 2-7 presents the values for individual endpoints adjusted to year 2020 income levels to illustrate the impact of the adjustment for income growth over time. The discussion below provides additional details on valuation of specific ozone and PM related endpoints.

MORTALITY VALUATION

To estimate the monetary benefit of reducing the risk of premature death, we used the "value of statistical lives" saved (VSL) approach, which is a summary measure for the value of small changes in mortality risk for a large number of people. The VSL approach applies information from several published value-of-life studies to determine a reasonable monetary value of preventing premature mortality. The mean value of avoiding one statistical death is estimated to be approximately $7.4 million at 1990 income levels (2006$), and $8.8 million (2006$) at 2020 income levels. This value is the mean of a distribution fitted to 26 VSL estimates that appear in the economics literature and that have been identified in the Section 812 Reports to Congress as "applicable to policy analysis." This represents an intermediate value from a variety of estimates, and it is a value EPA has frequently used in RIAs as well as in the Section 812 Retrospective and Prospective Analyses of the Clean Air Act.

The VSL approach and the set of selected studies mirrors that of Viscusi (1992) (with the addition of two studies), and uses the same criteria as Viscusi in his review of value-of-life studies. The $7.4 million estimate is consistent with Viscusi's conclusion (updated to 2006$) that "most of the reasonable estimates of the value of life are clustered in the $4.4 to $10.4 million range." Five of the 26 studies are contingent valuation (CV) studies, which directly solicit WTP information from subjects; the rest are wage-risk studies, which base WTP estimates on estimates of the additional compensation demanded in the labor market for riskier jobs. Because this VSL-based unit value does not distinguish among people based on the age at their death or the quality of their lives, it can be applied to all premature deaths.

[19] Projections of income growth in BenMAP are based on data from Standard and Poor's.

EXHIBIT 2-7. UNIT VALUES FOR ECONOMIC VALUATION OF HEALTH ENDPOINTS (2006$)

HEALTH ENDPOINT	CENTRAL ESTIMATE OF VALUE PER STATISTICAL INCIDENCE: 1990 INCOME LEVEL	CENTRAL ESTIMATE OF VALUE PER STATISTICAL INCIDENCE: 2020 INCOME LEVEL	DERIVATION OF DISTRIBUTIONS OF ESTIMATES
Premature Mortality (Value of a Statistical Life)	$7,400,000	$8,880,000	Mean Value of Statistical Life (VSL) based on the mean of a distribution fitted to 26 “value of statistical life” (VSL) estimates that appear in the economics literature and that have been identified in the Section 812 Reports to Congress as “applicable to policy analysis.” The VSL approach and the set of selected studies mirrors that of Viscusi (1992) (with the addition of two studies), and uses the same criteria as Viscusi in his review of value-of-life studies. The central estimate of $6.3 million (2000$) is consistent with Viscusi’s conclusion (updated to 2000$) that “most of the reasonable estimates of the value of life are clustered in the $3.8 to $8.9 million range.” Five of the 26 studies are contingent valuation (CV) studies, which directly solicit WTP information from subjects; the rest are wage-risk studies, which base WTP estimates on estimates of the additional compensation demanded in the labor market for riskier jobs. The fitted distribution is a Weibull with α=5.32x10-6 and ß=1.509588. See Abt Associates, 2008 for more details.
Chronic Bronchitis (CB)	$399,000	$490,000	The WTP to avoid a case of pollution-related CB is calculated as $WTP_x = WTP_{13} \cdot e^{-\beta \cdot (13-x)}$, where x is the severity of an average CB case, WTP13 is the WTP for a severe case of CB, and ß is the parameter relating WTP to severity, based on the regression results reported in Krupnick and Cropper (1992). The distribution of WTP for an average severity-level case of CB was generated by Monte Carlo methods, drawing from each of three distributions: (1) WTP to avoid a severe case of CB is assigned a 1/9 probability of being each of the first nine deciles of the distribution of WTP responses in Viscusi et al. (1991); (2) the severity of a pollution-related case of CB (relative to the case described in the Viscusi study) is assumed to have a triangular distribution, with the most likely value at severity level 6.5 and endpoints at 1.0 and 12.0; and (3) the constant in the elasticity of WTP with respect to severity is normally distributed with mean = 0.18 and standard deviation = 0.0669 (from Krupnick and Cropper (1992)). This process and the rationale for choosing it is described in detail in the Costs and Benefits of the Clean Air Act, 1990 to 2010 (EPA, 1999).

HEALTH ENDPOINT	CENTRAL ESTIMATE OF VALUE PER STATISTICAL INCIDENCE: 1990 INCOME LEVEL	CENTRAL ESTIMATE OF VALUE PER STATISTICAL INCIDENCE: 2020 INCOME LEVEL	DERIVATION OF DISTRIBUTIONS OF ESTIMATES
Nonfatal Myocardial Infarction (heart attack) 7% discount rate Age 0–24 Age 25-44 Age 45-54 Age 55-65 Age 66 and over	 $84,171 $93,802 $98,366 $166,222 $84,171		No distributional information available. Age-specific cost-of-illness values reflect lost earnings and direct medical costs over a 5-year period following a nonfatal MI. Lost earnings estimates are based on Cropper and Krupnick (1990). Direct medical costs are based on simple average of estimates from Russell et al. (1998) and Wittels et al. (1990). Lost earnings: Cropper and Krupnick (1990). Present discounted value of 5 years of lost earnings (2006$): age of onset: at 7%[a] 25-44 $9,631 45-54 $14,195 55-65 $82,051 Direct medical expenses: An average of (2006$): 1. Wittels et al. (1990) ($141,124—no discounting) 2. Russell et al. (1998), 5-year period ($28,787 at 3% discount rate; $21,113 $27,217 at 7% discount rate)

HEALTH ENDPOINT	CENTRAL ESTIMATE OF VALUE PER STATISTICAL INCIDENCE: 1990 INCOME LEVEL	CENTRAL ESTIMATE OF VALUE PER STATISTICAL INCIDENCE: 2020 INCOME LEVEL	DERIVATION OF DISTRIBUTIONS OF ESTIMATES
Hospital Admissions			
All respiratory (ages 65+)	$23,711	$23,711	No distributions available. The COI point estimates (lost earnings plus direct medical costs) are based on ICD-9 code level information (e.g., average hospital care costs and average length of hospital stay) reported in Agency for Healthcare Research and Quality, 2000 (www.ahrq.gov). As noted in the text, no adjustments are made to cost of illness values for income growth.
All respiratory (ages 0-2)	$10,002	$10,002	
Chronic Obstructive Pulmonary Disease (COPD) (ages 65+)	$17,308	$17,308	
Asthma Admissions (ages <65)	$10,040	$10,040	
Pneumonia Admissions (ages 65+)	$23,004	$23,004	
COPD, less asthma (ages 20-64)	$15,903	$15,903	
All Cardiovascular (ages 65+)	$27,319	$27,319	
All Cardiovascular (ages 20-64)	$29,364	$29,364	
Ischemic Heart Disease (ages 65+)	$33,357	$33,357	
Dysrhythmia (ages 65+)	$19,643	$19,643	
Congestive Heart Failure (ages 65+)	$19,619	$19,619	
Emergency Room Visits for Asthma	$369	$369	No distributional information available. Simple average of two unit COI values (2006$): (1) $401.62, from Smith et al. (1997) and (2) $336.03, from Stanford et al. (1999). As noted in the text, no adjustments are made to cost of illness values for income growth.

HEALTH ENDPOINT	CENTRAL ESTIMATE OF VALUE PER STATISTICAL INCIDENCE: 1990 INCOME LEVEL	CENTRAL ESTIMATE OF VALUE PER STATISTICAL INCIDENCE: 2020 INCOME LEVEL	DERIVATION OF DISTRIBUTIONS OF ESTIMATES
Respiratory Ailments Not Requiring Hospitalization			
Upper Respiratory Symptoms (URS)	$28.8	$30.7	Combinations of the three symptoms for which WTP estimates are available that closely match those listed by Pope et al. result in seven different "symptom clusters," each describing a "type" of URS. A dollar value was derived for each type of URS, using mid-range estimates of WTP (IEc, 1994) to avoid each symptom in the cluster and assuming additivity of WTPs. In the absence of information surrounding the frequency with which each of the seven types of URS occurs within the URS symptom complex, we assumed a uniform distribution between $10.8 and $50.5 (2006$).
Lower Respiratory Symptoms (LRS)	$18	$19	Combinations of the four symptoms for which WTP estimates are available that closely match those listed by Schwartz et al. result in 11 different "symptom clusters," each describing a "type" of LRS. A dollar value was derived for each type of LRS, using mid-range estimates of WTP (IEc, 1994) to avoid each symptom in the cluster and assuming additivity of WTPs. The dollar value for LRS is the average of the dollar values for the 11 different types of LRS. In the absence of information surrounding the frequency with which each of the 11 types of LRS occurs within the LRS symptom complex, we assumed a uniform distribution between $8.1 and $28.6 (2006$).
Asthma Exacerbations	$50	$54	Asthma exacerbations are valued at $45 per incidence, based on the mean of average WTP estimates for the four severity definitions of a "bad asthma day," described in Rowe and Chestnut (1986). This study surveyed asthmatics to estimate WTP for avoidance of a "bad asthma day," as defined by the subjects. For purposes of valuation, an asthma exacerbation is assumed to be equivalent to a day in which asthma is moderate or worse as reported in the Rowe and Chestnut (1986) study. The value is assumed have a uniform distribution between $18.3 and $82.9 (2006$).
Acute Bronchitis	$416	$512	Assumes a 6-day episode, with the distribution of the daily value specified as uniform with the low and high values based on those recommended for related respiratory symptoms in Neumann et al. (1994). The low daily estimate of $20.5 (2006$) is the sum of the mid-range values recommended by IEc (1994) for two symptoms believed to be associated with acute bronchitis: coughing and chest tightness. The high daily estimate was taken to be twice the value of a minor respiratory restricted activity day, or $118 (2006$). The low and high daily values are multiplied by six to get the 6-day episode values.
Work Loss Days (WLDs)	Variable (U.S. median = $149)		No distribution available. Point estimate is based on county-specific median annual wages divided by 50 (assuming 2 weeks of vacation) and then by 5—to get median daily wage. U.S. Year 2000 Census, compiled by Geolytics, Inc.

HEALTH ENDPOINT	CENTRAL ESTIMATE OF VALUE PER STATISTICAL INCIDENCE: 1990 INCOME LEVEL	CENTRAL ESTIMATE OF VALUE PER STATISTICAL INCIDENCE: 2020 INCOME LEVEL	DERIVATION OF DISTRIBUTIONS OF ESTIMATES
Minor Restricted Activity Days (MRADs)	$61	$64	Median WTP estimate to avoid one MRAD from Tolley et al. (1986). Distribution is assumed to be triangular with a minimum of $24 and a maximum of $94, with a most likely value of $59 (2006$). Range is based on assumption that value should exceed WTP for a single mild symptom (the highest estimate for a single symptom—for eye irritation—is $24) and be less than that for a WLD. The triangular distribution acknowledges that the actual value is likely to be closer to the point estimate than either extreme.
School Loss Days	$89	$89	No distribution available. Point estimate is based on (1) the probability that, if a school child stays home from school, a parent will have to stay home from work to care for the child, and (2) the value of the parent's lost productivity. Calculated using U.S. Bureau of Census data.

a Note that a seven percent discount rate is used to discount costs incurred over the 5-year period, while the remainder of this report uses a five percent discount rate. The use of a seven percent discount rate to estimate costs associated with nonfatal myocardial infarction results in a minor underestimation of benefits.

CHRONIC BRONCHITIS

The best available estimate of WTP to avoid a case of CB comes from Viscusi et al. (1991). The Viscusi et al. study, however, describes a severe case of CB to the survey respondents. We therefore employ an estimate of WTP to avoid a pollution-related case of CB, based on adjusting the Viscusi et al. (1991) estimate of the WTP to avoid a severe case. This is done to account for the likelihood that an average case of pollution-related CB is not as severe. The adjustment is made by applying the elasticity of WTP with respect to severity reported in the Krupnick and Cropper (1992) study. Details of this adjustment procedure are provided in the Benefits TSD for the Nonroad Diesel rulemaking (Abt Associates, 2003).

We use the mean of a distribution of WTP estimates as the central tendency estimate of WTP to avoid a pollution-related case of CB in this analysis. The distribution incorporates uncertainty from three sources: the WTP to avoid a case of severe CB, as described by Viscusi et al.; the severity level of an average pollution-related case of CB (relative to that of the case described by Viscusi et al.); and the elasticity of WTP with respect to severity of the illness. Based on assumptions about the distributions of each of these three uncertain components, we derive a distribution of WTP to avoid a pollution-related case of CB by statistical uncertainty analysis techniques. The expected value (i.e., mean) of this distribution, which is about $399,000 (2006$), is taken as the central tendency estimate of WTP to avoid a PM-related case of CB.

NONFATAL MYOCARDIAL INFARCTION VALUATION

We were not able to identify a suitable WTP value for reductions in the risk of nonfatal heart attacks. Instead, we use a COI unit value with two components: the direct medical costs and the opportunity cost (lost earnings) associated with the illness event. Because the costs associated with a myocardial infarction extend beyond the initial event itself, we consider costs incurred over five years. We used age-specific annual lost earnings estimated by Cropper and Krupnick (1990). Cropper and Krupnick (1990) do not provide lost earnings estimates for populations under 25 or over 65. As such, we do not include lost earnings in the cost estimates for these age groups.

Three sources were consulted for direct medical costs of myocardial infarction: Wittels et al. (1990), Eisenstein et al. (2001), and Russell et al. (1998). Because the wage-related opportunity cost estimates from Cropper and Krupnick (1990) cover a 5-year period, we used estimates for medical costs that similarly cover a 5-year period (i.e., estimates from Wittels et al. (1990) and Russell et al. (1998)). We used a simple average of the two 5-year estimates.[20]

[20] Note that a seven percent discount rate is used to discount costs incurred over the 5-year period, while the remainder of this report uses a five percent discount rate. The use of a seven percent discount rate to estimate costs associated with nonfatal myocardial infarction results in a minor underestimation of benefits.

HOSPITAL ADMISSIONS VALUATION

In the absence of estimates of societal WTP to avoid hospital visits/admissions for specific illnesses, estimates of total cost of illness (total medical costs plus the value of lost productivity) typically are used as conservative, or lower bound, estimates. These estimates are biased downward, because they do not include the willingness-to-pay value of avoiding pain and suffering.

The International Classification of Diseases (ICD-9, 1979) code-specific COI estimates used in this analysis consist of estimated hospital charges and the estimated opportunity cost of time spent in the hospital (based on the average length of a hospital stay for the illness). We based all estimates of hospital charges and length of stays on statistics provided by the Agency for Healthcare Research and Quality (AHRQ, 2000). We estimated the opportunity cost of a day spent in the hospital as the value of the lost daily wage, regardless of whether the hospitalized individual is in the workforce. To estimate the lost daily wage, we divided year 2000 median annual wage by (52*5) to get median daily wage and inflated the result to year 2006$ using the EPA standard inflator wage index. The resulting estimate is $149. The total cost-of-illness estimate for an ICD code-specific hospital stay lasting *n* days, then, was the mean hospital charge plus $109 multiplied by *n.*

ASTHMA-RELATED EMERGENCY ROOM VISITS VALUATION

To value asthma emergency room visits, we used a simple average of two estimates from the health economics literature. The first estimate comes from Smith et al. (1997), who reported approximately 1.2 million asthma-related emergency room visits in 1987, at a total cost of $186.5 million (1987$). The average cost per visit that year was $155; in 2006$, that cost was $401.62 (using the EPA standard inflator medical cost index). The second estimate comes from Stanford et al. (1999), who reported the cost of an average asthma-related emergency room visit at $336.03 (adjusted to 2006$), based on 1996–1997 data. A simple average of the two estimates yields a (rounded) unit value of $369.

MINOR RESTRICTED ACTIVITY DAYS VALUATION

No studies are reported to have estimated WTP to avoid a minor restricted activity day. However, one of EPA's contractors, IEc (1993) has derived an estimate of willingness to pay to avoid a minor *respiratory* restricted activity day, using estimates from Tolley et al. (1986) of WTP for avoiding a combination of coughing, throat congestion and sinusitis. The IEc estimate of WTP to avoid a minor respiratory restricted activity day is about $61 ($2006).

Although Ostro and Rothschild (1989) statistically linked ozone and minor restricted activity days, it is likely that most MRADs associated with ozone exposure are, in fact, minor *respiratory* restricted activity days. For the purpose of valuing this health endpoint, we used the estimate of mean WTP to avoid a minor respiratory restricted activity day.

SCHOOL LOSS DAYS

To value a school absence, we: (1) estimated the probability that if a school child stays home from school, a parent will have to stay home from work to care for the child; and (2) valued the lost productivity at the parent's wage. To do this, we estimated the number of families with school-age children in which both parents work, and we valued a school-loss day as the probability that such a day also would result in a work-loss day. We calculated this value by multiplying the proportion of households with school-age children by a measure of lost wages.

We used this method in the absence of a preferable WTP method. However, this approach suffers from several uncertainties. First, it omits willingness to pay to avoid the symptoms/illness that resulted in the school absence; second, it effectively gives zero value to school absences that do not result in work-loss days; and third, it uses conservative assumptions about the wages of the parent staying home with the child. Finally, this method assumes that parents are unable to work from home. If this is not a valid assumption, then there would be no lost wages.

For this valuation approach, we assumed that in a household with two working parents, the female parent will stay home with a sick child. From the Statistical Abstract of the United States (U.S. Census Bureau, 2001), we obtained: (1) the numbers of single, married and "other" (widowed, divorced or separated) working women with children; and (2) the rates of participation in the workforce of single, married and "other" women with children. From these two sets of statistics, we calculated a weighted average participation rate of 72.85 percent.

Our estimate of daily lost wage (wages lost if a mother must stay at home with a sick child) is based on the year 2000 median weekly wage among women ages 25 and older (U.S. Census Bureau, 2001). This median weekly wage is $551 (2000$). Dividing by five gives an estimated median daily wage of $103. To estimate the expected lost wages on a day when a mother has to stay home with a school-age child, we first estimated the probability that the mother is in the workforce then multiplied that estimate by the daily wage she would lose by missing a workday: 72.85 percent times $103, for a total loss of $75 in 2000$, or $89 in 2006$. This valuation approach is similar to that used by Hall et al. (2003).

RESULTS AND IMPLICATIONS

OZONE BENEFIT ESTIMATES

Ozone benefit estimates are calculated for a "stitched" National domain, created by merging results from the two original modeling domains, Eastern United States (EUS) and Western United States (WUS), and eliminating double-counting in the areas of overlap (see Exhibit 2-1). Exhibit 2-8 summarizes the mean valuation of ozone benefits for the nation. Exhibits 2-9 through 2-11 give detailed ozone benefit estimates in each target year for the nation. In addition to the mean incidence and valuation estimates, we have included 5^{th} and 95^{th} percentile estimates.

Based in part on prior Council HES advice, EPA has typically assumed that there is a time lag between changes in pollution exposures and the total realization of changes in health effects. Within the context of benefits analyses, this term is often referred to as "cessation lag". The existence of such a lag is important for the valuation of premature mortality incidence because economic theory suggests that benefits occurring in the future should be discounted. In this analysis, we apply a twenty-year distributed lag to PM mortality reductions - this method is consistent with the most recent recommendation by the Council HES (EPA – SAB, 2004a) – but not to premature mortality reduction attributed to reduced ozone exposure. Alternative cessation lag structures for PM-related mortality risk are explored in the accompanying Second Prospective uncertainty analysis report. For the primary results, a five percent discount rate is used to discount future benefits back to the target year of the analysis (i.e., 2000, 2010, or 2020).

Benefits of reduced morbidity account for roughly four percent of the total primary ozone benefits. Exhibit 2-12 presents a more detailed comparison of the primary ozone morbidity estimates. Benefits of reduced mortality make up the remainder of the total ozone benefits.

EXHIBIT 2-8. NATIONAL SUMMARY MEAN OZONE VALUATION RESULTS

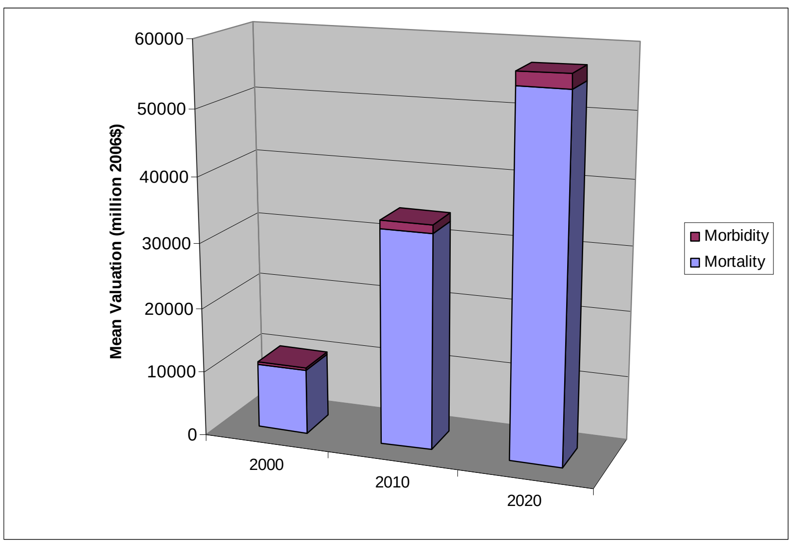


EXHIBIT 2-9. NATIONAL OZONE BENEFITS OF CAAA IN 2000

ENDPOINT GROUP	INCIDENCE			VALUATION (MILLION 2006$)		
	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95
Mortality						
Mortality – All Cause[1]	210	1,400	2,800	$530	$10,000	$32,000
Morbidity						
Hospital Admissions, Respiratory (>64)	100	3,000	5,700	$2.5	$70	$140
Hospital Admissions, Respiratory (<2)	1,400	3,000	4,600	$14	$30	$46
Emergency Room Visits, Respiratory	0	2,200	6,200	$0	$0.81	$2.2
Minor Restricted Activity Days	1,300,000	3,100,000	4,800,000	$70	$180	$330
School Loss Days	480,000	1,200,000	1,900,000	$43	$110	$170
Outdoor Worker Productivity				$30	$30	$30

Results are rounded to two significant figures.
[1]Mortality results from Ito et al. (2005), Schwartz (2005), Bell et al. (2004), Bell et al. (2005), Levy et al. (2005), and Huang et al. (2005) are pooled using equal weights.

EXHIBIT 2-10. NATIONAL OZONE BENEFITS OF CAAA IN 2010

ENDPOINT GROUP	INCIDENCE			VALUATION (MILLION 2006$)		
	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95
Mortality						
Mortality - All Cause[1]	790	4,300	8,700	$2,000	$33,000	$98,000
Morbidity						
Hospital Admissions, Respiratory (>64)	740	9,900	18,000	$17	$230	$440
Hospital Admissions, Respiratory (<2)	4,300	9,000	14,000	$43	$90	$140
Emergency Room Visits, Respiratory	0	6,600	18,000	$0	$2.4	$6.4
Minor Restricted Activity Days	4,400,000	9,500,000	15,000,000	$230	$560	$1,000
School Loss Days	1,400,000	3,200,000	5,100,000	$120	$290	$450
Outdoor Worker Productivity				$100	$100	$100

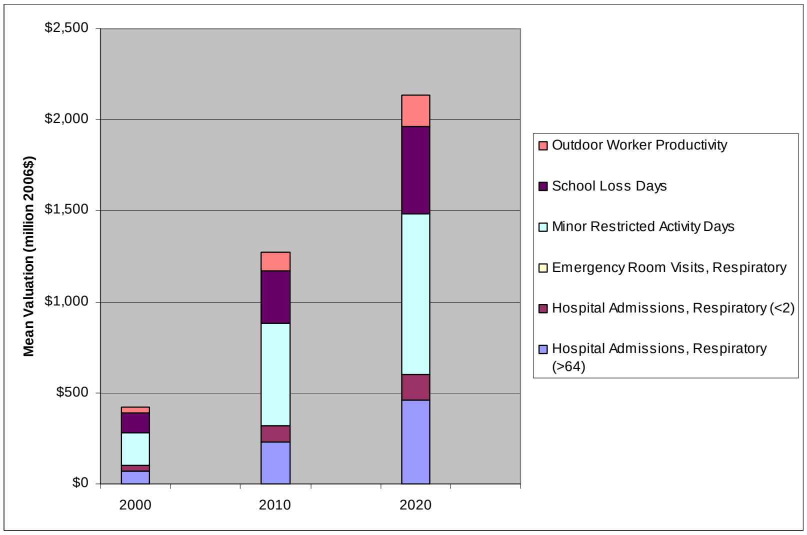
Results are rounded to two significant figures.
[1]Mortality results from Ito et al. (2005), Schwartz (2005), Bell et al. (2004), Bell et al. (2005), Levy et al. (2005), and Huang et al. (2005) are pooled using equal weights.

EXHIBIT 2-11. NATIONAL OZONE BENEFITS OF CAAA IN 2020

ENDPOINT GROUP	INCIDENCE			VALUATION (MILLION 2006$)		
	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95
Mortality						
Mortality - All Cause[1]	1,200	7,100	15,000	$3,200	$55,000	$170,000
Morbidity						
Hospital Admissions, Respiratory (>64)	990	19,000	36,000	$23	$460	$860
Hospital Admissions, Respiratory (<2)	6,600	14,000	22,000	$65	$140	$220
Emergency Room Visits, Respiratory	0	11,000	31,000	$0	$4.1	$11
Minor Restricted Activity Days	6,400,000	15,000,000	23,000,000	$330	$880	$1,600
School Loss Days	2,200,000	5,400,000	8,600,000	$190	$480	$770
Outdoor Worker Productivity				$170	$170	$170

Results are rounded to two significant figures.
[1]Mortality results from Ito et al. (2005), Schwartz (2005), Bell et al. (2004), Bell et al. (2005), Levy et al. (2005), and Huang et al. (2005) are pooled using equal weights.

EXHIBIT 2-12. NATIONAL OZONE MORBIDITY BENEFITS



PM BENEFIT ESTIMATES

PM benefit estimates are calculated at the national level for the contiguous 48 states. Exhibit 2-13 summarizes the valuation of PM benefits. Exhibits 2-14 through 2-16 give detailed PM benefit estimates in each target year. In addition to the mean incidence and valuation estimates, we have included 5th and 95th percentile estimates.

Benefits of reduced morbidity account for approximately four percent of the total PM benefits, depending on the mortality incidence estimate used. Exhibit 2-17 presents a more detailed comparison of the PM morbidity estimates. Benefits of reduced mortality make up the remainder of the total PM benefits.

EXHIBIT 2-13. NATIONAL SUMMARY MEAN PM VALUATION RESULTS

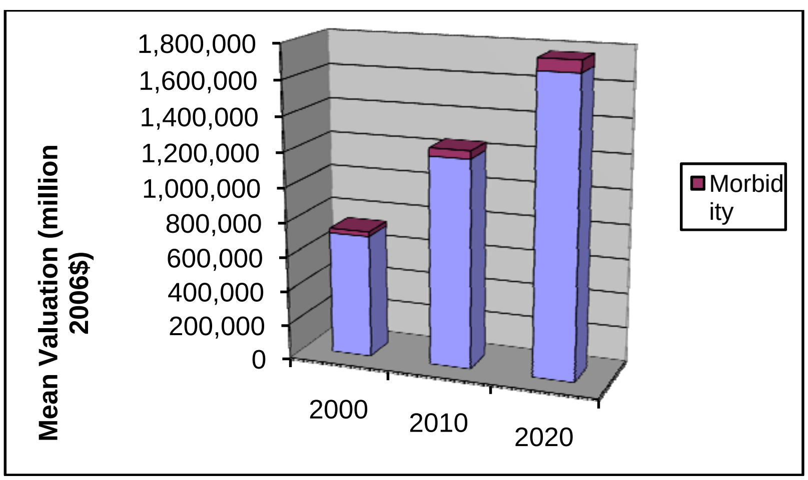


EXHIBIT 2-14. NATIONAL PM BENEFITS OF CAAA IN 2000

ENDPOINT GROUP	INCIDENCE			VALUATION (MILLION 2006$)		
	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95
Mortality						
Mortality – Weibull distribution	20,000	110,000	230,000	$66,000	$710,000	$2,200,000
Morbidity						
Infant Mortality - Woodruff et al., 1997	81	160	250	$190	$1,300	$3,200
Chronic Bronchitis	5,500	34,000	62,000	$1,200	$14,000	$51,000
Nonfatal Myocardial Infarction	31,000	79,000	120,000	$2,300	$8,100	$20,000
Hospital Admissions, Respiratory	6,800	14,000	21,000	$94	$190	$280
Hospital Admissions, Cardiovascular	20,000	26,000	32,000	$550	$760	$990
Emergency Room Visits, Respiratory	34,000	56,000	77,000	$12	$21	$31
Acute Bronchitis	-4,000	96,000	180,000	-$2.0	$42	$100
Lower Respiratory Symptoms	600,000	1,200,000	1,800,000	$9.0	$22	$40
Upper Respiratory Symptoms	310,000	980,000	1,700,000	$8.4	$30	$63
Asthma Exacerbation	130,000	1,200,000	3,400,000	$7.1	$61	$190
Minor Restricted Activity Days	39,000,000	46,000,000	53,000,000	$1,600	$2,700	$4,000
Work Loss Days	7,000,000	8,000,000	9,100,000	$1,100	$1,300	$1,400
Notes: Results are rounded to two significant figures.						

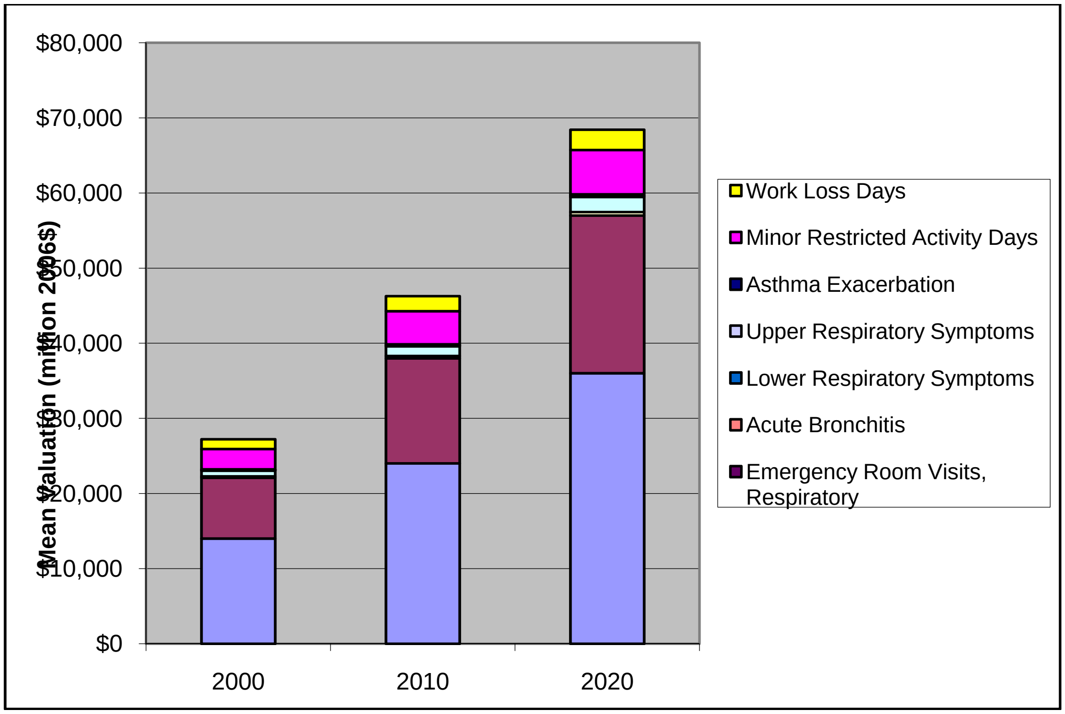
EXHIBIT 2-15. NATIONAL PM BENEFITS OF CAAA IN 2010

ENDPOINT GROUP	INCIDENCE			VALUATION (MILLION 2006$)		
	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95
Mortality						
Mortality - Weibull distribution	31,000	160,000	350,000	$110,000	$1,200,000	$3,600,000
Morbidity						
Infant Mortality - Woodruff et al., 1997	120	230	350	$280	$1,900	$4,900
Chronic Bronchitis	8,800	54,000	96,000	$2,000	$24,000	$84,000
Nonfatal Myocardial Infarction	53,000	130,000	200,000	$4,100	$14,000	$33,000
Hospital Admissions, Respiratory	11,000	22,000	33,000	$150	$310	$460
Hospital Admissions, Cardiovascular	34,000	45,000	54,000	$930	$1,300	$1,700
Emergency Room Visits, Respiratory	49,000	80,000	110,000	$17	$29	$44
Acute Bronchitis	-5,000	130,000	250,000	-$2.0	$61	$150
Lower Respiratory Symptoms	840,000	1,700,000	2,400,000	$13	$30	$55
Upper Respiratory Symptoms	440,000	1,400,000	2,300,000	$12	$42	$89
Asthma Exacerbation	190,000	1,700,000	4,900,000	$11	$90	$270
Minor Restricted Activity Days	63,000,000	74,000,000	85,000,000	$2,600	$4,400	$6,300
Work Loss Days	11,000,000	13,000,000	14,000,000	$1,700	$2,000	$2,200
Notes: Results are rounded to two significant figures.						

EXHIBIT 2-16. NATIONAL PM BENEFITS OF CAAA IN 2020

ENDPOINT GROUP	INCIDENCE			VALUATION (MILLION 2006$)		
	PERCENTILE 5	MEAN	PERCENTILE 95	PERCENTILE 5	MEAN	PERCENTILE 95
Mortality						
Mortality - Weibull distribution	44,000	230,000	480,000	$170,000	$1,700,000	$5,300,000
Morbidity						
Infant Mortality - Woodruff et al., 1997	140	280	420	$370	$2,500	$6,400
Chronic Bronchitis	12,000	75,000	130,000	$3,100	$36,000	$130,000
Nonfatal Myocardial Infarction	80,000	200,000	300,000	$6,200	$21,000	$48,000
Hospital Admissions, Respiratory	16,000	33,000	49,000	$230	$460	$680
Hospital Admissions, Cardiovascular	52,000	69,000	84,000	$1,400	$2,000	$2,600
Emergency Room Visits, Respiratory	66,000	110,000	150,000	$23	$39	$58
Acute Bronchitis	-7,000	180,000	340,000	-$4.0	$94	$220
Lower Respiratory Symptoms	1,200,000	2,300,000	3,300,000	$18	$42	$76
Upper Respiratory Symptoms	620,000	2,000,000	3,300,000	$17	$60	$130
Asthma Exacerbation	270,000	2,400,000	6,700,000	$15	$130	$390
Minor Restricted Activity Days	84,000,000	99,000,000	110,000,000	$3,500	$5,900	$8,500
Work Loss Days	15,000,000	17,000,000	19,000,000	$2,300	$2,700	$3,000
Notes: Results are rounded to two significant figures.						

EXHIBIT 2-17. NATIONAL PM MORBIDITY BENEFITS



CHAPTER 3 | ESTIMATION OF VISIBILITY IMPROVEMENTS AND ECONOMIC VALUATION

OVERVIEW

Air pollution impairs visibility in both residential and recreational settings, and an individual's willingness to pay (WTP) to avoid reductions in visibility differs in these two settings. Benefits of residential visibility relate to the impact of visibility changes on an individual's daily life (e.g., at home, at work, and while engaged in routine recreational activities). Benefits of recreational visibility relate to the impact of visibility changes manifested at parks and wilderness areas that are expected to be experienced by recreational visitors.

We calculate household WTP for improvements in both residential and recreational visibility. We base our calculations on simulations of future visibility conditions at the 36-km grid-cell level, as estimated by EPA's Community Multiscale Air Quality (CMAQ) model. The relationship between a household's WTP and changes in visibility is derived from a number of contingent valuation (CV) studies published in the peer-reviewed economics literature. The approach we apply to estimate the benefit of improvements in recreational visibility is consistent with methods EPA has used for Regulatory Impact Analyses (RIAs) conducted since EPA's First Prospective analysis was completed. In particular, this chapter relies heavily on the research done for the PM NAAQS RIA (U.S. EPA, 2006). Our estimate of the benefit of residential visibility is consistent with methods applied in past analyses as well, but in the past the Council had expressed concerns about residential visibility estimates based on WTP estimates from the McClelland et al. (1991) study. As a result, our estimates in this chapter rely on a new benefits transfer estimate of WTP derived from other published sources of residential visibility WTP.

A fundamental issue with respect to visibility valuation is whether estimated values reflect only visibility conditions and do not include other perceived benefits such as health or ecological improvements. Similarly, it is important to try to distinguish residential from recreational visibility–that is, can these be treated as distinct and additive benefit categories based on the available literature? In our selection of underlying valuation studies and our recommended approach, we attempt to address both of these issues.

VISIBILITY CHANGES

This analysis is the first Section 812 prospective analysis to use an integrated modeling system, CMAQ, to simulate national and regional-scale pollutant concentrations and deposition. The CMAQ model (Byun and Ching, 1999) is a state-of-the-science, regional air quality modeling system that is designed to simulate the physical and chemical processes that govern the formation, transport, and deposition of gaseous and particulate species in the atmosphere. The CMAQ model was applied for seven core scenarios that include four different years spanning a 30-year period – 1990, 2000, 2010 and 2020.

As outlined in Chapter 1 of this report, scenarios that incorporate the emission reductions associated with the Clean Air Act Amendments (CAAA) are referred to as *with-CAAA* while those that do not are referred to as *without-CAAA*.

The outputs from the CMAQ model provide the basis for the calculation of health and ecological benefits of the Clean Air Act, as described elsewhere in this document. The airborne criteria pollutants of interest include ozone and fine particulate matter ($PM_{2.5}$), where $PM_{2.5}$ consists of particles less than 2.5 microns in diameter. Visibility is calculated using the CMAQ Chemistry-Transport Model (CCTM). The CCTM integrates output from emissions and meteorology models to simulate continuous atmospheric chemical conditions. Particular to visibility, CCTM's AERO module integrates Mie scattering (a generalized particulate light-scattering mechanism that follows from the laws of electro-magnetism applied to particulate matter) over the entire range of particle sizes to obtain a single visibility value for each grid cell (CMAS Center, 2007).

The visibility data used in this analysis is annual mean visibility data, by county, measured in deciviews. The data was aggregated from the 36-km grid-cell level to the county level using the BenMAP version 3.0.15 "Air Quality Grid Aggregation" algorithm. The fourth quarter data is corrected for a missing day (the CMAQ runs modeled 364 days, omitting December 31) by reweighting the mean to account for the missing day.

Exhibit 3-1 depicts the change in visibility (measured in deciviews) over the 30-year time frame of this analysis (i.e., from 1990 to 2020 *with-CAAA*). This map shows that, overall, changes in visibility due to the CAAA are greater in the eastern U.S. than the western U.S. Additionally, the largest changes in visibility occur in the Midwestern states.

Exhibit 3-2 summarizes trends in visibility at the 13 most-visited U.S. National Parks. Visibility estimates (measured in deciviews) are provided for each of the seven core CAAA scenarios. Exhibit 3-3 presents the data from Exhibit 3-2 graphically. Note that deciviews are inversely related to visual range, such that a decrease in deciviews implies an increase in visual range (i.e., improved visibility). Conversely, an increase in deciviews implies a decrease in visual range (i.e., decreased visibility). These exhibits show that the CAAA greatly affects visibility at National Parks – over the 1990 to 2020 period, visibility markedly improves with the CAAA, and markedly declines without the CAAA. Particularly great differences in visibility *with-* and *without-CAAA* are seen at Great Smoky Mountains National Park, which is the most visited park in the U.S.

EXHIBIT 3-1. ESTIMATED CHANGE IN VISIBILITY WITH CAAA: 1990 TO 2020

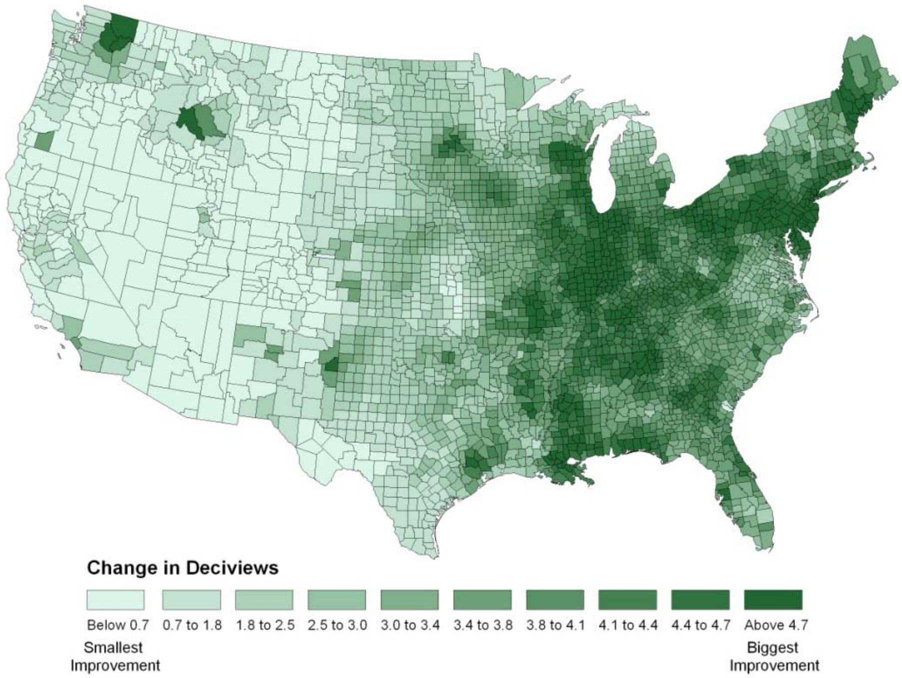


EXHIBIT 3-2. VISIBILITY IN DECIVIEWS AT THE 13 MOST-VISITED U.S. NATIONAL PARKS[A]

			WITHOUT CAAA			WITH CAAA		
RANK	NATIONAL PARK	1990	2000	2010	2020	2000	2010	2020
1	Great Smoky Mountains	20.83	21.27	21.71	22.18	19.53	18.21	16.79
2	Grand Canyon	7.91	8.44	8.70	9.07	7.90	7.78	7.78
3	Yosemite	9.48	9.67	10.03	11.11	9.43	9.21	9.21
4	Yellowstone	9.46	9.13	9.53	10.17	8.68	8.63	8.62
5	Sequoia-Kings	11.36	12.03	12.66	13.52	11.88	11.34	11.26
6	Rocky Mountain	10.20	9.68	10.03	10.64	9.27	9.11	8.86
7	Grand Teton	9.46	9.13	9.53	10.17	8.68	8.63	8.62
8	Olympic	12.01	11.21	11.43	11.66	10.81	10.79	10.68
9	Kings Canyon	11.78	11.94	12.64	13.62	11.53	10.98	10.91
10	Zion	6.81	9.23	9.73	10.49	7.56	7.51	7.56
11	Mount Rainier	15.13	14.33	14.65	15.43	13.43	12.90	12.82
12	Glacier	12.11	11.51	11.71	11.94	11.35	11.25	11.19
13	Acadia	17.63	17.55	17.77	17.43	15.21	14.61	13.60

Note: (A) According to the 2000 National Parks Statistical Abstract.

EXHIBIT 3-3. VISIBILITY TRENDS FOR THE 13 MOST-VISITED U.S. NATIONAL PARKS

VISIBILITY BENEFITS

Visibility directly affects people's enjoyment of a variety of daily activities. Individuals value visibility in the places they live and work, in the places they travel to for recreational purposes, and at sites of unique public value, such as Great Smoky Mountains National Park. Changes in the level of ambient PM caused by the reduction in emissions associated with the CAAA will change the level of visibility throughout the United States. This section discusses the measurement of the economic benefits of improved visibility.

It is difficult to quantitatively define a visibility endpoint that can be used for valuation. Increases in PM concentrations cause increases in light extinction, a measure of how much the components of the atmosphere scatter and absorb light. More light extinction means that the clarity of visual images and visual range is reduced, ceteris paribus. Light extinction is a variable that can be accurately measured. Pitchford and Malm (1993) created a unitless measure of visibility, the deciview, based directly on the amount of light extinction. Deciviews are standardized for a reference distance in such a way that one deciview corresponds to a change of about 10% in available light. Pitchford and Malm characterize a change in light extinction of one deciview as "a small but perceptible scenic change under many circumstances." Air quality models are used to predict the change in visibility, measured in deciviews, of the areas affected by the CAAA.[21]

Our analysis considers benefits from two categories of visibility changes: residential visibility and recreational visibility. In both cases economic benefits are believed to consist of use values and nonuse values. Use values include the aesthetic benefits of better visibility, improved road and air safety, and enhanced recreation in activities like hunting and bird watching. Nonuse values are based on an individual's belief that the environment ought to exist free of human-induced haze. Nonuse values may be more important for recreational areas, particularly national parks and monuments.

For the purposes of this analysis, recreational visibility improvements are defined as those that occur specifically in federal Class I areas, and residential visibility improvements are those that occur within the boundaries of Census Metropolitan Statistical Areas (MSAs).[22] A key distinction between recreational and residential benefits is that only those people living in residential areas are assumed to receive benefits from residential visibility, while all households in the United States are assumed to derive some benefit from improvements in Class I areas. Values are assumed to be higher if the Class I area is located close to their home.[23]

METHODOLOGY

VALUING RECREATIONAL VISIBILITY BENEFITS

Benefits of recreational visibility relate to the impact of visibility changes expected to be experienced by visitors to recreational areas with notable vistas. Our current methodology for valuing recreational visibility differs from the approach used in the First Prospective Analysis. In this Second Prospective Analysis, we follow a methodology used in EPA's Particulate Matter NAAQS RIA. As discussed in more detail in Appendix 1 of the RIA, this approach to valuing recreational visibility changes is an application of the Constant Elasticity of Substitution (CES) utility function approach and is based on the preference calibration method developed by Smith, Van Houtven, and Pattanayak (1999). Exhibit 3-4 outlines the key data sources and assumptions for this analysis of benefits to recreational visibility.

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[21] An instantaneous change of less than one deciview (i.e., less than 10% of the light extinction budget) represents a measurable improvement in visibility, but may not be perceptible to the eye. This analysis considers annual average changes in visibility, which are likely made up of periods with changes less than one deciview and periods with changes exceeding one deciview. One alternative to using annual average changes would be to evaluate changes in visibility during daylight hours for the year displayed as a frequency distribution. Such an approach would enable an analysis of the frequency of time when the visibility changes are likely to be perceptible. Our analysis instead relies on the simpler annual average changes in visibility because this measure appears to more closely correspond to the WTP literature relied upon in this analysis.

[22] The Clean Air Act designates 156 national parks and wilderness areas as Class I areas for visibility protection.

[23] For details of the visibility estimates discussed in this chapter, please refer to the Benefits TSD for the Nonroad Diesel rulemaking (Abt Associates, 2003).

EXHIBIT 3-4. KEY DATA SOURCES AND ASSUMPTIONS FOR PRIMARY ECONOMIC VISIBILITY BENEFITS ESTIMATES

DATA SOURCE	ASSUMPTION	POTENTIAL EFFECT ON RESULTS
Recreational Visibility		
Chestnut and Rowe, 1990a Chestnut and Rowe, 1990b Chestnut, 1997	Chestnut and Rowe study covers parks in three regions: California, Southwest, and Southeast. The results from these regions are transferred to other regions in the U.S.	Unclear
	Chestnut and Rowe study conducted on populations in five states. These results are applied to the entire U.S. population.	Unclear
	Only includes benefits to National Parks and Wilderness Areas, other recreational settings, such as National Forests and state parks, are not included in this analysis.	Potential Underestimate
	Individuals have a greater WTP for visibility changes in parks within their region.	Unclear
	WTP values reflect only visibility improvements and not overall air quality improvements.	Potential Overestimate
Residential Visibility		
Tolley et al., 1986 Brookshire et al., 1979 Loehman et al., 1984	Residential and recreational visibility benefits are distinct and separable.	Potential Overestimate
	Estimates residential visibility benefits within the boundaries of MSAs. Areas outside of an MSA are not included in this analysis.	Potential Underestimate
	WTP values reflect only visibility improvements and not overall air quality improvements.	Potential Overestimate
	WTP values from studies in Atlanta, Boston, Chicago, Denver, Los Angeles, Mobile, San Francisco, and Washington D.C. can be accurately transferred to MSAs across the U.S.	Unclear

For the purposes of this report, we interpret recreational settings applicable for this category of effects to include National Parks and Wilderness Areas. Other recreational settings may also be applicable, for example National Forests, state parks, or even hiking trails or roadside areas with scenic vistas. In those cases, a lack of suitable economic valuation literature to identify these other areas and/or a lack of visitation data prevents us from generating estimates for those recreational vista areas. Moreover, we develop estimates of recreational visibility changes that account for the tendency of individuals to value visibility changes based on proximity to the National Parks. The underlying assumption is that individuals are more likely to visit parks within their region and would therefore place a higher value on visibility changes within these parks. Recreational visibility benefits may, however, reflect the value an individual places on visibility improvements regardless of whether the person plans to visit the park.[24]

Household WTP for a visibility improvement at an in-region park takes the following form:

$$WTP(\Delta Q_{ik}) = m - \left[m^{\rho} + \gamma_{ik}\left(Q_{0ik}^{\rho} - Q_{1ik}^{\rho}\right)\right]^{1/\rho} \qquad (1)$$

where:

i indexes region,

k indexes park,

m = household income,

ρ = shape parameter,

γ = parameter corresponding to the visibility at in-region parks,

Q_0 = starting visibility, and

Q_1 = visibility after change.

A similar WTP function is used for out-of-region parks, replaying γ_{ik} for δ_{ik}.

Only one existing study provides defensible monetary estimates of the value of recreational visibility (Chestnut and Rowe, 1990b; 1990c). Although the Chestnut and Rowe study is unpublished, it was originally developed as part of the National Acid Precipitation Assessment Program (NAPAP) and, therefore, has been subject to peer-review as part of that program. Moreover, this study is frequently cited and recommended for use in published analyses of visibility valuation.[25] In EPA's judgment, the Chestnut and Rowe study contains many of the elements of a valid CV study and is sufficiently reliable to serve as the basis for monetary estimates of the benefits of visibility changes in recreational areas.[26] This study serves as an essential input to our estimates of the benefits of recreational visibility improvements in the primary benefits estimates.

The Chestnut and Rowe study measures the demand for visibility in Class I areas managed by the National Park Service (NPS) in three broad regions of the country:

[24] This type of valuation is typically labeled "existence value." For more discussion see Chestnut and Rowe, 1990a.

[25] For example see Desvousges et al. (1998).

[26] A Council advisory letter indicates that "many members of the Council believe that the Chestnut and Rowe study is the best available" (EPA-SAB-COUNCIL-ADV-00-002, 1999, p. 13). However, the committee did not formally approve use of these estimates because of concerns about the peer-reviewed status of the study. EPA believes the study has received adequate review and has been cited in numerous peer-reviewed publications (Chestnut and Dennis, 1997).

California, the Southwest, and the Southeast. Respondents in five states were asked about their WTP to protect national parks or NPS-managed wilderness areas within a particular region.[27] The survey used photographs reflecting different visibility levels in the specified recreational areas. The visibility levels in these photographs were later converted to deciviews for the current analysis.

WTP responses reported in the Chestnut and Rowe study were region-specific, rather than park-specific. As visibility improvements are not constant across all parks in a region, we must infer park-specific visibility parameters (i.e., γ and δ) in order to calculate WTP for projected visibility changes. As the quantity and quality of parks differs between regions, we apportion the visibility parameters based on relative visitation rates at the different parks, as this statistic is likely to get at the issues of both park quality (more people visit better parks, so collective WTP is likely higher) and quantity (more people visit parks in a region if the parks are more numerous, so collective WTP is likely higher).[28] This method has several limitations, including the fact that visitation rates count both foreign and domestic visitors and that it is not necessarily a good indicator of non-use value. The park-specific visibility parameters are used to calculate park-specific WTP values along with household income and visibility (measured in deciviews) in the *with-* and *without-CAAA* scenarios following Equation 1.[29] A more detailed explanation of how park-specific γ and δ are calculated is provided in Appendix I of the PM NAAQS RIA (U.S. EPA, 2006).

The Chestnut and Rowe study focused on visibility improvements in national parks and wilderness areas in California, the Southwest, and the Southeast. These regions cover 86 of the 156 Class I areas in the United States. Given that national parks and wilderness areas exhibit unique characteristics, it is not clear whether the WTP estimate obtained from Chestnut and Rowe can be transferred to other national parks and wilderness areas, without introducing additional uncertainty. As a result, for the primary estimate, we value

[27] The application of the estimated values to populations outside those states requires that preferences of populations in the five surveyed states be similar to those of nonsurveyed states. This assumption is applied in this analysis.

[28] We use park visitation data from the National Park Service Statistical Abstracts. To estimate recreational benefits in 2010 and 2020, we use visitation data from 2008, as this is the most current data available. Where the data for a particular park was not representative of normal visitation rates at that park (for example due to fire damage that occurred during that year), we substitute data from the prior year. We chose to use 2008 data rather than projecting to 2020 based on current visitation trends, as atypical years in visitation data pose problems for establishing an overall rate of increase or decrease, and it is not clear that visitation trends could reliably be projected so far into the future as they depend on many external factors. We use 1997 visitation data for those wilderness areas not included in the National Park Service Statistical Abstracts, as more current data is not readily available. As visitation rates for Wilderness Areas are small compared to visitation rates in National Parks, the inaccuracies generated by using 1997 data are likely to be small. As we have only one year of visitation data for wilderness areas, and because it is unclear whether visitation trends would be comparable across parks and wilderness areas, we chose to use the 1997 data as is rather than projecting it to the years of the analysis.

[29] For this analysis EPA has concluded that cross-sectional income adjustments are not appropriate for these types of benefits transfers. As a result, household income is adjusted longitudinally across time (i.e. 2000, 2010, and 2020), but not cross-sectionally across space (i.e. to reflect income differences across regions). Longitudinal income adjustments were made using an income elasticity of 0.9, indicating that a 1 percent increase in income is associated with a 0.9 percent increase in WTP for a given change in visibility.

only those recreational benefits in the areas that were directly analyzed in the original Chestnut and Rowe study. An alternative estimate is provided that includes all Class I areas. To calculate this alternative estimate region-specific visibility parameters must be inferred for regions not covered by the Chestnut and Rowe study.[30]

VALUING RESIDENTIAL VISIBILITY BENEFITS

Benefits of residential visibility relate to the impact of visibility changes on an individual's daily life; at home, at work, and while engaged in routine recreational activities. Residential visibility refers to conditions in large metropolitan areas, cities, towns and associated views and landscapes that individuals interact with on a regular basis. As defined in this analysis, residential visibility is distinct from recreational visibility, which refers specifically to conditions in Class I areas (e.g., certain NPS parks and wilderness areas). While improved visibility conditions in Class I areas has been recognized in previous policy analyses, most recent benefits analyses do not quantify or monetize residential visibility improvements as part of the primary benefits estimates.

In the First Prospective analysis, we omitted the results of the benefits estimate for residential visibility from the primary benefits estimate due to technical concerns about the methodology of the study upon which our original calculations were based (McClelland et al., 1991).[31] There exists a wide range of published, peer-reviewed literature, however, that supports a non-zero value for residential visibility. As a result, we have revised our methodology for valuing residential visibility, and now include these benefits in our overall primary visibility benefits estimate.

For valuing residential visibility improvements, we rely upon a benefits transfer approach detailed in Paterson et al. (2005) and summarized here, drawing upon information from the published Brookshire (1979), Loehman (1984) and Tolley (1986) studies. Exhibit 3-4 outlines the key data sources and assumptions for this analysis of benefits to residential visibility. Each of the studies used provides estimates of household WTP to improve visibility conditions from a status quo visual range to an improved visual range. While uncertainty exists regarding the precision of these older, stated-preference residential valuation studies, we believe their results support the argument that individuals have a non-zero value for residential visibility improvements. To express these value estimates in comparable terms, we rely upon a function similar to that used in the First Prospective analysis to express household WTP for a change in visual range:

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[30] A more detailed description of the benefits transfer method used to infer values for visibility changes in Class I areas outside the study regions is provided in the Benefits TSD for the Nonroad Diesel rulemaking (Abt Associates, 2003).

[31] Council review of early drafts of the First Prospective analysis noted that the McClelland et al. (1991) study may not incorporate two potentially important adjustments. First, their study does not account for the "warm glow" effect, in which respondents may provide higher willingness to pay estimates simply because they favor "good causes" such as environmental improvement. Second, while the study accounts for non-response bias, it may not employ the best available methods. As a result of these concerns, a prior Council recommended that residential visibility be omitted from the overall primary benefits estimate in the First Prospective.

$$WTP(\Delta VR) = b * \ln\left[\frac{VR_1}{VR_0}\right] \tag{2}$$

where:

VR_0 = mean annual visual range in miles before the improvement,

VR_1 = mean annual visual range in miles after the improvement, and

b = parameter.

As originally described by Chestnut and Rowe (1990c), this function implies a constant WTP for a given percentage change in visual range. This is consistent with the EPA's current use of the deciview scale, which relates to the above function in the following manner:

$$WTP(\Delta DV) = \frac{b}{10} * [DV_0 - DV_1] \tag{3}$$

where:

$$DV\ (deciviews) = 10 * [\ln(243/VR)]$$

Five principal residential visibility valuation studies were identified and reviewed for quality and applicability: Brookshire et al. (1979), Loehman et al. (1984), McClelland et al. (1991), Rae (1983) and Tolley et al. (1986). Of these, we exclude McClelland (1991) due to various concerns articulated by a previous Council, as noted above. In addition, we exclude Rae (1983) because it represents a novel application of a choice method for which there existed no established practices for design, implementation and data analysis. While the remaining three studies represent early applications of the contingent valuation method, and therefore do not benefit from more recent methodological advances or best-practice guidelines established by the NOAA Blue Ribbon Panel on Contingent Valuation (Arrow et al, 1993) and other diagnostic research, they nonetheless build upon previous literature and incorporate varying degrees of tests for internal consistency.

Of these remaining three studies, Loehman et al. (1984) and Brookshire et al. (1979) were subsequently published in peer-reviewed journals (see Loehman et al., 1994 and Brookshire et al., 1982). The Tolley et al. (1986) work was not published, but was subject to peer review during study development. Previous visibility literature summaries (e.g., Chestnut and Rowe, 1990c and Chestnut and Dennis, 1997) provide detailed descriptions of the three studies. These sources, as well as a review of the Tolley et al. study (Chestnut and Rowe, 1986) and a Project Team memorandum (Leggett et al., 2004) discuss criticisms associated with each study.

Following Chestnut and Rowe (1990c), we utilize value estimates and the associated change in visual range from each study to estimate the b parameter for the eight study areas. Where studies provide multiple estimates for visual range improvements, we estimate b by regressing the natural log of the ratio of visual range following and prior to improvement on WTP (see Equation 2). Exhibit 3-5 below provides a summary of these estimates, as well as an illustrative implied WTP value for a 10-percent improvement in visual range. All estimates are expressed in 2006$ using the Consumer Price Index.[32]

As shown, the implied annual per-household WTP estimates for a hypothetical 10-percent improvement ranges from $14 to $145, with a mean of $69 and median of $53. It is not surprising that such a range of values exists, as these areas all feature different landscapes and vistas, populations and prevailing visibility conditions. Fortunately, the three recommended studies provide primary visibility values for a variety of cities throughout the United States: Atlanta, Boston, Chicago, Denver, Los Angeles, Mobile, San Francisco, and Washington D.C.

EXHIBIT 3-5. SUMMARY OF RESIDENTIAL VISIBILITY PARAMETER ESTIMATES

CITY[A]	STUDY	*B* ESTIMATE[B]	IMPLIED WTP FOR 10% IMPROVEMENT IN VISUAL RANGE[C]
Atlanta	Tolley et al. (1986)	321	$47
Boston	Tolley et al. (1986)	398	$59
Chicago	Tolley et al. (1986)	310	$46
Denver	Tolley et al. (1986)	696	$102
Los Angeles	Brookshire et al. (1979)	94	$14
Mobile	Tolley et al. (1986)	313	$46
San Francisco	Loehman et al. (1984)	989	$145
Washington, DC	Tolley et al. (1986)	614	$90

a Recognizing potential fundamental issues associated with data collected in Cincinnati and Miami (e.g., see Chestnut and Rowe, 1986 and 1990c), we do not include values for these cities in our analysis.

b b/10 = WTP for a one deciview improvement

c Annual household willingness to pay, 2006$ at 1990 income levels. Income adjustments across time are applied after total benefits have been calculated.

To estimate visibility benefits in locations other than those considered in the three studies, we transfer the b parameters from the eight study areas to other areas of the country based primarily on geographic proximity. The studies we rely upon were all conducted in urban/metropolitan and surrounding areas and generally do not provide information on values for residential visibility improvements in rural areas. Thus, we restrict transfer of values to Metropolitan Statistical Areas (MSAs).[33] While MSAs account for roughly 20

[32] As we are considering only MSAs, we have chosen to use the CPI-U as the most representative measure of CPI.

[33] MSA boundaries are as most recent defined (2003).

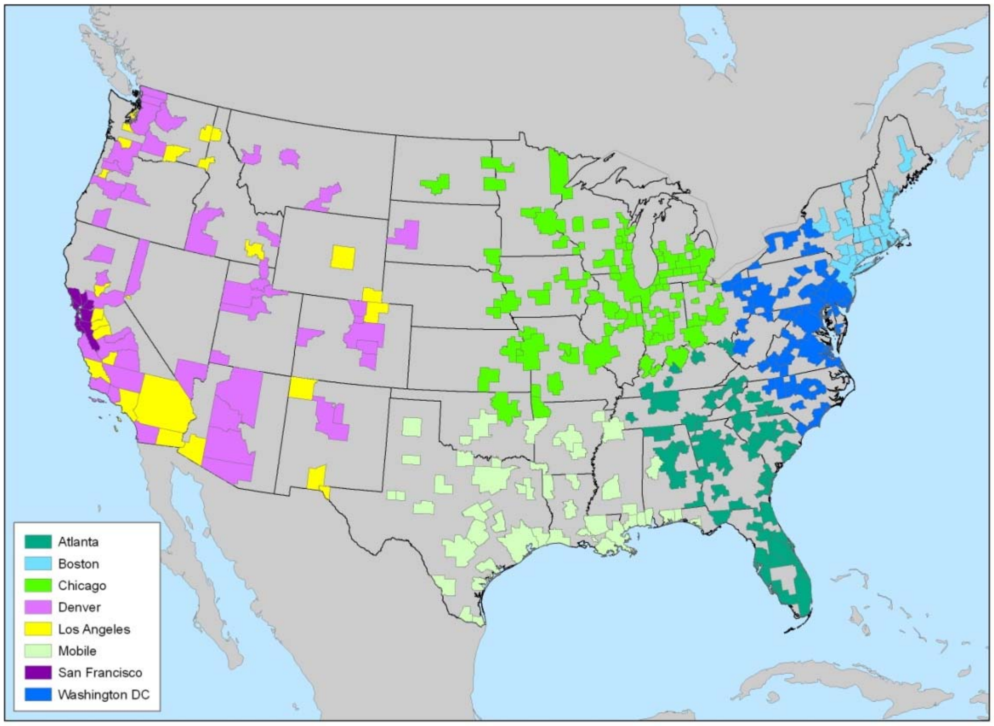
percent of total U.S. land area, over 80 percent of the population resides within them (Census, 2000).

We assign each of the 359 MSAs in the contiguous U.S. a value based on geographic proximity to one of the eight study cities, with two exceptions. We apply the Loehman et al. (1984) value only to the six San Francisco Bay area MSAs. The Loehman et al. study is unique among the three in the manner in which visibility changes were described to respondents (i.e., a distribution of days versus average conditions). In addition, the study area is unique in the landscape and vistas it offers, as well as prevailing weather conditions. In light of these factors, and considering that the Loehman et al. (1984) value is over 30 percent higher than the next highest value in the range, we believe is conservative and appropriate to restrict this value to the San Francisco study region.

In addition to different baseline levels of visibility, different weather conditions, and different resident characteristics, different locations provide dramatically different vistas. For example, one would expect that residents of Denver, with a dramatic view of the Rocky Mountains that is rarely obstructed by trees, would have a greater interest in protecting visibility than a city without a dramatic skyline or nearby mountains. We therefore add an additional constraint: values associated with Denver are not assigned on the basis of proximity but are instead assigned only to MSAs which meet an elevation range threshold of 1500 meters within the MSA.[34] While not a perfect way to identify areas with superb mountain vistas, the range of elevation within the MSA is nonetheless a reasonable, objective, and feasibly applied measure to identify where it would seem more appropriate to attribute the larger visibility values derived from the Denver study instead of the values from studies of the next closest city in our grouping. Exhibit 3-6 depicts assignment of the study cities to MSAs.

[34] The geographic proximity assignment is preserved for the Los Angeles and Riverside MSAs although these MSAs meet the elevation range threshold of 1500 meters. The assignment is preserved because Los Angeles is one of the study cities and also because Los Angeles has a particular set of location-specific characteristics that set it apart from Denver. As a conservative measure, Riverside MSA is also assigned to the Los Angeles study area because a significant portion of Riverside County itself is located in the South Coast Air Quality Management District, and therefore is considered by at least some measures to be part of the same regulated airshed as Los Angeles.

EXHIBIT 3-6. RESIDENTIAL VISIBILITY STUDY CITY ASSIGNMENT



In this analysis, we assume that residential and recreational visibility benefits are distinct and separable. Under this approach residential values from the existing literature are transferred to all MSAs in the conterminous U.S.; however, it is conceivable that respondents to Chestnut and Rowe's (1990b) recreational visibility survey may have partially included values for their own residential visibility when evaluating changes at national parks and wilderness areas in their region.

We also must assume that individuals care about visibility for aesthetic reasons rather than viewing visibility as a proxy for other impacts associated with air pollution, such as health effects. As health effects are evaluated separately from aesthetic effects, we assume that any observed response to visibility is linked to aesthetic concerns rather than concerns about health. Otherwise, health benefits would be double counted in the benefits analysis. Unfortunately, the visibility valuation literature indicates that individuals have trouble separating visibility from other impacts of air pollution (e.g., McClelland et al., 1991; Chestnut and Rowe, 1990c; Carson, Mitchell, and Ruud, 1990).

Contingent valuation studies designed to value visibility improvements must successfully separate respondents' preferences for visibility from their preferences for health. The three studies that we have selected to inform our calculations of the value of visibility accomplish this objective in somewhat different ways.[35] Tolley et al. (1986) specify a hypothetical pollution control program that will only affect visibility: "Suppose a program could be set up to prevent the decline in visibility, realizing that there would be no health effects." In contrast, Brookshire et al. (1979) specify a more general pollution control program, but they ask respondents to focus only on their preferences for visibility improvements: "I am only interested in how you value being able to see long distances." Finally, Loehman et al. (1986) present summary tables to respondents that describe the expected number of days per year at various health and visibility levels for both the baseline and the improved situations. Respondents are asked to provide WTP for air quality improvements with an increased number of good visibility days but with health levels held constant.

The degree to which the three studies were successful in convincing respondents to focus solely on visibility is unclear, as none of the three studies includes follow-up questions necessary to investigate the issue. Furthermore, no other residential visibility CV studies provide evidence regarding the degree to which health effects are embedded in visibility values. Although the McClelland et al. (1991) study has a follow-up question designed to allocate WTP across several categories, the CV question in the McClelland et al. study was focused on air pollution generally rather than visibility. As a result, we do not adjust the results from these studies to account for potentially embedded health effects.

RESULTS

The primary estimate of benefits to recreational and residential visibility is provided in Exhibit 3-7. The primary estimate for recreational visibility only includes benefits in the original study regions (i.e., California, the Southwest, and the Southeast). The primary estimate for residential visibility includes benefits in all MSAs. In general, benefits to visibility increase over time as visibility improves due to the CAAA. Benefits to residential visibility are approximately three times as large as benefits to recreational visibility.

Exhibit 3-8 provides an alternative estimate of benefits to recreational visibility. This alternative estimate includes all Class I areas, not just those that were directly analyzed in the original Chestnut and Rowe study. The alternative recreational visibility benefits estimate is approximately 40 percent greater than the primary estimate.

EXHIBIT 3-7. PRIMARY ESTIMATE OF BENEFITS TO VISIBILITY (BILLION 2006$)

	2000 BENEFITS	2010 BENEFITS	2020 BENEFITS
Recreational Benefits	$3.3	$8.6	$19
Residential Benefits	$11	$25	$48
Total Benefits	$14	$34	$67

[35] See Leggett et al. (2004) for a more detailed discussion of this issue.

EXHIBIT 3-8. ALTERNATIVE ESTIMATE OF BENEFITS TO VISIBILITY (BILLION 2006$)

	2000 BENEFITS	2010 BENEFITS	2020 BENEFITS
Recreational Benefits	$4.9	$12	$26
Residential Benefits	$11	$25	$48
Total Benefits	$16	$37	$74

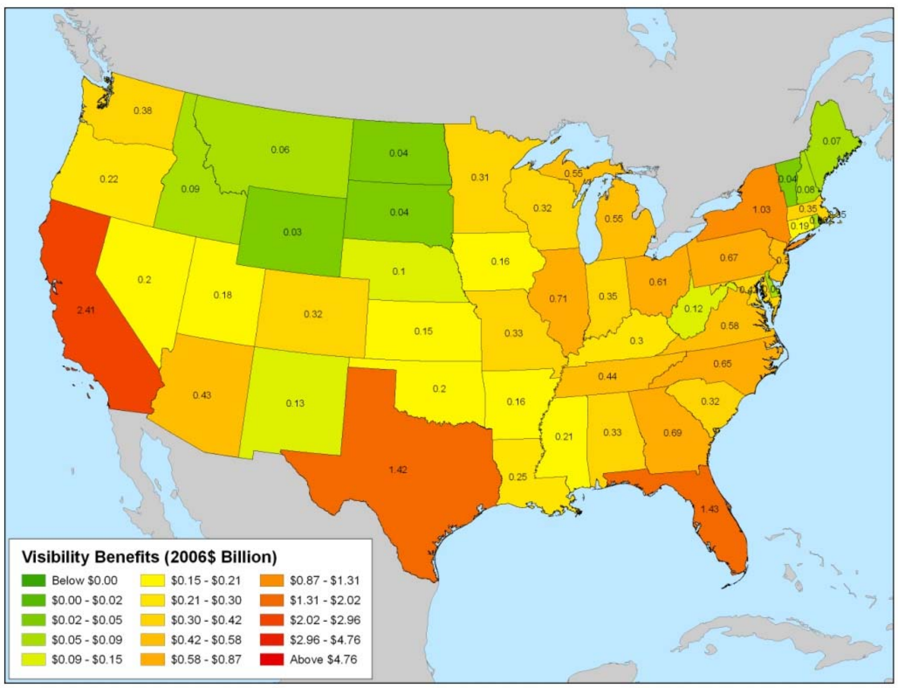
Exhibit Exhibits 3-9 through 3-11 map the primary estimate of benefits to recreational, residential, and total visibility by state in 2020. Exhibit 3-12 ranks states by their level of benefits to recreational, residential and total visibility. Exhibit 3-13 provides a visual comparison of the primary benefits estimate visibility across all years (i.e., 2000, 2010, and 2020). The full set of primary results by State is given in Appendix A. Overall, the spatial pattern of benefits is similar for recreational and residential visibility. Totals benefits are lowest in Wyoming, North Dakota, Vermont, South Dakota, and Montana. Total benefits are highest in California, New York, Texas, Pennsylvania, and Florida. Benefits appear to be largely driven by population as these are some of the least and most populous states.

Recreational visibility benefits are driven by population and park location. The primary benefits estimate includes only those Class I areas located within the original study regions of Chestnut and Rowe (1990a). These regions are California, the Southwest (Arizona, Nevada, Utah, Colorado, and New Mexico), and the Southeast (Delaware, Maryland, West Virginia, Virginia, Kentucky, Tennessee, North Carolina, South Carolina, Georgia, Alabama, Florida, and Mississippi). Households express WTP for visibility improvements in Class I areas located in-region as well as out-of-region. For this reason, there may be high recreational benefits in a state that has no Class I areas. Although household WTP is higher for in-region parks, this effect seems to be dominated by the effect of population. For example, less populated states such as New Mexico and Utah with Class I areas have low benefits to recreational visibility, while more populated states such as New York without Class I areas have high benefits to recreational visibility (see Exhibit 3-12). In some cases, the effect of being an in-region state is evident, for example Florida is ranked second in recreational benefits, but fifth in residential benefits (see Exhibit 3-12).

Residential visibility benefits are driven by population and visibility improvements. Overall, benefits are greater in the East. This is due in part to greater population levels as well as greater visibility improvements (see Exhibit 3-1). Benefits are also very high in California due to the state's large population and visibility improvements, especially in and around Los Angeles and San Francisco. Residential visibility is also dependent upon the WTP value applied. Much of the West uses the WTP value for Denver (see Exhibit 3-6), which is highest WTP value being widely applied. Yet, the West still has lower overall benefits to residential visibility.[36] This impact shows that the effect of population and visibility improvement dominates the effect of WTP value applied.

The First Prospective Analysis (U.S. EPA, 1999) only considers benefits to recreational visibility due to concerns about the methods used in the residential visibility study by McClelland et al. (1991). The First Prospective Analysis finds benefits to recreational visibility of $3.1 billion in 2000 and $4.5 billion in 2010 (2006$).[37] These results are smaller than those found in this analysis ($3.3 billion in 2000 and $8.6 billion in 2010). The difference in benefits is largely due to differences in the air quality estimates between the First and Second Prospective Analyses. This analysis attributes greater visibility improvements to the CAAA, and thus has to higher benefits estimates.

EXHIBIT 3-9. PRIMARY ESTIMATE OF RECREATIONAL BENEFITS TO VISIBILITY IN 2020 (BILLION 2006$)



[36] The WTP value for San Francisco is higher than Denver, but the San Francisco value is not applied to other MSA's.

[37] Adjusted from 1990$ to 2006$ using the CPI-U

EXHIBIT 3-10. PRIMARY ESTIMATE OF RESIDENTIAL BENEFITS TO VISIBILITY IN 2020 (BILLION 2006$)

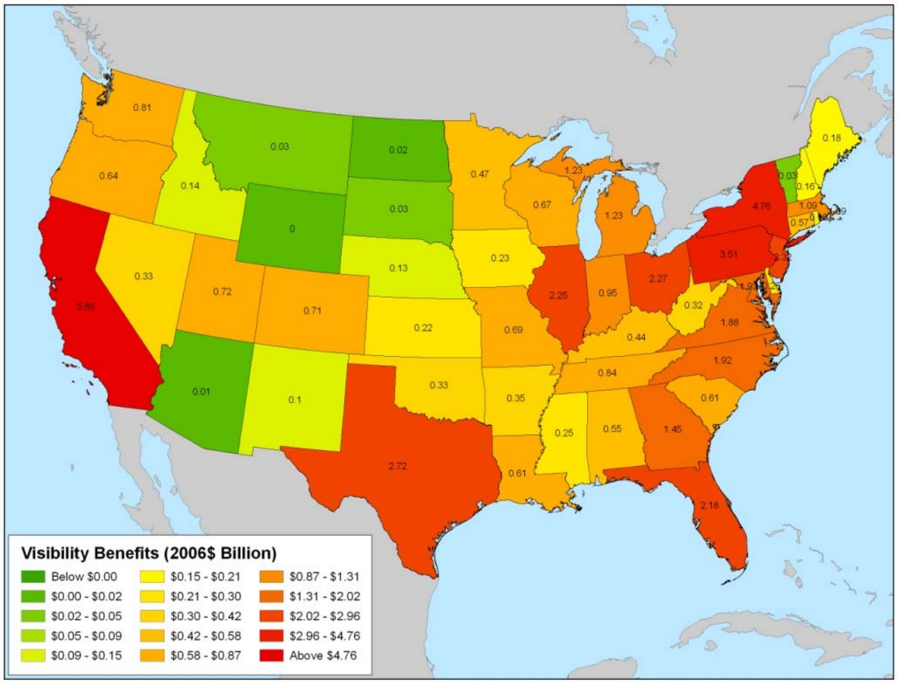


EXHIBIT 3-11. PRIMARY ESTIMATE OF TOTAL BENEFITS TO VISIBILITY IN 2020 (BILLION 2006$)

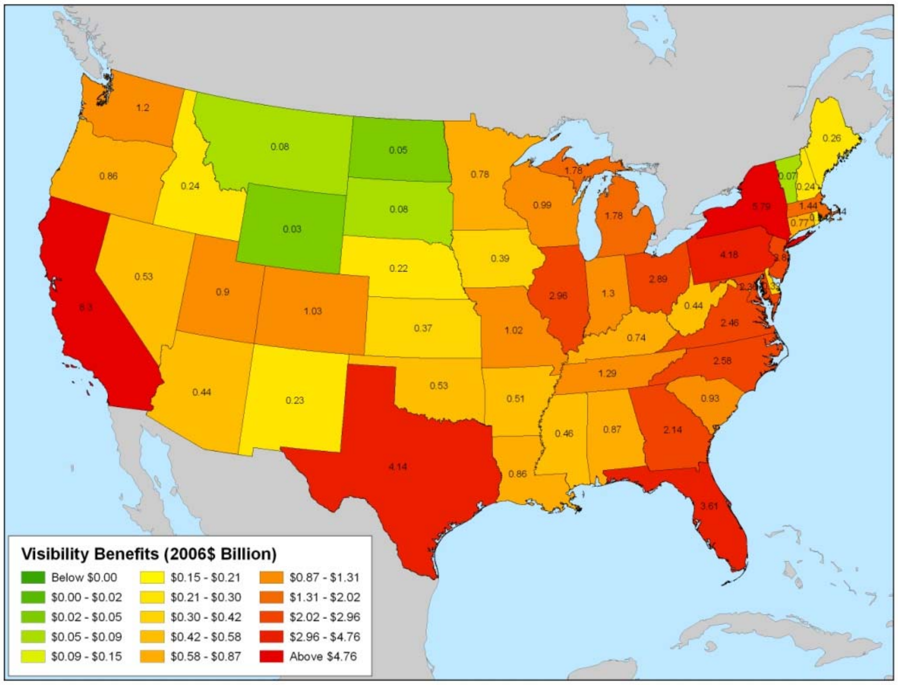
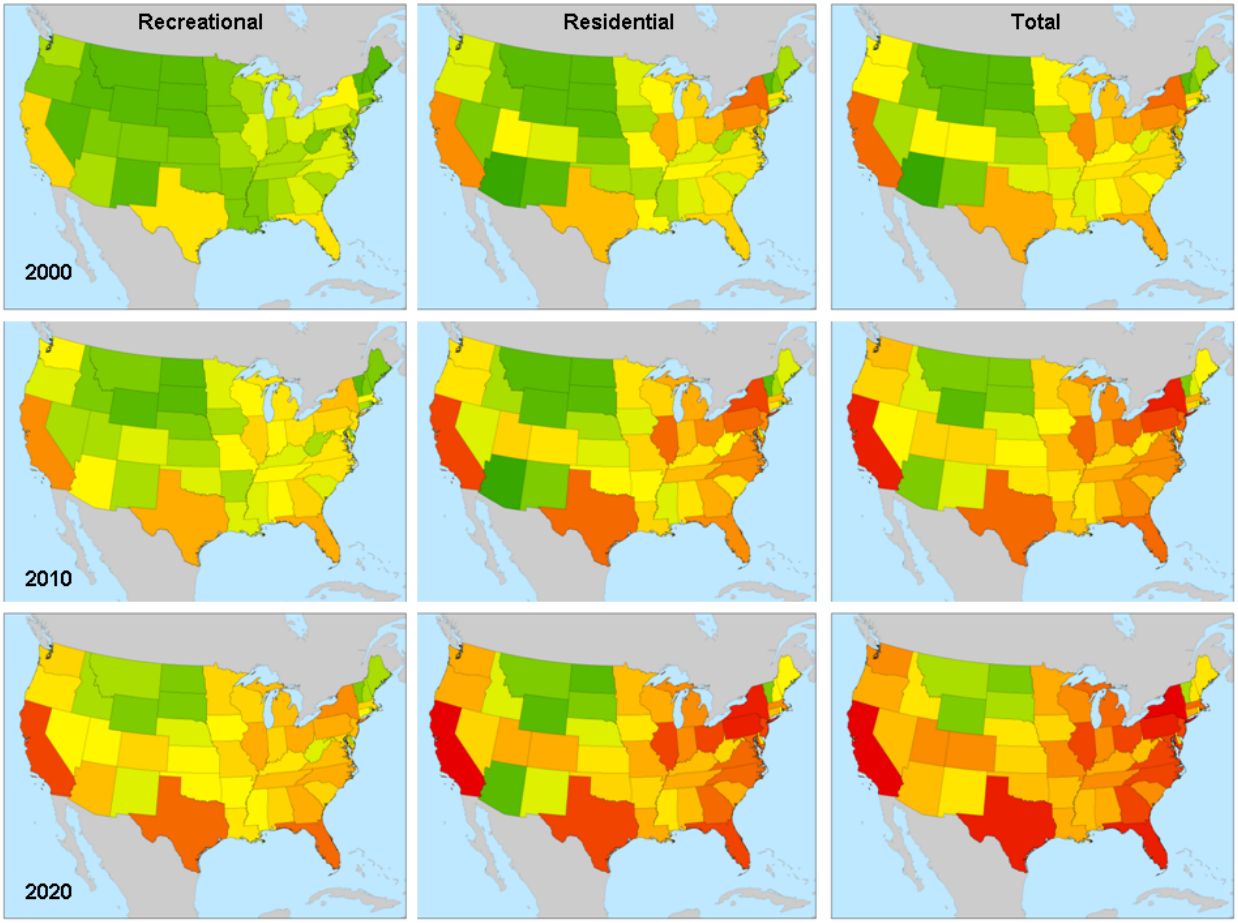


EXHIBIT 3-12. PRIMARY ESTIMATE OF BENEFITS TO VISIBILITY IN 2020, STATE RANK

RANK	RECREATIONAL BENEFITS	RESIDENTIAL BENEFITS	TOTAL BENEFITS
1	California	California	California
2	Florida	New York	New York
3	Texas	Pennsylvania	Pennsylvania
4	New York	Texas	Texas
5	Illinois	New Jersey	Florida
6	Georgia	Ohio	Illinois
7	Pennsylvania	Illinois	Ohio
8	North Carolina	Florida	New Jersey
9	Ohio	Maryland	North Carolina
10	Virginia	North Carolina	Virginia
11	Michigan	Virginia	Maryland
12	New Jersey	Georgia	Georgia
13	Tennessee	Michigan	Michigan
14	Arizona	Massachusetts	Massachusetts
15	Maryland	Indiana	Indiana
16	Washington	Tennessee	Tennessee
17	Indiana	Washington	Washington
18	Massachusetts	Utah	Colorado
19	Missouri	Colorado	Missouri
20	Alabama	Missouri	Wisconsin
21	South Carolina	Wisconsin	South Carolina
22	Colorado	Oregon	Utah
23	Wisconsin	South Carolina	Alabama
24	Minnesota	Louisiana	Oregon
25	Kentucky	Connecticut	Louisiana
26	Louisiana	Alabama	Minnesota
27	Oregon	Minnesota	Connecticut
28	Mississippi	Kentucky	Kentucky
29	Oklahoma	Arkansas	Oklahoma
30	Nevada	Oklahoma	Nevada
31	Connecticut	Nevada	Arkansas
32	Utah	West Virginia	Mississippi
33	Arkansas	Delaware	West Virginia
34	Iowa	Mississippi	Arizona
35	Kansas	Iowa	Iowa
36	New Mexico	Kansas	Kansas
37	West Virginia	Maine	Delaware
38	Nebraska	Rhode Island	Maine
39	Idaho	District of Columbia	New Hampshire
40	New Hampshire	New Hampshire	Rhode Island
41	Maine	Idaho	Idaho
42	Delaware	Nebraska	New Mexico

RANK	RECREATIONAL BENEFITS	RESIDENTIAL BENEFITS	TOTAL BENEFITS
43	Rhode Island	New Mexico	Nebraska
44	Montana	Vermont	District of Columbia
45	South Dakota	South Dakota	Montana
46	Vermont	Montana	South Dakota
47	North Dakota	North Dakota	Vermont
48	District of Columbia	Arizona	North Dakota
49	Wyoming	Wyoming	Wyoming

EXHIBIT 3-13. PRIMARY ESTIMATE OF BENEFITS TO VISIBILITY IN 2000, 2010, AND 2020 (BILLION 2006$, SAME SCALE AS PREVIOUS MAPS)



CHAPTER 4 | AGRICULTURAL AND FOREST PRODUCTIVITY BENEFITS OF THE CAAA

BACKGROUND

A significant body of literature exists addressing the effects of tropospheric ozone on plants, including commercial tree species and agricultural crops. In a companion report prepared to support the Second Prospective study, we summarize peer-reviewed research that characterizes these effects.[38] In general, elevated levels of tropospheric ozone have been shown to reduce overall plant health and growth by reducing photosynthesis and altering carbon allocation. In order to estimate the magnitude of plant growth reductions due to elevated tropospheric ozone levels, laboratory studies, such as Lee and Hogsett (1996), have developed exposure-response functions describing the functional relationship between plant yield and ozone exposure for a variety of plant species.[39] Applying exposure-response functions, this analysis estimates yield losses in agricultural crops and commercial tree species under the counterfactual, *without-CAAA* scenario relative to the baseline, *with-CAAA* scenario. Relative yield losses (i.e., reductions in crop and tree yield under the counterfactual scenario relative to the baseline scenario) measure the amount crop and tree yields would be reduced in the absence of CAAA regulations, and therefore, indicate a benefit of the CAAA.[40]

Commercial timber and agriculture operations generally manage their land to maximize profits. As such, changes in crop yields between the baseline and counterfactual scenarios may affect the distribution of commercial species planted; for example, landowners may shift production towards plants that are less sensitive to elevated ozone concentrations under the counterfactual scenario. This may occur at the individual plant level, replacing one crop or tree species for another with a higher growth rate; or, it may occur at the community level, converting agricultural lands to timberlands, or vice versa, to adjust for combined yield losses to agricultural crops and commercial trees.

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[38] Industrial Economics, Inc., Effects of Air Pollutants on Ecological Resources: Literature Review and Case Studies, Draft Report to USEPA Office of Air and Radiation, February 2010.

[39] Lee, E.H. and W.E. Hogsett. 1996. Methodology for Calculating Inputs for Ozone Secondary Standard Benefits Analysis: Part II. Prepared for the U.S. EPA, Office of Air Quality Planning and Standards, Air Quality Strategies and Standards Division.

[40] Relative yield losses are estimated instead of relative yield gains because the baseline (with CAAA) scenario in this analysis defines current conditions, whereas, the counterfactual (no CAAA) scenario defines a change in current conditions. The models applied in this analysis forecast changes in yield relative to current conditions (i.e., relative to the baseline scenario).

Changes in the distribution and yield of crop and tree species may in turn affect the supply of and demand for agricultural crops and commercial tree species, resulting in changes in producer and consumer surplus within the agricultural and timber sectors of the economy. This chapter documents our approach and results to estimating the welfare effects of changes in agriculture and timber markets resulting from the passage of the CAAA; ozone concentration estimates exist for years 2000 through 2020, however, changes in ozone concentration during this period with and without the CAAA may result in welfare effects that extend beyond 2020.

This analysis finds that crop and timber yields increase over time with reductions in ozone concentration associated with implementation of the CAAA. Yield increases are greatest in the geographic areas exhibiting the largest reduction in ozone concentration with the CAAA; specifically, along the East Coast (the Southeast, in particular), in the Midwest (within the Ohio River Valley), and in California (Exhibits 4-4 and 4-5).

The remainder of this chapter consists of three sections. The first section presents the analytical framework for the overall analysis, from forecasting ozone concentrations to estimating welfare effects. The second and third sections describe, respectively, the analytical methods and results of: 1) the analysis of relative yield losses in crops and trees under the counterfactual, no CAAA scenario; and 2) the analysis of welfare effects stemming from changes in crop and tree yields.

ANALYTICAL FRAMEWORK

This analysis applies three steps to estimate the welfare benefits of the CAAA with respect to commercial agriculture and timber management:

1. Estimate tropospheric ozone concentrations between 2000 and 2020 across the conterminous U.S. under two scenarios: 1) the current state of regulation, including the CAAA ("baseline scenario"); and 2) a counterfactual scenario assuming a hypothetical rollback of the CAAA ("counterfactual scenario");
2. Estimate relative yield losses for various commercial tree and agricultural crop species due to increased ozone concentrations under the counterfactual scenario (as opposed to the baseline scenario);[41] and,
3. Estimate the economic welfare effects (i.e., changes in both producer and consumer surplus) of increased yield in agricultural crops and commercial tree species under the baseline scenario relative to the counterfactual scenario.

Exhibit 4-1 describes the conceptual framework for this analysis. Additional detail on the specific models used to complete the three main steps applied in this analysis is provided in Exhibit 4-2. The following section details the first two analytic steps described above and in Exhibit 4-1, while the final section of this chapter describes the third analytical step described above and in Exhibit 4-1.

[41] Relative yield losses indicate percentage crop and timber yields are reduced under the counterfactual scenario *relative* to the baseline scenario.

EXHIBIT 4-1. DIAGRAM OF THE ANALYTICAL STEPS APPLIED TO ESTIMATE BENEFITS OF THE CAAA WITH RESPECT TO AGRICULTURE AND COMMERCIAL TIMBER PRODUCTION

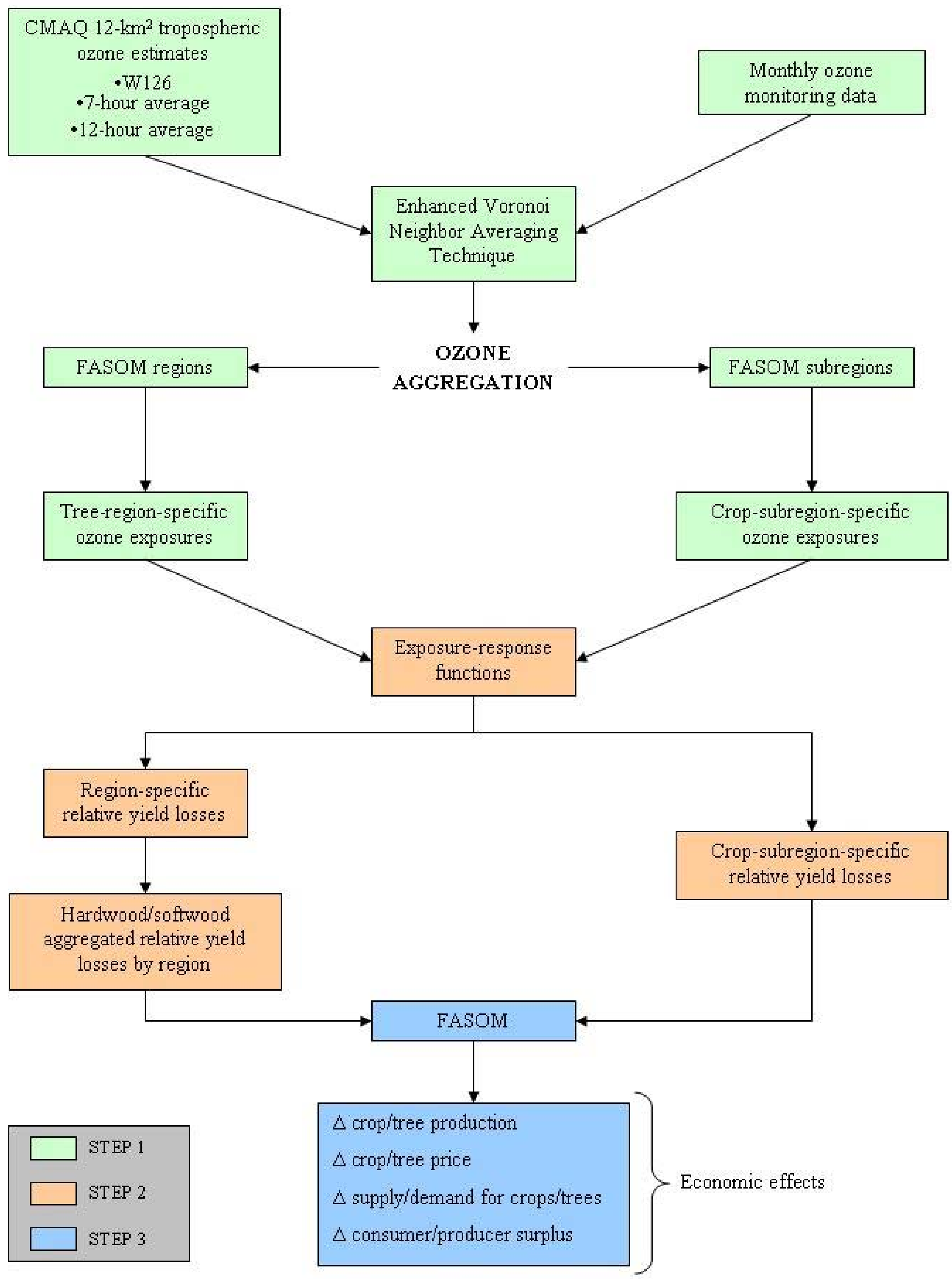


EXHIBIT 4-2. DETAILS ON THE FORMAT AND CONTENT OF DATA INPUT AND OUTPUT FOR THE DIFFERENT MODELS APPLIED

MODEL	INPUT REQUIREMENTS	OUTPUT	OUTPUT FORMAT
Community Multiscale Air Quality (CMAQ) Modeling System /Enhanced Voronoi Neighbor Averaging (eVNA)[a]	Climate and contaminant parameters for CMAQ; hourly ozone monitoring data combined with CMAQ results for eVNA	Tropospheric ozone concentrations under both CAAA scenarios for 2000, 2010, and 2020	12-km^2 grid cells
Exposure-response Functions[b]	Crop-subregion-specific and region-specific ozone metrics (W126, 7-hour average, 12-hour average)	Relative yield losses for select agricultural crops and commercial tree species under no CAAA scenario for 2000, 2010, 2020	Crop-subregion-specific and tree-region-specific relative yield losses
Forest and Agricultural Sector Optimization Model (FASOM)[c]	Relative yield losses at the subregional-level for crops and at the regional-hardwood- and regional-softwood-level for trees	Changes in consumer/producer surpluses for the agricultural and timber sectors	Changes in agricultural sector surpluses at the subregional-level and changes in the agricultural and timber surpluses at the regional- and national-levels.

Notes:

a) CMAQ model results provided by ICF International on October 8, 2008; eVNA results provided by Stratus Consulting on July 20, 2009 and September 28, 2009.

b) Exposure-response functions used in analysis from: Lee, E.H. and W.E. Hogsett. 1996. Methodology for Calculating Inputs for Ozone Secondary Standard Benefits Analysis: Part II. Prepared for the U.S. EPA, Office of Air Quality Planning and Standards, Air Quality Strategies and Standards Division.

c) FASOM results provided by RTI International on July 30, 2010.

ANALYTICAL METHODS AND RESULTS: RELATIVE YIELD LOSS

This section describes the methods and results of the analysis of relative yield losses in crops and trees under the counterfactual, no CAAA scenario. As described above, there are two distinct steps necessary to estimate relative yield losses: 1) estimate tropospheric ozone concentrations over time under the baseline and counterfactual scenarios; and, 2) calculate relative yield losses based on ozone concentration estimates. The section is organized by analytic step. For each step, the methods applied to complete the step are described, followed by the results of the step.

Step 1: Estimating Tropospheric Ozone Concentrations With and Without the CAAA

This section describes the methodology used to estimate tropospheric ozone levels over time (2000-2020) both with and without the CAAA.[42] Further, this section describes the steps taken to aggregate tropospheric ozone estimates in accordance with the input requirements of exposure-response functions (Exhibit 4-2). Finally, disaggregated and aggregated tropospheric ozone estimates are presented in this section.

Tropospheric ozone concentrations were estimated using Enhanced Voronoi Neighbor Averaging (eVNA), which considers both the modeled ozone concentration results and monthly ozone monitoring data. Specifically, the Community Multiscale Air Quality (CMAQ) Modeling System version 4.6 was used to estimate tropospheric ozone concentrations at a 12 square-kilometer grid level for both the eastern and western U.S. These estimates were then adjusted according to EPA hourly ozone monitoring data (EPA Air Quality System Data for 2002) using eVNA, a modified inverse distance weighted interpolation technique in which the ozone concentration at a given point is adjusted by weighting the concentrations at surrounding points by the distance from the point of interest. The eVNA analysis is based on the assumption that the distance between points and the variation in ozone concentrations between points are correlated.[43]

This analysis considered three different ozone concentration metrics: W126, 7-hour average, and 12-hour average. These metrics are described in Exhibit 4-3. Each metric was calculated on a monthly basis for the May through September period. For the W126 metric (a cumulative exposure metric), monthly values were estimated by summing the daily W126 values for each day in the month. For the 7-hour and 12-hour averages, monthly values were estimated by taking the average 7- or 12-hour average estimated for each day in a given month. The same methodologies used to estimate monthly values were used to estimate combined W126 values and 7- and 12-hour averages for the entire May through September period.

The Forest and Agricultural Sector Optimization Model (FASOM), the economic model employed in this analysis, requires species growth inputs at a subregion-level for crops and at a region-level for trees; the subregions and regions defined by the model are highlighted in Exhibits 4-4 and 4-5. Subregions define state or sub-state areas. There are a total of 63 subregions defined in FASOM.[44] Regions define sets of multiple states or sub-state areas. There are a total of 11 regions defined in FASOM.[45]

[42] Welfare effects associated with changes in crop and commercial timber yield may be experienced beyond 2020.

[43] The eVNA methodology is described in greater detail in: EPA. 2007. Technical Report on Ozone Exposure, Risk, and Impact Assessments for Vegetation. EPA 452/R-07-002. Prepared by Abt Associates Inc. for U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Health and Environmental Impacts Division.

[44] FASOM subregions refer to each of the 48 states of the coterminous U.S. However, some states including Texas, California, Indiana, Illinois, Ohio, and Iowa are subdivided into multiple subregions.

[45] FASOM regions include: Northeast, Lake States, Corn Belt, Great Plains, Southeast, South Central, Southwest, Rocky Mountains, Pacific Southwest, Pacific Northwest (East side), and Pacific Northwest (West side).

EXHIBIT 4-3. DETAILS ON OZONE METRICS APPLIED IN EXPOSURE-RESPONSE FUNCTIONS

METRIC	DESCRIPTION	FORMULA
W126	Weighted sum of all tropospheric ozone concentration values observed hourly between 8 am and 8 pm	$\sum_{i=8am}^{i<8pm} w_{C_i} C_i$ where: $w_{c_i} = \frac{1}{1+4403e^{-126C_i}}$
7-Hour Average	Average of all tropospheric ozone concentration values observed hourly between 9 am and 4 pm	$\frac{1}{7}\sum_{i=9am}^{i<4pm} C_i$
12-Hour Average	Average of all tropospheric ozone concentration values observed hourly between 8 am and 8 pm	$\frac{1}{12}\sum_{i=8am}^{i<8pm} C_i$

Note: C_i = hourly ozone concentration at hour *i* in parts per million (ppm)

Sources:

1. EPA. 2007. Technical Report on Ozone Exposure, Risk, and Impact Assessments for Vegetation. EPA 452/R-07-002. Prepared by Abt Associates Inc. for U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Health and Environmental Impacts Division.
2. Olszyk, D.M., H. Cabrera and C.R. Thompson. 1988. California statewide assessment of the effects of ozone on crop productivity. APCA Notebook. 38(7):928-931.

Given the requirements for FASOM inputs, differences in ozone concentration were estimated at the subregion level and at the region level. Ozone metrics were aggregated by region and subregion by calculating weighted averages for the CMAQ 12 square-kilometer grid cells intersecting each region and subregion. Grid cell weights were derived by calculating the area of a grid cell intersecting a given region or subregion divided by the total area of the region or subregion. Specifically, the following equation was used to aggregate ozone metrics by region or subregion.

$$C_{region/subregion} = \sum_{i=1}^{N} w_i C_i$$

$$\text{where: } w_i = \text{weight of cell } i = \frac{a_i}{\sum_{i=1}^{N} a_i} \quad (a_i = \text{area of cell } i \text{ in region/subregion})$$

$$C_i = \text{W126, 7-hour average, or 12-hour average value for cell } i$$

$$N = \text{total number of grid cells intersecting a given region or subregion}$$

Step 1 Results: Tropospheric Ozone Estimates With and Without the CAAA

Exhibits 4-4 and 4-5 present differences in W126 values with and without the CAAA by region and subregion, respectively, for each year in the analysis (differences are calculated by deducting W126 values with the CAAA from W126 values without the

CAAA).[46] CMAQ estimates of tropospheric ozone levels were generated for 2000, 2010, and 2020. Thus, the results of the eVNA analysis are limited to these years.

Exhibits 4-4 and 4-5 indicate that the differences in ozone concentration between the two CAAA scenarios increase over time. That is, ozone concentrations without the CAAA increase over time while concentrations with the CAAA decrease, leading to increased differences between the two scenarios. The differences in ozone concentrations vary by region and subregion. Specifically, the Pacific Southwest and Southeast regions exhibit the greatest differences in ozone concentration over time followed closely by the South Central, Cornbelt, and Northeast regions.

The subregion map (Exhibit 4-5) provides differences in ozone concentration at a finer spatial resolution than the region map. It appears that while the regions listed above exhibit the greatest differences in ozone concentration between the two scenarios, on-the-whole, some states and/or portions of states within these regions exhibit greater differences than others. Specifically, Virginia, North Carolina, South Carolina, Tennessee, and southern California exhibit the greatest differences in ozone concentration between the two scenarios over time. Secondarily, Pennsylvania, West Virginia, Kentucky, Indiana, Illinois, and Ohio exhibit large differences in ozone concentration.

Step 2: Estimating Effects of Changes in Tropospheric Ozone Concentrations on Crop and Tree Growth

This section describes the calculation of relative yield losses for crops and trees due to elevated tropospheric ozone concentrations under the counterfactual scenario. In order to estimate relative yield losses, this analysis relies on species-specific exposure-response functions that estimate plant yield as a function of W126, 7-hour average, or 12-hour average ozone metrics. This section presents the exposure-response functions applied in this analysis; describes the methodology used to derive the appropriate ozone metric inputs for each crop-subregion combination and each region; and, describes the methodology used to estimated relative yield losses based on exposure-response functions. Finally, relative yield losses are presented for select crops and forest types by FASOM region and subregion for each year in the analysis (2000, 2010, and 2020).

[46] Differences in 7-hour and 12-hour average ozone concentrations are not displayed because the majority of exposure-response functions used in this analysis require W126 values as a measure of ozone concentration. The geographic distribution of differences between 7-hour and 12-hour averages with and without the CAAA, in terms of the areas with the greatest or smallest differences, is similar to the differences presented in Exhibits 4 and 5. However, the magnitude of the differences between the 7-hour and 12-hour averages with and without the CAAA are smaller than the differences between the W126 data with and without the CAAA because the 7-hour and 12-hour average metrics are not additive metrics, as is the W126 metric.

EXHIBIT 4-4. REDUCTIONS IN OZONE CONCENTRATION WITH THE CAAA BY FASOM REGION (PERIOD = MAY - SEPTEMBER; METRIC = W126)

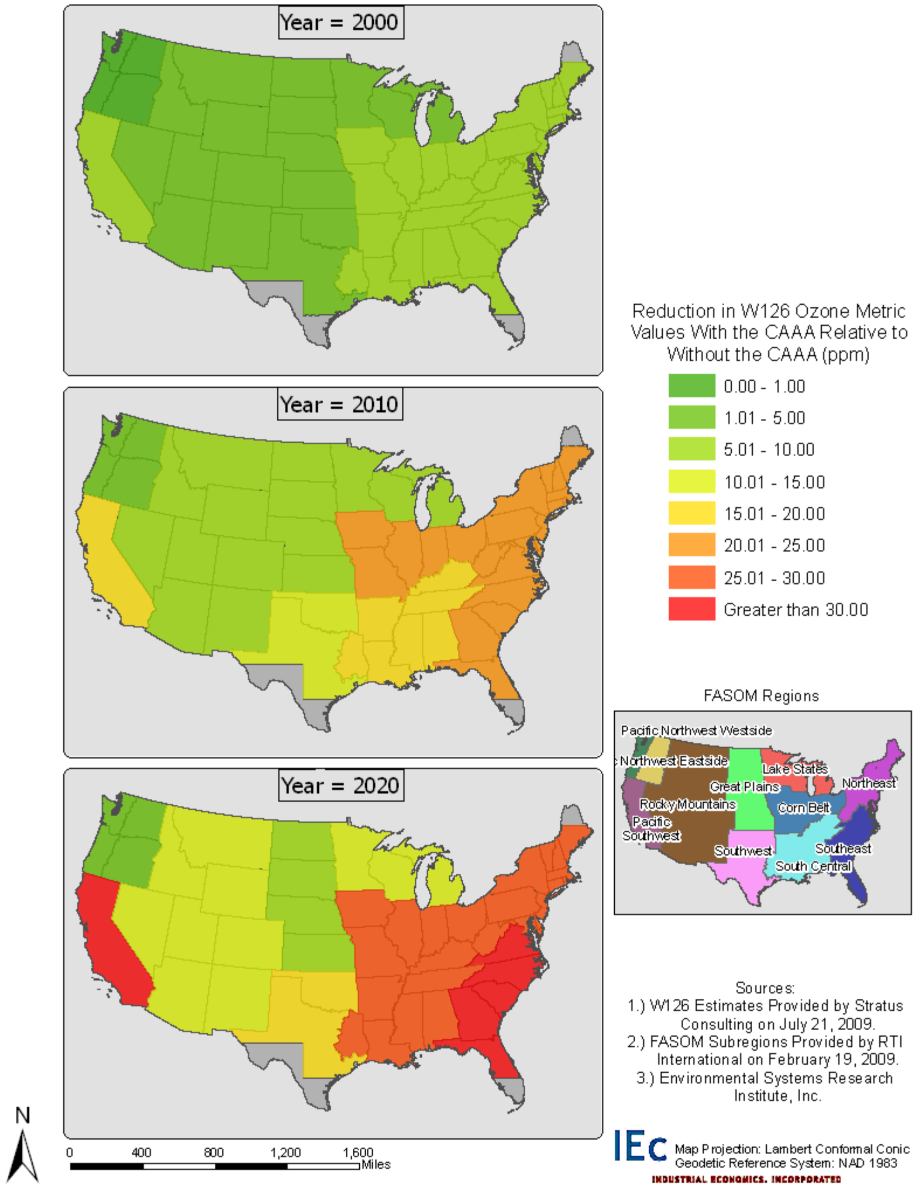
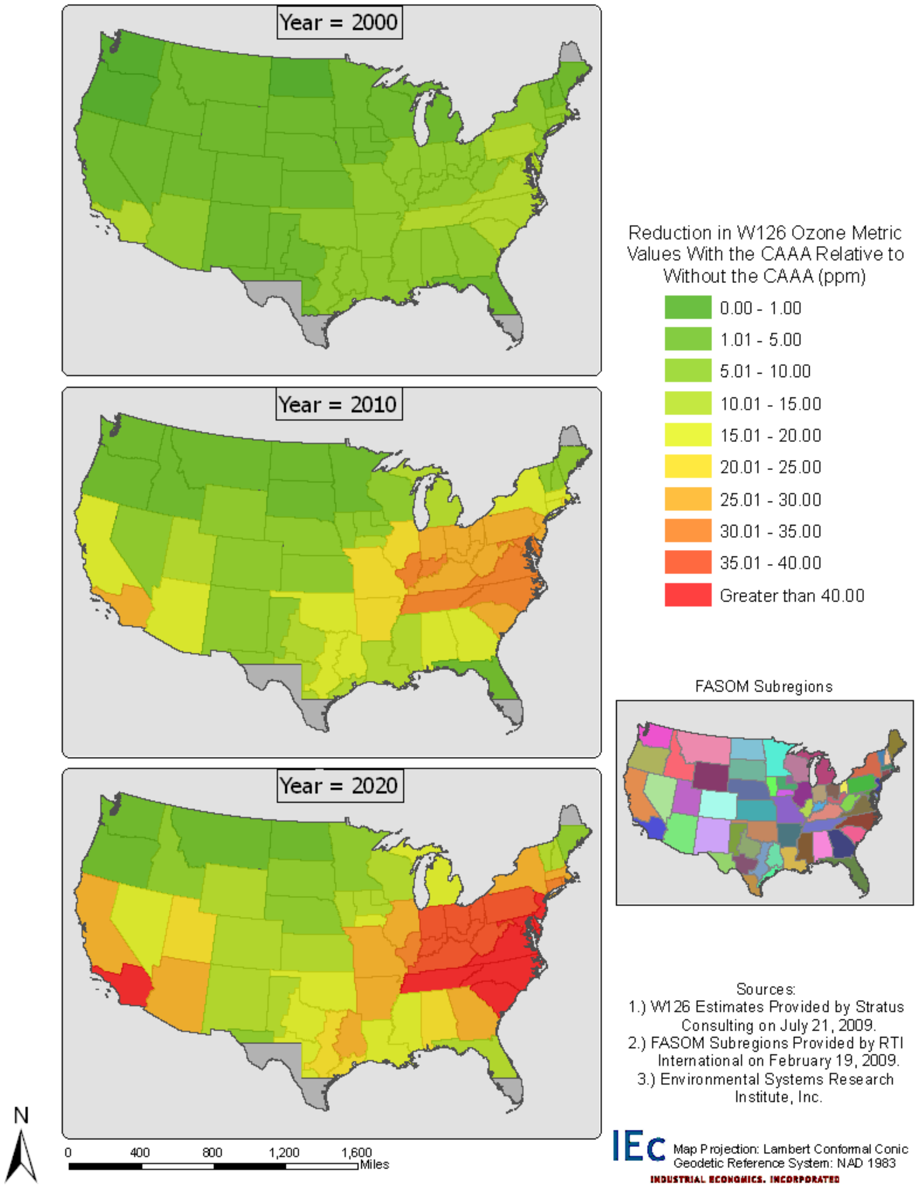


EXHIBIT 4-5. REDUCTIONS IN OZONE CONCENTRATION WITH THE CAAA BY FASOM SUBREGION (PERIOD = MAY - SEPTEMBER; METRIC = W126)



- **Exposure-Response Functions:** Exposure-response functions are derived through laboratory studies measuring the growth effects of various ambient ozone concentrations on plants. The functions used in this analysis are either exponential or linear regression equations describing plant growth as a function of ozone concentration. While the use of laboratory-derived functions may not be ideal (i.e., field studies may be preferable), for many species the laboratory studies provide the best available information regarding responses to ozone exposure. This analysis applies exposure-response functions from a Lee and Hogsett study (1996), which was developed for EPA and has been applied in other recent EPA analyses.[47] The specific exposure-response functions used in this analysis are each based on one of the three different ozone concentration metrics: W126, 7-hour average, and 12-hour average, as defined in Exhibit 4-3. Exhibit 4-6 presents the exposure-response functions applied in this analysis for different crops and trees.[48]

- **Ozone Metric Inputs for Crops:** Crop-subregion-specific ozone metrics were derived by determining each crop's harvest date using, "Usual Planting and Harvesting Dates for U.S. Field Crops" released by the U.S. Department of Agriculture, and then rolling back by the number of growing days to determine the crop planting date (the period between the planting date and the harvest date is the growing period; crops are only exposed to ozone during their growing period).[49] Ozone metrics were then calculated for the growing period. Some crops, including tomatoes and potatoes, are grown throughout the year. For these crops, the growing period within the May through September period which yields the greatest difference in ozone concentration between the baseline and counterfactual scenarios was applied. The growing period for some crops falls outside of the May through September period for which ozone estimates exist (i.e., the planting date is before May 1 or the harvest date is after September 30). For these crops, the ozone metric was calculated utilizing only those growing days within the May through September period. This methodology is based on the assumption that ozone levels outside of the May through September period are not elevated to levels that would affect plant growth.[50]

- **Ozone Metric Inputs for Trees:** The harvest rotation for trees spans multiple years. Therefore, tree species do not have a specific growing period. Region-specific ozone metrics were derived by calculating the relevant ozone metric over

[47] Lee, E.H. and W.E. Hogsett. 1996. Methodology for Calculating Inputs for Ozone Secondary Standard Benefits Analysis: Part II. Prepared for the U.S. EPA, Office of Air Quality Planning and Standards, Air Quality Strategies and Standards Division. For example, EPA applied functions from Lee and Hogsett (1996) in: USEPA. July 2007. Review of the National Ambient Air Quality Standards for Ozone: Policy Assessment of Scientific and Technical Information. EPA-452/R-07-007.

[48] The crop and tree species included in Exhibit 4-6 are selected for inclusion in this analysis because: a) the functional relationship between ozone exposure and yield is established for each species (i.e., an exposure-response function has been estimated); and, b) each species is explicitly considered in FASOM.

[49] U.S. Department of Agriculture. 1997. Usual Planting and Harvesting Dates for U.S. Field Crops. USDA, National Agricultural Statistics Service. Agricultural Handbook No. 628.

[50] Given that ozone concentrations and crop growing periods vary by subregion, ozone concentration inputs are specific to each crop-subregion combination.

the three-month period between May and September that yields the greatest difference in ozone concentration between the baseline and counterfactual scenarios for each region. This methodology is also based on the assumption that ozone levels outside of May through September are not elevated to levels that would affect plant growth.

EXHIBIT 4-6. EXPOSURE-RESPONSE FUNCTIONS AND FUNCTION PARAMETERS FOR CROPS AND TREES

SPECIES	OZONE METRIC	A (PPM)	B	GROWING DAYS	FUNCTION[a]
CROP SPECIES					
Barley	W126	6,998.50	1.39	95	$Y = Ce^{-\left(\frac{O_3}{A}\right)^B}$
Corn	W126	97.90	2.97	83	
Cotton	W126	96.10	1.48	114	
Oranges[b]	12-Hour Average	53.70	261.10	214	$Y = C[A-(B*O_3)]$
Potatoes	W126	99.50	1.24	66	$Y = Ce^{-\left(\frac{O_3}{A}\right)^B}$
Rice[c]	7-Hour Average	0.20	2.47	85	
Sorghum	W126	205.90	1.96	85	
Soybeans	W126	110.20	1.36	93	
Processing Tomatoes[c]	12-Hour Average	9,055.00	32,367.00	66	$Y = C[A-(B*O_3)]$
Wheat (Spring & Winter)[b]	W126	53.40	2.37	58	$Y = Ce^{-\left(\frac{O_3}{A}\right)^B}$
TREE SPECIES					
Aspen	W126	109.81	1.22	N/A	$Y = Ce^{-\left(\frac{O_3}{A}\right)^B}$
Black Cherry		38.92	0.99		
Douglas Fir		106.83	5.96		
Eastern White Pine		63.23	1.66		
Ponderosa Pine		159.63	1.19		
Red Maple		318.12	1.38		
Sugar Maple		36.55	5.78		

SPECIES	OZONE METRIC	A (PPM)	B	GROWING DAYS	FUNCTION[a]
Tulip Poplar		51.38	2.09		
Virginia Pine		1,714.64	1.00		

Notes: Variables defined as follows:
C = theoretical constant equivalent to the theoretical yield at zero ozone exposure in the exponential functions and 2.70 in the linear functions making C*A equal to the theoretical yield at zero ozone exposure;
A = scale parameter for ozone exposure at which the expected growth response in 37 percent of the theoretical yield at zero ozone exposure;
B = the shape parameter affecting the change in the predicted rate of loss.

(a) Exposure-response functions do not exist for different types of oranges and spring wheat, both of which are included in FASOM, therefore the same function parameters are used for all orange types, and winter and spring wheat, based on the assumption that the growth of these crops is similar.

(b) The number of growing days for rice and processing tomatoes applied in the: EPA. 2007. Technical Report on Ozone Exposure, Risk, and Impact Assessments for Vegetation. EPA 452/R-07-002. Prepared by Abt Associates Inc. for U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, Health and Environmental Impacts Division, differs from the growing days applied for these crops in this analysis. The 2007 report applied a growing period of 69 days for rice and 76 days for processing tomatoes. The use of different growing periods for these crops does not result in significant changes to relative yield loss estimates (maximum differences < +/- 0.2%).

Source:

Lee, E.H. and W.E. Hogsett. 1996. Methodology for Calculating Inputs for Ozone Secondary Standard Benefits Analysis: Part II. Prepared for the U.S. EPA, Office of Air Quality Planning and Standards, Air Quality Strategies and Standards Division.

Relative Yield Loss Estimation: Relative yield losses were calculated based on exposure-response functions according to the following formula:

$$RYL = 1 - \frac{Y_{NoCAAA}}{Y_{WithCAAA}} \quad \text{where } Y = plant\ yield$$

Crop-subregion- and tree-region-specific relative yield losses are calculated for each year in the analysis (2000, 2010, and 2020).[51]

Because FASOM models tree growth by hardwood and softwood forest types, relative yield losses for individual tree species were aggregated by hardwoods and softwoods. This was accomplished through averaging the relative yield losses of each hardwood and softwood species potentially present in a given region. If no hardwood or softwood species for which relative yield losses were estimated is potentially present in a region, the national average of hardwood or softwood relative yield losses was applied.

[51] Not all crop and tree species are present in every subregion or region. Relative yield gains are not estimated for crops in subregions where the given crop is not potentially present as defined by FASOM. Similarly, relative yield gains are not estimated for trees in regions where the given tree species is not potentially present as defined by FASOM.

Step 2 Results: Relative Yield Losses for Crops and Trees

Maps presenting crop-subregion- and tree-region-specific relative yield losses for the different crops and forest types included in this analysis are provided in Appendix B (Exhibits B-1 through B-13). Exhibit 4-7 provides a summary of relative yield losses by crop/forest type and year. Relative yield losses indicate a benefit of the CAAA; the larger the relative yield loss without the CAAA, the greater the crop or tree yield with the CAAA.

Outside of reductions in ozone concentration with the CAAA, a number of factors affect yield changes in crops and trees including sensitivity to ozone, geographic distribution, growing period length, and the specific time of year the growing period occurs. Given these factors, relative yield losses vary between the different crops and forest types included in this analysis, with some crops and forest types exhibiting limited changes in growth (e.g., barley, rice, and sorghum) and others exhibiting relatively great changes in growth (e.g., cotton, potato, winter wheat, hardwoods, and softwoods). In general, relative yield losses range from 0 to 23 percent across all years, crops, and forest types. Relative yield losses tend to increase over time, with the smallest yield losses occurring in 2000 and the largest occurring in 2020.

The maximum relative yield loss for crops is estimated for potatoes growing in Maryland in 2020 (relative yield loss without the CAAA equals 20.80 percent). The minimum relative yield loss is estimated for soybeans growing in Florida in 2010 (relative yield loss equals -0.55 percent). The negative relative yield loss for soybeans in Florida in 2010 indicates that soybean growth is improved without the CAAA. The growing period for soybeans in Florida is roughly mid-July through September. The negative relative yield loss is due to reductions in W126 ozone metric values under the counterfactual, no CAAA scenario in Florida in September of 2010. Ozone concentrations are lower under the baseline, with CAAA scenario in Florida for all other months in 2010. Thus, ozone concentrations aggregated across all months of interest, May through September, are reduced in Florida in 2010 with the CAAA (Exhibit 4-5). The negative relative yield loss for soybeans, however, is minimal given the relatively minor differences in forecast ozone concentrations between the scenarios (a relative yield loss of -0.55 percent indicates that yield with the CAAA is 99.5 percent of yield without the CAAA). No other crops exhibit negative yield losses in Florida in 2010.

Negative yield losses are also estimated for rice in the California-North and California-South subregions in 2000 (relative yield losses of -0.02 and -0.08 percent, respectively). The relative yield loss function for rice is a function of the 7-hour ozone metric (Exhibit 4-6). Although W126 ozone metric values are lower under the baseline, with CAAA scenario for all months (May through September) in these subregions, the 7-hour average values for these subregions are lower under the counterfactual, no CAAA scenario in 2000, leading to negative yield losses for rice. Similar to soybeans, the effects of the negative relative yield losses for rice are minimal given the relatively minor differences in forecast ozone concentrations between the scenarios.

Hardwood forests exhibit greater relative yield losses than softwood forests across all years in the analysis. The maximum relative yield losses in hardwoods and softwoods are estimated for the Southeast region in 2020 (relative yield losses equal 23.04 and 12.27 percent for hardwoods and softwoods, respectively). The minimum relative yield loss across both forest types is estimated for softwoods in the Pacific Northwest East region in 2000 (relative yield loss equal to 0.06 percent).

As presented in Exhibits 4-4 and 4-5, reductions in tropospheric ozone concentrations are greatest along the East Coast, particularly the Southeast, in the Midwest (within the Ohio River Valley), and in California. Relative yield losses in crops and trees, therefore, are expected to be greatest in these geographic areas because of large reductions in tropospheric ozone concentrations attributable to the CAAA. Overall, relative yield losses appear to be greatest in the geographic areas with the greatest reduction in ozone concentration (see maps in Appendix B). In particular, the greatest relative yield losses for both crops and trees occur in the Southeast, frequently in Virginia, North Carolina, South Carolina, and Tennessee.

ANALYTICAL METHODS AND RESULTS: AGRICULTURE AND TIMBER MARKETS WELFARE EFFECTS

This section describes the methods and results of the analysis of welfare effects stemming from changes in crop and tree yields under the baseline scenario relative to the counterfactual scenario. Commercial timber and agriculture operations generally manage land to maximize profits. As such, changes in crop yields between the baseline and counterfactual scenarios may affect the distribution of commercial species planted; for example, landowners may shift production towards plants that are less sensitive to elevated ozone concentrations under the counterfactual scenario. This may occur at the individual plant level, replacing one crop or tree species for another with a higher growth rate; or, it may occur at the community level, converting agricultural lands to timberlands, or vice versa, to adjust for combined yield losses to agricultural crops and commercial tree species.

Changes in the distribution and yield of crop and tree species may in turn affect the supply of and demand for agricultural crops and commercial tree species, resulting in changes in the welfare of consumers and within agricultural and timber sectors of the economy. To quantify this economic benefit of cleaner air, we used FASOM. FASOM development was funded by EPA's Climate Economics Branch (CEB) and other EPA, U.S. government, and non-governmental funders over several decades as a partial equilibrium tool to evaluate the welfare and market impacts of public policies affecting agriculture and forestry. The model simulates biophysical and economic processes affecting land management and land allocation decisions over time to potentially competing agriculture and forest activities. Although the latest version of FASOM was developed to evaluate climate and biofuels policies, the model is capable of assessing a

EXHIBIT 4-7. MINIMUM, MAXIMUM, AND AVERAGE RELATIVE YIELD LOSSES ACROSS ALL FASOM SUBREGIONS FOR CROPS AND ALL FASOM REGIONS FOR TREES BY YEAR (2000, 2010, 2020)

CROP/FOREST TYPE	2000			2010			2020		
	MINIMUM	MAXIMUM	AVERAGE	MINIMUM	MAXIMUM	AVERAGE	MINIMUM	MAXIMUM	AVERAGE
Barley	0.00%	0.02%	0.01%	0.00%	0.06%	0.02%	0.00%	0.07%	0.02%
Corn	0.00%	1.12%	0.18%	0.00%	3.07%	0.44%	0.00%	3.45%	0.56%
Cotton	0.00%	6.60%	1.15%	0.00%	16.67%	3.00%	0.00%	20.31%	3.81%
Oranges	0.00%	1.95%	0.09%	0.00%	4.68%	0.25%	0.00%	7.87%	0.43%
Potato	0.00%	6.17%	1.76%	0.00%	17.54%	4.99%	0.00%	20.80%	6.50%
Rice	-0.08%	0.14%	0.00%	0.00%	1.03%	0.11%	0.00%	1.66%	0.18%
Sorghum	0.00%	0.87%	0.14%	0.00%	2.17%	0.35%	0.00%	2.65%	0.47%
Soybean	0.00%	3.60%	1.24%	-0.55%	11.73%	3.07%	0.00%	12.74%	4.26%
Processing Tomatoes	0.00%	1.82%	0.31%	0.00%	5.54%	0.96%	0.00%	8.21%	1.47%
Spring Wheat	0.00%	1.50%	0.06%	0.00%	3.67%	0.15%	0.00%	6.98%	0.28%
Winter Wheat	0.00%	6.53%	1.00%	0.00%	18.23%	2.49%	0.00%	19.23%	3.29%
Hardwood Forests	1.60%	7.16%	5.06%	4.20%	19.12%	13.86%	6.61%	23.04%	16.68%
Softwood Forests	0.06%	3.85%	1.77%	0.25%	10.49%	4.88%	0.42%	12.27%	6.11%

Note: Negative relative yield losses indicate yield reductions with the CAAA.

broad range of factors that might affect plant growth; for this project, we worked with the model's developers to develop input files to characterize the impact of ozone on plant and tree growth at a regional and crop-specific level, using the exposure-response results described above.[52]

Although FASOM has been widely applied to agricultural sector analysis and has been peer reviewed in many contexts, it has not to date been subject to a validation exercise comparing the model results for an historical period to historical data for that period.[53] As a result, the performance of the model in forecasting future agricultural sector effects, such as those estimated for this study, has not yet been assessed. Two other potential limitations may pertain in EPA's application of FASOM for this study. First, FASOM adopts a model simulation approach which assumes perfect foresight by economic actors in the agricultural sector. A perfect foresight assumption may be of concern for some long-term analyses, but is likely to be less problematic for this study because our time horizon extends only to 2020. Furthermore, USDA projections of commodity prices and outputs also extend nearly to 2020, and FASOM's projections for their base case agree well with the USDA projections. As a result, the effect of perfect foresight on model outcomes in the present study is reduced.[54] A second potential limitation of FASOM is its approach to estimating the sensitivity of imports to changes in domestic prices. Although FASOM is not a full international model, it does incorporate an import elasticity estimate for the largest and most important commodity crops. This allows the model to capture, for example, increases in agricultural imports to the U.S. under a scenario in which domestic crop prices are projected to rise. For a number of minor crops, traded in very small quantities, however, FASOM holds imports fixed. The effect of this factor on our results is not clear, but we estimate that a more flexible import sector for these much less important crops would have only a minor effect on our estimates of the net benefits of reducing ozone exposure for U.S. crops. We expect the directional bias of holding minor crop imports fixed, while small, would be to slightly reduce our estimates of the net welfare benefit of reducing ozone exposure, and thereby improving productivity, of domestic agricultural crops.

[52] Note that we performed two runs of the FASOM model, one where the response to ozone for those crop/region combinations without specific individual concentration-response functions are assumed to be zero, and a second where impacts on crop/region combinations without specific concentration-response functions were set to the values used in adjacent regions and/or proxy crops where possible (for example, soft white wheat was used for barley and sugarbeets; tomatoes for processing were used for potatoes; soybeans for fresh tomatoes; corn for fresh tomatoes if there is not a value for soybeans; etc.). We found that the difference in the overall national results between these two runs was negligible, however. As a result, in this chapter we report the results from the run that applies proxy crop/region concentration-response functions. Note further that the version of FASOM used for this analysis is the version current as of July 21, 2010.

[53] See, for example, a review commissioned by USEPA for its application of FASOM to support regulatory analysis of renewable fuels standards, concluded in July of 2010 and available at the following web site (accessed November 26, 2010): http://www.epa.gov/otaq/fuels/renewablefuels/regulations.htm

[54] Perfect foresight is a basic assumption of the modeling approach on which FASOM is based. Structuring the model based on perfect foresight rather than a myopic (recursive) approach allows an expanded array of policy simulations and potential insights, which is the main purpose of this type of model.

The economic welfare results of the FASOM modeling are presented in Exhibit 4-8. FASOM generates total welfare estimates for the agricultural and forest sectors for each of our scenarios, for each target year, reflecting the sum of total consumer and producer surplus derived from agriculture and forest production. In general, higher ozone concentrations in the *without-CAAA* scenario lead to reduced agricultural and forest productivity, raising prices for these products, which in turn increases producer surplus but reduces consumer surplus by a larger amount. As a result, FASOM estimates the net welfare benefits of the CAAA to be approximately $1 billion in 2000, $5.5 billion in 2010, and $10.7 billion in 2020, increasing over time as the differences in ozone concentrations grows.[55]

EXHIBIT 4-8. SUMMARY OF FASOM RESULTS: TOTAL CONSUMER AND PRODUCER SURPLUS VALUES FOR THE AGRICULTURAL AND FOREST SECTORS

VARIABLE	MODEL RUN	2000	2010	2020
Annual Welfare, US Forest Sector	With Clean Air Act ($ billion)	$637	$877	$1426
	Without Clean Air Act ($ billion)	$636	$875	$1426
	Damage Estimate ($ billion)	**$1.5**	**$1.7**	**$0**
	Percent change	0.24%	0.20%	0%
Annual Welfare, US Agriculture Sector	With Clean Air Act ($ billion)	$1706	$1831	$1916
	Without Clean Air Act ($ billion)	$1706	$1828	$1905
	Damage Estimate ($ billion)	**–$0.5**	**$3.8**	**$10.6**
	Percent change	-0.03%	0.21%	0.55%
Annual Welfare, Forest and Agriculture Sector Combined	With Clean Air Act ($ billion)	$2343	$2708	$3341
	Without Clean Air Act ($ billion)	$2242	$2703	$3331
	Damage Estimate ($ billion)	**$1.0**	**$5.5**	**$10.7**
	Percent change	0.05%	0.20%	0.32%

Notes:

1. Results are expressed in year 2006 dollars.

In general, FASOM forecasts a relative shift towards forestry and away from agriculture under the *without-CAAA* scenario, indicating that the net impacts of the ozone effects on forests and agriculture would make forestry relatively more profitable than in the baseline compared with agriculture, resulting in a shift in land use. The model forecasts a sizable increase in cropland in the *without-CAAA* scenario, however there is an even greater

[55] Note that the year 2000 in FASOM represents average annual activity over the 5-year period from 2000 to 2004; 2010 represents 2010 through 2014; and 2020 represents 2020 through 2024. Values provided for ozone impacts in 2000, 2010, and 2020 were applied to the 2000, 2010, and 2020 model periods in FASOM, respectively. The results presented here do not includes losses Canada and the rest of the world; for example, in 2020, higher US prices in the without-CAAA scenario result in additional consumer surplus losses to non-US consumers of $1.7 billion in the forest sector and $3.3 billion in the agricultural sector.

decline in pasture as the returns to crop production rise relative to livestock production with higher crop prices. As is shown in Exhibit 4-8, the shift towards forestry results in a decrease in the damage estimate to this sector over time; by 2020 the damage estimate is $0.

As noted above, the model suggests that the damages attributed to higher ozone concentrations indicate that producers gain in many cases, while consumers are always substantially worse off with the ozone impacts reducing productivity. The reason that producers often are better off is that most forest and agricultural products have relatively inelastic demands, which means that a general decline in productivity will tend to increase prices by more than the reduction in quantity, increasing revenue and often profits as well. In general, FASOM attributes large price increases in response to the reductions in productivity for these inelastic products, and production declines in the *without-CAAA* scenario for most agricultural commodities, with larger declines in general for those products experiencing larger ozone impacts, and also sizable reductions in exports.

FASOM also is capable of modeling land-use changes in response to the higher ozone concentrations in the *without-CAAA* scenario. The model indicates changes in major land use categories at the national level over time under the ozone impacts scenario, which leads to a net increase in forest of about 6.1 million acres by the 2020 model period and a increase in cropland of 7.6 million acres by 2020 in response to the productivity declines. At the same time, the model indicates that cropland pasture (high-quality land that is suitable for cropland but is being used as pasture) and pasture (lower-quality land that is not suitable for growing crops without improvement) decline by a total of 12.7 million acres and Conservation Reserve Program (CRP) land decreases by about 1 million acres. The crop experiencing the largest reduction in acreage is soybeans, while there is an increase in wheat acreage and a number of smaller shifts between alternative crops.

CHAPTER 5 | ESTIMATION OF MATERIALS DAMAGE AND ECONOMIC BENEFITS

INTRODUCTION

Since the mid-19th century air pollution as been suspected of accelerating the degradation of natural and man-made materials that are exposed to the outdoor environment. Concern over the effect of pollutants on materials has mainly been directed towards the economic consequences of damage to materials used in construction, but aesthetic damage to historic buildings and monuments is also a concern. Wet and dry acidic deposition, alone or combined with other air pollutants, contribute to the increased rate of materials damage. The principal components of acid deposition considered injurious to building materials are hydrogen ion (H^+), sulfur oxides (SO_x), and nitrogen oxides (NO_x). In addition, volatile organics and oxidizing agents such as ozone (O_3) and hydrogen peroxide (H_2O_2) have been shown to play an ancillary role (NAPAP, 1991). Acidic deposition has been shown to have an effect on materials including zinc/galvanized steel and other metal, carbonate stone (as monuments and building facings), and surface coatings (paints) (NAPAP, 1991).

Metal structures are usually coated by alkaline corrosion product layers and thus are subject to increased corrosion by acidic deposition. In addition, research has demonstrated that iron, copper, and aluminum based products are subject to increased corrosion due to pollution, in particular SO_2 (NAPAP, 1991). Research has shown that acidic deposition (wet deposition of hydrogen ion and dry deposition of SO_2 and nitric acid) accelerates the rate of erosion of carbonate stone (marble and limestone) and the formation of gypsum crusts on the stone (NAPAP, 1991). Acidic deposition has numerous negative effects on painted wood and, in general, increases the weathering rate. In addition, acidic pollutants negatively affects painted metals resulting in adsorption, weight gain, discoloration, adhesion strength loss and/or failure at the metal/primer interface. Acidic deposition may also cause damage to automotive finishes (NAPAP, 1991).

This analysis will focus on quantifying the impact of sulfur dioxide deposition on exterior building and infrastructural materials including carbonate stone, galvanized steel, carbon steel, and painted wood. Exhibit 1 lists the materials damage effects that are quantified and unquantified in this analysis. The economic impact of materials damage will be calculated for six scenarios: *with-* and *without-CAAA* in 2000, 2010, and 2020. The difference between the *with-* and *without-CAAA* scenarios in each year represents the benefits of reduced materials damage due to CAAA-related programs.

EXHIBIT 5-1. MATERIALS DAMAGE EFFECTS

POLLUTANT	QUANTIFIED EFFECTS—DAMAGE TO:	UNQUANTIFIED EFFECTS[A]—DAMAGE TO:
Sulfur oxides	Infrastructural materials - galvanized and painted carbon steel Commercial buildings - carbonate stone, metal, and painted wood surfaces Residential buildings - carbonate stone, metal, and painted wood surfaces	Monuments - carbonate stone and metal Structural aesthetics Automotive finishes - painted metal
Hydrogen ion and nitrogen oxides		Infrastructural materials - galvanized and painted carbon steel Zinc-based metal products, such as galvanized steel Commercial and residential buildings - carbonate stone, metal, and wood surfaces Monuments - carbonate stone and metal Structural aesthetics Automotive finishes - painted metal
Carbon dioxide		Zinc-based metal products, such as galvanized steel
Formaldehyde		Zinc-based metal products, such as galvanized steel
Particulate matter		Household cleanliness (i.e., household soiling)
Ozone		Rubber products (e.g., tires)
a The categorization of unquantified effects is not exhaustive.		

METHODOLOGY

This analysis applies the Air Pollution Emissions Experiments and Policy (APEEP) analysis model, described in Muller and Mendelsohn (2007, 2009), to link SO2 emissions to ambient SO2 levels. Using emission inputs, the air quality model in APEEP predicts seasonal and annual average county concentrations for SO2, amongst other pollutants. As reported in Muller and Mendelsohn (2007), APEEP's air quality modeling has been statistically tested against the predictions generated by the Community Multi-scale Air Quality Model (CMAQ).

Materials damage estimates are derived using dose-response functions that relate material mass loss to ambient SO2. A key piece of information needed in the dose-response functions is the existing materials inventories. Categorization of materials inventories has been a challenge in the past. This analysis presents a method for estimating materials inventories by county. The materials inventory characterizes the quantity of four exterior building and infrastructural materials in each county in the lower 48 states. These include inventories of carbonate stone, galvanized steel, carbon steel, and painted wood surfaces.

The inventory is developed for infrastructure, commercial buildings and residential buildings separately. The commercial inventory uses empirical results from the U.S. Department of Energy (U.S.DOE) Information Administration's Commercial Buildings Energy Consumption Survey (U.S. DOE, 2006). The residential materials inventory employs data from the U.S. DOE's Residential Energy Consumption Survey and the Annual Housing Survey conducted by the U.S. Census Bureau (USDOE, 2005; Census Bureau, 2007).

The inventory differentiates buildings based on their reported size, given how the primary survey data are reported. That is, the surveys provide structure size in terms of floor space (ft^2). Thus, a simplifying assumption regarding the shape of the structure (it is posited that each structure is cubic with two stories of living space) permits the conversion from floor space to wall space. This implies that the total area of living space is equivalent to twice the area of one story. Thus, given the cubic shape assumption, the area of the four walls is equivalent to four times the area of one story, or two times the total reported area.

This inventory also estimates the number of buildings based on the share of regional and state population in each county. Since the U.S. DOE reports total commercial buildings (by size) by region, the inventory extrapolates to state-level inventories by assuming that the number of commercial buildings in each state is proportional to the share of regional population in each state. The same approach is used to extrapolate from the state to the county level. For both the commercial and residential inventory, the survey provides number of buildings, by size, by region which permits an assessment of the number of buildings by size, for each state and county.

Having estimated the number and size of buildings by county, the next step involves calculating the probability of each material being used in each region of the country, for each building type. Materials use for commercial buildings is computed directly from the U.S. DOE's commercial survey since the number of buildings using each exterior building material is estimated in the survey. Proportions of total buildings using each material type are computed from the survey data directly. Materials used for residential buildings is computed in an analogous manner from the U.S. DOE's residential survey; the proportion of total residential buildings using particular building materials is computed directly from the reported materials use probabilities by region.

The building surface area calculations assume the following form:

$$SA_{mc} = \sum_t (N_{ct})(S_{ct})(P_{mc})$$

where: SA_{mc} = exposed surface area of building material (m) in receptor county (c),

N_{ct} = number of structures type (t) in county (c),

S_{ct} = area of exterior wall space per structure type (t) and county (c), and

P_{mc} = probability that material (m) is used on exterior wall space in county (c).

For infrastructural materials (galvanized and painted carbon steel), the materials inventory relies on methods developed in the National Acid Precipitation Assessment Program (NAPAP) (NAPAP, 1991). In particular, NAPAP reported surface area estimates for galvanized and carbon steel (focusing on bridges, transmission towers, railroads, and guardrail) for particular areas of the country. The ratios of exposed surface area to land area are then extrapolated to states and regions not covered by the original NAPAP surveys.

Dose-response functions for man-made materials damages are obtained from two sources; the NAPAP studies (Atteraas, Haagenrud, 1982; Haynie, 1986) and from the International Cooperative Programme on Effects on Materials (ICP, 1998). The materials corrosion dose-response functions assume three slightly different forms. The function representing the effect of ambient SO_2 on galvanized steel is from Atteraas and Haagenrud (1982). The function is based on analysis of mass loss data of standard material test panels using regression techniques. Field data from 22 sites in Norway were used to obtain this dose-response function. The function predicts that mass loss is a linear function of ambient SO_2 concentration. The dose-response function for galvanized steel assumes the following form:

$$\Delta M_c = (\beta_0 SO_{2c} + \beta_1) M_c$$

where: ΔM_c = mass loss of material by county (c),

β_0, β_1 = statistically estimated parameters from the literature,

SO_{2c} = ambient concentration of SO_2 by county (c), and

M_c = existing material by county (c).

For painted surfaces, the dose-response relationship is from Haynie (1986). Haynie developed this equation on the basis of the erosion data obtained from painted specimens exposed to SO_2 and moisture. The model predicts the increase in erosion over the estimated erosion at a pH of 5.2 and an SO_2 concentration of zero (representative of a clean environment). The pH data used in this function is from the National Atmospheric Deposition Program (NADP) and varies by region. It should be noted that pH, frequency exposed surface area is wet, and annual rainfall do not vary across scenarios. The dose-response function for painted surfaces takes the following form:

$$\Delta M_c = R_c\beta_0(10^{-pH} - 10^{-5.2}) + \beta_1 SO_{2c}F_c \qquad (3)$$

where: ΔM_c = mass loss of material by county (c),

β_0, β_1 = statistically estimated parameters from the literature,

SO_{2c} = ambient concentration of SO_2 by county (c),

pH = average pH by region,

F_c = frequency exposed surface area is wet by county (c), and

R_c = annual rainfall.

The dose-response function representing the effect of ambient SO_2 on carbonate stone surfaces comes from the International Cooperative Programme on Effects on Materials Report No 30. This report summarizes the results obtained from an extensive field exposure program. The program gathered data on materials corrosion at 39 exposure sites in 12 European countries, the U.S., and Canada and measured gaseous pollutants, precipitation, and climate parameters at or nearby the exposure sites. Regression techniques were then used to relate the materials corrosion data to the environmental parameters. It should be noted that ambient temperature, annual rainfall, and hydrogen concentration of precipitation do not vary across scenarios. The resulting dose-response function for carbonate stone surfaces takes the following form:

$$\Delta S_c = (\beta_0 SO_{2c}^{\kappa})\exp(\gamma T_c) + \beta_1 R_c)H^+$$

where: ΔS_c = surface recession of material by county (c),

β_0, β_1,γ,κ = statistically estimated parameters from the literature,

SO_{2c} = ambient concentration of SO_2 by county (c),

M_c = existing material by county (c),

T_c = ambient temperature by county (c),

R_c = annual rainfall by county (c), and

H^+ = hydrogen concentration of precipitation.

Materials damage is valued as the cost of future materials maintenance activities. The accelerated rate of materials decay due to pollution exposure increases the frequency of regularly scheduled future maintenance activities. Under baseline emission conditions we assume a five-year maintenance schedule. The present value of materials maintenance costs occurring on a five-year schedule is calculated using the following formula:

$M_{rb} = \delta \times (RC_{rb}(e^{-rt})/(1 - e^{-rt})$

where: M_{rb} = annual maintenance costs in county (r), baseline SO_2,

δ = market interest rate (4%),[56]

RC_{rb} = replacement costs in receptor county (r), baseline SO_2, and

t= time of repairs (5,10,15,...,T).

A change in the frequency of maintenance activities due to a change in emissions is calculated as the ratio of the materials inventory after the emission change (I_p) to the materials inventory before the change (I_b). This ratio characterizes the extent to which a change in emissions has enhanced or mitigated materials decay rates. If the emission change increases pollution, then $I_p<I_b$, and the optimal maintenance schedule will occur earlier than every five years. This ratio is then multiplied by the five-year maintenance schedule, as shown in Equation 6, to yield the timing of the amended maintenance schedule due to the change in pollution (t^*):

$t^* = 5 \times (I_p/I_b)$.

The materials maintenance cost equation (Equation 5) is adjusted to account for the amended maintenance schedule as follows:

$M_{rp} = \sum_t [\delta \times (RC_{rp}(1+r)^{-t^*})]$

where: M_{rp} = annual maintenance costs in county (r), change emission SO_2,

δ= market interest rate (4%),

RC_{rp} = Replacement costs in receptor county (r), change emission SO_2, and

t^* = new schedule of maintenance.

The change in the present value of the maintenance schedules extending into the future constitutes the monetary impact of an emission change on materials damage. The effect of an emission change from source (s) is the sum of the change in all affected pollution receptor counties:

$\Delta M_s = \sum_r (M_{rp} - M_{rb})$.

56 The APEEP model used for this analysis incorporates a four percent discount rate. A five percent discount rate has been used in other portions of the Second Prospective Analysis. Use of a five percent discount rate would lead to somewhat lower present value benefits.

RESULTS

Exhibit 2 summarizes the benefits of reduced materials damage due to CAAA programs in 2000, 2010, and 2020. Benefits are given by EPA region. As expected, benefits of CAAA programs to materials damage increase over time. The spatial distribution of the benefits is primarily owing to the distribution of the materials inventory and SO_2 exposure. The effect of SO_2 exposure seems to be driving the results. For example, the benefits in Region 5 are approximately twice as large as those in any other EPA region. This is due to the significant decrease in SO_2 exposure associated with the CAAA in this region.

EXHIBIT 5-2. BENEFITS OF REDUCED MATERIALS DAMAGE DUE TO CAAA PROGRAMS

EPA REGION	VALUATION (THOUSAND 2006$)		
	2000	2010	2020
1: CT, ME, MA, NH, RI, VT	$720	$2,100	$2,100
2: NY, NY	$9,000	$10,000	$12,000
3: DE, DC, MD, PA, VA, WV	$9,400	$19,000	$23,000
4: AL, FL, GA, KY, MS, NC, SC, TN	$8,400	$16,000	$21,000
5: IL, IN, MI, MN, OH, WI	$26,000	$38,000	$38,000
6: AR, LA, NM, OK, TX	$2,200	$4,000	$7,300
7: IA, KS, MO, NE	$2,000	$1,600	$1,600
8: CO, MT, ND, SD, UT, WY	$400	$570	$730
9: AZ, CA, NV	-$100	$490	$640
10: ID, OR, WA	$340	$510	$560
Total	**$58,000**	**$93,000**	**$110,000**

Notes: Results are rounded to two significant figures. Totals may not sum due to rounding.

CHAPTER 6 | SUMMARY OF PRIMARY BENEFITS

This chapter presents an integrated summary of the quantified and monetized primary benefits estimates described in this report and in the companion Second Prospective Section 812 study report, *Ecological Benefits Analyses to Support the Second Section 812 Prospective Benefit-Cost Analysis of the Clean Air Act.*

SUMMARY OF ANNUAL BENEFITS

The results of this benefits analysis demonstrate that implementation of the CAAA's programs on air emissions yields substantial human health and welfare benefits across the U.S. over the period from 1990 to 2020. These benefits include reductions in mortality risk, reductions in respiratory and cardiovascular morbidity, improved visibility, improved productivity of agricultural crops and commercial forests, and reduced materials damage to resources as bridges, architectural coatings, and other materials that can be damaged by air pollution. Exhibit 6-1 presents a summary of the mean primary annual economic benefits results from the Second Prospective analysis for 2000, 2010, and 2020. Total annual benefits range from $770 billion in 2000 to $2,000 billion 2020 across all monetized benefit categories, with increasing benefits for each target year.

The bulk of the economic benefits result from improvements in human health; primarily from the reduction in premature mortality, which constitutes 88 percent of the total monetized benefits value in 2020. As we acknowledge throughout this report, there are numerous effects of improved air quality, including most of the ecological benefits that we currently are unable to quantify and/or monetize. A proper economic accounting of these benefits would likely lead to even greater benefit values and would alter the relative contribution of the different categories of effects. Exhibit 6-2 presents a list of the un-quantified and/or un-monetized benefit associated with CAAA improvements in air quality.

SUMMARY OF CUMULATIVE MONETIZED BENEFITS

Although this analysis focused on estimating annual benefits for each of three target years, benefits of improved air quality due to the CAAA are expected to accrue through the study period. We estimate these cumulative benefits by interpolating between the target years, using information on the expected trend and trajectory of benefits throughout the period, and aggregating the resulting values to produce a discounted present value estimate of the cumulative benefits of Titles I through V of the CAAA.

EXHIBIT 6-1. SUMMARY OF MEAN PRIMARY BENEFITS RESULTS

BENEFIT CATEGORY	MONETIZED BENEFITS (MILLION 2006$) BY TARGET YEAR			NOTES
	2000	2010	2020	
Health Effects				
PM Mortality PM Morbidity Ozone Mortality Ozone Morbidity	$710,000 $27,000 $10,000 $420	$1,200,000 $46,000 $33,000 $1,300	$1,700,000 $68,000 $55,000 $2,100	- PM mortality estimates based on Weibull distribution derived from Pope et. al (2002) and Laden et al., 2006. - Ozone mortality estimates based on pooled function
Subtotal Health Effects	$750,000	$1,300,000	$1,900,000	
Visibility				
Recreational Residential	$3,300 $11,000	$8,600 $25,000	$19,000 $48,000	Recreational visibility only includes benefits in the regions analyzed in Chestnut and Rowe, 1990 (i.e., California, the Southwest, and the Southeast).
Subtotal Visibility	$14,000	$34,000	$67,000	
Agricultural and Forest Productivity	$1,000	$5,500	$11,000	
Materials Damage	$58	$93	$110	
Ecological	$6.9	$7.5	$8.2	Reduced lake acidification benefits to recreational fishing assuming effect threshold of 50 microequivalents per liter.
Total: all categories	$770,000	$1,300,000	$2,000,000	
Note: See Chapters 2 through 5 of this report for detailed results summaries. Values presented are means from results reported as distributions. Additional, alternative estimates are provided in the separate companion report on uncertainty. Estimates presented with two significant figures.				

EXHIBIT 6-2. SUMMARY OF UNQUANTIFIED BENEFITS

BENEFIT CATEGORY	UNQUANTIFIED BENEFITS IN PRIMARY ESTIMATE [a]
Health Effects - PM	• Subchronic bronchitis cases • Low birth weight • Pulmonary function • Chronic respiratory diseases other than • chronic bronchitis • Morphological changes • Altered host defense mechanisms • Cancer • Non-asthma respiratory emergency room • Visits • UVb exposure (+/-) b • Stroke/cerebrovascular disease
Health Effects - Ozone	• Cardiovascular emergency room visits • Asthma attacks • Respiratory symptoms • Chronic respiratory damage • Increased responsiveness to stimuli • Inflammation in the lung • Premature aging of the lungs • Acute inflammation and respiratory cell damage • Increased susceptibility to respiratory infection • Non-asthma respiratory emergency room • Visits • UVb exposure (+/-)[b]
Visibility	Recreational benefits for Class I areas outside of California, Southwest, and Southeast.
Agricultural and Forest Productivity	Productivity benefits not related to ozone (e.g., sulfur deposition effects on timber).[d]
Materials Damage	• Monuments – carbonate stone and metal (sulfur oxides, Hydrogen ion and nitrogen oxides) • Structural aesthetics (sulfur oxides, Hydrogen ion and nitrogen oxides) • Automotive finishes – painted metal (sulfur oxides, Hydrogen ion and nitrogen oxides) • Infrastructural materials – galvanized and painted carbon steel (Hydrogen ion and nitrogen oxides) • Zinc-based metal products, such as galvanized steel (Hydrogen ion and nitrogen oxides, Carbon dioxide, formaldehyde) • Commercial and residential buildings – carbonate stone, metal, and wood surfaces(Hydrogen ion and nitrogen oxides) • Household cleanliness (i.e., household soiling) (PM) • Rubber products (e.g., tires) (Ozone)
Ecological	The majority of ecological benefits are qualitative. [c]

Notes:

[a] The categorization of unquantified health effects is not exhaustive.

[b] May result in benefits or disbenefits.

[c] Chapter 2 of the ecological report (Effects of Air Pollutants on Ecological Resources: Literature Review and Case Studies) provides a qualitative characterization of ecological effects of the CAAA. Specifically, Exhibits 2-2, 2-4, 2-6, and 2-8 summarize by pollutant class and level of biological organization the potential effects of pollutants regulated by the CAAA on ecosystem structures and functions. Based on the availability of both ecological and economic data and models, we identified a subset of ecological endpoints amenable to monetization: a case study of the effects of acidic deposition effects on recreational fishing, and a national level analysis focused on the effects of tropospheric ozone exposure on commercial agriculture and silviculture. Categories of potential ecological benefit not quantified include: forest productivity benefits due to decreased acidic deposition; commercial freshwater fishing; preservation of biodiversity; increased carbon sequestration in forests; and decreased eutrophication of estuaries.

[d] Chapter 4 only focuses on the effects of tropospheric ozone. Effects of other pollution on agricultural and forest productivity are not quantified.

Air quality modeling was carried out only for the three target years (2000, 2010, and 2020). The resulting annual benefit estimates indicate an increasing temporal trend of monetized benefits across the period resulting from the annual changes in air quality. They do not, however, characterize the uncertainty associated with the yearly estimates for intervening years. In an effort to generate improved estimates of the trajectory of benefits in these years, the 812 Project Team generated emissions reduction trajectories across the study period for seven pollutants in the *with-* and *without-CAAA* scenarios. Appendix O of the Second Section 812 Prospective Emissions Analysis describes the methods used to derive trajectories for each major emitting sector and presents emissions trajectories for VOC, NO_x, CO, SO_2, PM10, $PM_{2.5}$, and NH_3, which we reproduce here as Exhibits 6-3a and 6-3b. In general, these trajectories show flat to slightly increasing reductions in the early 1990s followed by relatively rapid increases in reductions between the mid-1990s and 2000. From 2000 through the end of the study period, the seven pollutants show a steady linear increase in reductions.

To estimate benefits between each of the target years, the 812 Project Team developed a benefits index by multiplying the emission trajectories for each pollutant/source category by dollar per ton values taken from the Ozone NAAQS RIA. The 812 Project Team used this index to interpolate benefits between each of the target years. Our interpolation approach is illustrated in Exhibit 6-4.

EXHIBIT 6-3A. TRAJECTORY OF CAAA-RELATED REDUCTIONS IN VOC, NO_X, AND SO_2 EMISSIONS: 1990 THROUGH 2020 (TONS OF POLLUTANT REDUCED)

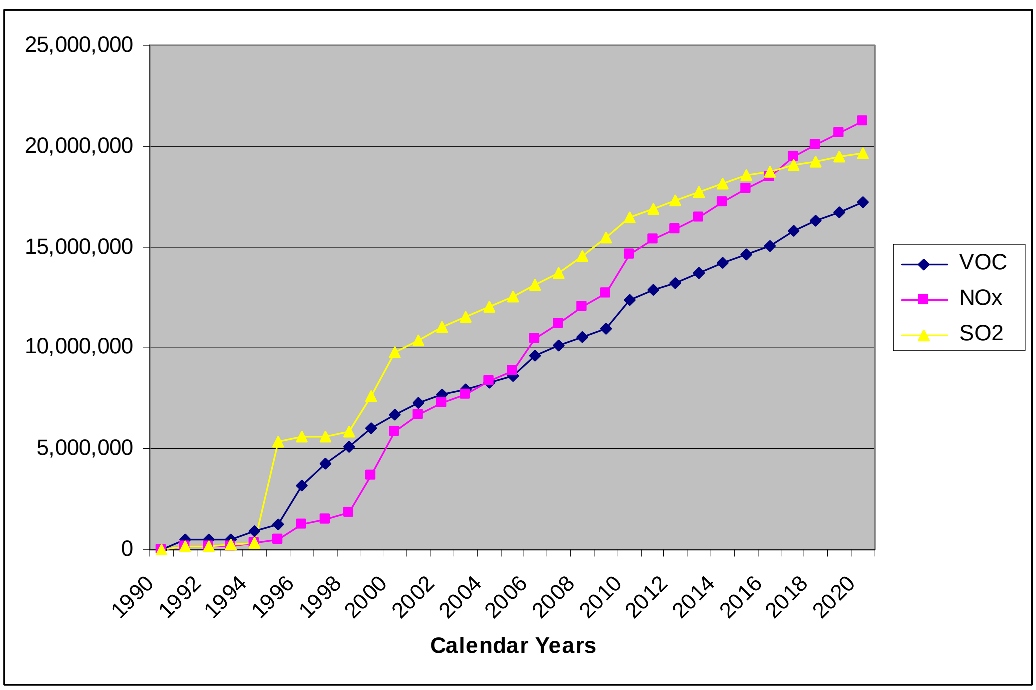


EXHIBIT 6-3B. TRAJECTORY OF CAAA-RELATED REDUCTIONS IN PM_{10} AND $PM_{2.5}$ EMISSIONS: 1990 THROUGH 2020 (TONS OF POLLUTANT REDUCED)

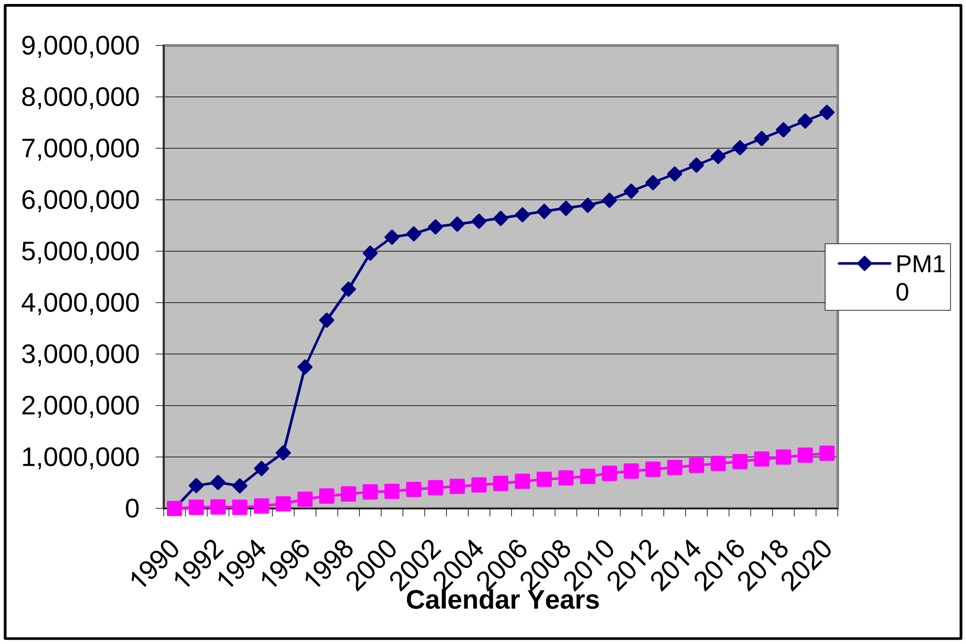
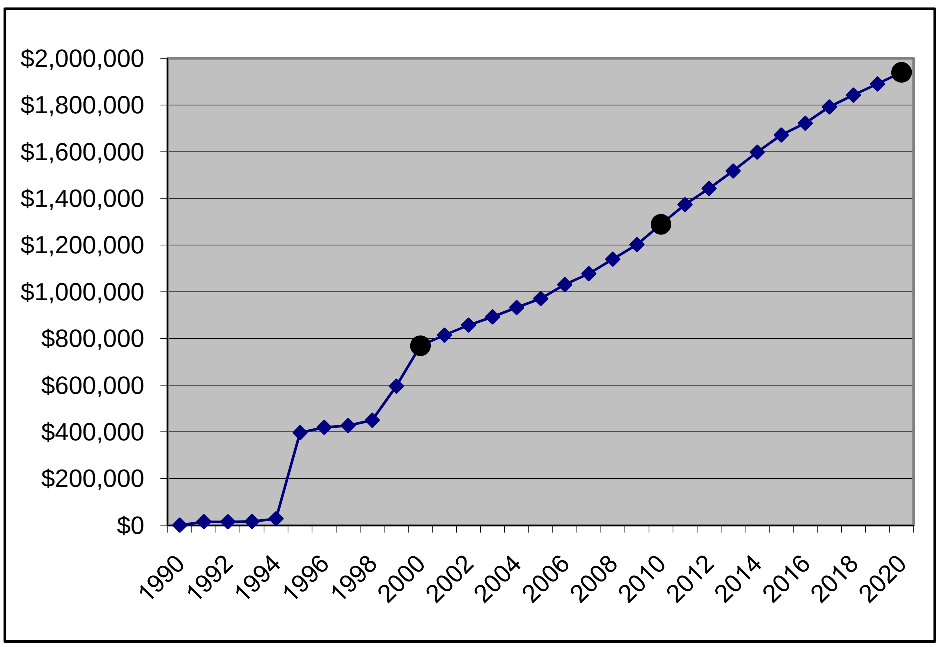


EXHIBIT 6-4. INTERPOLATION STRATEGY FOR CUMULATIVE BENEFITS



In an attempt to represent uncertainty associated with these estimates, we relied on the ratios of the 5th percentile to the mean and the 95th percentile to the mean in the target years. In general, these ratios were fairly constant across the target years, for a given endpoint. The ratios were interpolated between the target years, yielding ratios for the intervening years. Multiplying the ratios for each intervening year by the central estimate generated for that year provided estimates of the 5th and 95th percentiles, which we use to characterize uncertainty about the Primary Central estimate. In Exhibit 6-5 we present the cumulative monetized benefits aggregated from 1990 to 2020. We present the mean estimate from the aggregation procedure, along with the Primary Low (i.e., 5th percentile of the distribution) and Primary High (i.e., 95th percentile of the distribution) estimates, for all provisions of Titles I through V. Aggregating the stream of monetized benefits across years involved discounting the stream of monetized benefits estimated for each year to the 1990 present value (using a five percent discount rate).

EXHIBIT 6-5. CUMULATIVE MONETIZED BENEFITS OF CAAA TITLES I THROUGH V IN THE U.S.

PRESENT VALUE (MILLIONS 2006$, DISCOUNTED TO 1990 AT 5 PERCENT)		
PRIMARY LOW	PRIMARY CENTRAL	PRIMARY HIGH
$1,400,000	$12,000,000	$35,000,000

Note: Values presented in this table are in millions of 2006$, discounted to 1990 using a 5 percent discount rate.

COMPARISON WITH RESULTS FROM THE FIRST PROSPECTIVE

The health effects estimates for the second prospective are much larger than the estimates EPA developed for the first prospective. The 2020 estimates are new to the second prospective, but the comparable mean estimate of health benefits in 2000 and 2010 for the first prospective were $71 billion in 2000 and $110 billion in 2010, in 1990$[57] - if updated to 2006$, these estimates would be $110 billion in 2000 and $170 billion in 2010. There are six key reasons we have identified for the increase in benefits:

1. ***Scenario differences*:** The *with-CAAA* scenario, especially for the 2010 target year, includes new rules with substantial additional pollutant reductions that were not included in the comparable first prospective scenario, such as the Clean Air Interstate Rule (CAIR).

[57] See The Benefits and Costs of the Clean Air Act 1990 to 2010, USEPA Office of Air and Radiation and Office of Policy, EPA-410-R-99-001, November 1999.

2. ***Improved air quality models*:** The first prospective relied on the Regional Acid Deposition Model/Regional Particulate Model (RADM/RPM) for PM and deposition estimates in the eastern U.S., the Regulatory Modeling System for Aerosols and Acid Deposition (REMSAD) for PM estimates in the western U.S., and the Urban Airshed Model (versions V and IV) at various regional and urban scales to generate ozone estimates. The second prospective relies on the integrated CMAQ modeling tool, which reflects substantial improvements in air quality modeling, provides more comprehensive spatial coverage, and achieves improved model performance.

3. ***Better, more comprehensive exposure estimates*:** The first prospective relied on first generation exposure extrapolation tools to generate monitor-adjusted exposure estimates away from monitors. Since then, the monitor network, availability of speciated data, and the performance of speciated exposure estimation tools have improved substantially.

4. ***Updated dose-response estimates***: Since 1999, some concentration response functions have been updated, most notably the PM-premature mortality C/R function, whose central estimate of the mortality impact of fine PM has nearly doubled. In addition, health effects research has addressed endpoints that were not covered in the first prospective, including premature mortality associated with ozone exposure.

Although the Agency has not yet conducted a rigorous quantitative analysis to assess the impact of these methodology and data improvements, the impact of most of these factors is to increase the estimates of benefits.

BENEFITS UNCERTAINTIES

The benefits values presented in this report are subject to a number of uncertainties related to data limitations, analytical choices related to models and input parameters, difficulties predicting future scenarios, and other factors. Among the most significant uncertainties is the extensive list of benefits categories, mostly in the ecological area, for which we currently lack the data and/or tools to quantify and monetize benefits. These categories are implicitly treated as having zero value though in reality they may include physical benefits that have a positive economic value. The unquantified and unmonetized benefits thus represent an underestimation bias in the summary benefit results.

The uncertainties in our quantified and monetized estimates that are most likely to significantly influence the primary benefit results are those affecting the largest benefit category: the estimation and valuation of reductions in premature mortality due to decreases in $PM_{2.5}$. Three key uncertainties affecting economic estimates of avoided PM mortality include: (1) the C-R function estimate; (2) the PM/mortality cessation lag structure; and (3) the mortality valuation estimate. These are influential assumptions in our analysis and those for which plausible alternative quantitative estimates are available. The companion Second Prospective Section 812 report, *Uncertainty Analyses to Support the Second Section 812 Benefit-Cost Analysis of the Clean Air Act*, presents detailed quantitative analyses of the sensitivity of benefits results to these and other factors. It also presents tables describing in a qualitative manner additional uncertainties that are not currently amenable to quantitative analysis, indicating the potential direction and significance of any potential bias introduced by each uncertain factor.

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APPENDIX A | PRIMARY ESTIMATES OF VISIBILITY BENEFITS BY STATE

This appendix gives the primary estimate of benefits to visibility from the CAAA by State in 2000, 2010, and 2020.

EXHIBIT A-1. PRIMARY ESTIMATE OF BENEFITS TO VISIBILITY BY STATE - 2000 (BILLION 2006$)

STATE	RECREATIONAL BENEFITS	RESIDENTIAL BENEFITS	TOTAL BENEFITS
Alabama	$0.06	$0.14	$0.20
Arizona	$0.06	-$0.24	-$0.18
Arkansas	$0.03	$0.08	$0.11
California	$0.39	$1.1	$1.4
Colorado	$0.05	$0.12	$0.17
Connecticut	$0.04	$0.14	$0.18
Delaware	$0.01	$0.06	$0.07
District of Columbia	$0.01	$0.05	$0.05
Florida	$0.22	$0.42	$0.64
Georgia	$0.11	$0.26	$0.37
Idaho	$0.01	$0.03	$0.04
Illinois	$0.13	$0.86	$0.99
Indiana	$0.07	$0.27	$0.33
Iowa	$0.03	$0.06	$0.09
Kansas	$0.03	$0.04	$0.07
Kentucky	$0.06	$0.11	$0.16
Louisiana	$0.05	$0.19	$0.24
Maine	$0.01	$0.08	$0.09
Maryland	$0.07	$0.37	$0.45
Massachusetts	$0.07	$0.25	$0.31
Michigan	$0.11	$0.37	$0.48
Minnesota	$0.05	$0.11	$0.16
Mississippi	$0.04	$0.06	$0.10
Missouri	$0.06	$0.20	$0.26
Montana	$0.01	$0.01	$0.02
Nebraska	$0.02	$0.02	$0.04
Nevada	$0.02	$0.03	$0.06
New Hampshire	$0.01	$0.04	$0.05
New Jersey	$0.09	$0.55	$0.64
New Mexico	$0.02	$0.01	$0.03
New York	$0.21	$1.6	$1.8

STATE	RECREATIONAL BENEFITS	RESIDENTIAL BENEFITS	TOTAL BENEFITS
North Carolina	$0.11	$0.30	$0.41
North Dakota	$0.01	$0.00	$0.01
Ohio	$0.12	$0.54	$0.66
Oklahoma	$0.04	$0.07	$0.11
Oregon	$0.04	$0.15	$0.18
Pennsylvania	$0.13	$0.91	$1.0
Rhode Island	$0.01	$0.04	$0.05
South Carolina	$0.06	$0.10	$0.15
South Dakota	$0.01	$0.01	$0.01
Tennessee	$0.08	$0.18	$0.26
Texas	$0.23	$0.57	$0.79
Utah	$0.03	$0.15	$0.18
Vermont	$0.01	$0.01	$0.02
Virginia	$0.10	$0.28	$0.38
Washington	$0.06	$0.12	$0.18
West Virginia	$0.02	$0.08	$0.11
Wisconsin	$0.06	$0.20	$0.26
Wyoming	$0.01	$0.00	$0.01
TOTAL	**$3.3**	**$11**	**$14**

EXHIBIT A-2. PRIMARY ESTIMATE OF BENEFITS TO VISIBILITY BY STATE - 2010 (BILLION 2006$)

STATE	RECREATIONAL BENEFITS	RESIDENTIAL BENEFITS	TOTAL BENEFITS
Alabama	$0.16	$0.29	$0.44
Arizona	$0.18	-$0.16	$0.03
Arkansas	$0.08	$0.17	$0.25
California	$1.1	$2.7	$3.8
Colorado	$0.14	$0.25	$0.39
Connecticut	$0.09	$0.29	$0.38
Delaware	$0.03	$0.14	$0.17
District of Columbia	$0.02	$0.10	$0.12
Florida	$0.63	$1.1	$1.8
Georgia	$0.31	$0.68	$1.00
Idaho	$0.04	$0.06	$0.10
Illinois	$0.34	$1.4	$1.8
Indiana	$0.17	$0.57	$0.73
Iowa	$0.08	$0.12	$0.20
Kansas	$0.07	$0.11	$0.18
Kentucky	$0.14	$0.26	$0.40
Louisiana	$0.12	$0.32	$0.43
Maine	$0.04	$0.12	$0.15
Maryland	$0.19	$0.97	$1.2
Massachusetts	$0.17	$0.54	$0.71
Michigan	$0.27	$0.71	$0.98
Minnesota	$0.14	$0.23	$0.37
Mississippi	$0.10	$0.13	$0.23
Missouri	$0.15	$0.39	$0.55
Montana	$0.03	$0.01	$0.04
Nebraska	$0.05	$0.06	$0.11
Nevada	$0.08	$0.12	$0.20
New Hampshire	$0.04	$0.08	$0.12
New Jersey	$0.23	$1.2	$1.5
New Mexico	$0.06	$0.05	$0.10
New York	$0.50	$2.9	$3.4
North Carolina	$0.30	$0.95	$1.2
North Dakota	$0.02	$0.01	$0.03
Ohio	$0.30	$1.3	$1.6
Oklahoma	$0.09	$0.17	$0.26
Oregon	$0.10	$0.24	$0.33
Pennsylvania	$0.33	$2.0	$2.3
Rhode Island	$0.03	$0.09	$0.12
South Carolina	$0.15	$0.29	$0.44
South Dakota	$0.02	$0.01	$0.04
Tennessee	$0.20	$0.44	$0.64
Texas	$0.63	$1.38	$2.01
Utah	$0.08	$0.33	$0.40

STATE	RECREATIONAL BENEFITS	RESIDENTIAL BENEFITS	TOTAL BENEFITS
Vermont	$0.02	$0.02	$0.04
Virginia	$0.26	$0.92	$1.2
Washington	$0.17	$0.30	$0.47
West Virginia	$0.06	$0.19	$0.25
Wisconsin	$0.15	$0.36	$0.51
Wyoming	$0.01	$0.00	$0.01
TOTAL	**$8.6**	**$25**	**$34**

EXHIBIT A-3. PRIMARY ESTIMATE OF BENEFITS TO VISIBILITY BY STATE - 2020 (BILLION 2006$)

STATE	RECREATIONAL BENEFITS	RESIDENTIAL BENEFITS	TOTAL BENEFITS
Alabama	$0.33	$0.55	$0.87
Arizona	$0.43	$0.01	$0.44
Arkansas	$0.16	$0.35	$0.51
California	$2.4	$5.9	$8.3
Colorado	$0.32	$0.71	$1.0
Connecticut	$0.19	$0.57	$0.77
Delaware	$0.06	$0.26	$0.32
District of Columbia	$0.03	$0.17	$0.20
Florida	$1.4	$2.2	$3.6
Georgia	$0.69	$1.4	$2.1
Idaho	$0.09	$0.14	$0.24
Illinois	$0.71	$2.3	$3.0
Indiana	$0.35	$0.95	$1.3
Iowa	$0.16	$0.23	$0.39
Kansas	$0.15	$0.22	$0.37
Kentucky	$0.30	$0.44	$0.74
Louisiana	$0.25	$0.61	$0.86
Maine	$0.07	$0.18	$0.26
Maryland	$0.42	$1.9	$2.4
Massachusetts	$0.35	$1.1	$1.4
Michigan	$0.55	$1.2	$1.8
Minnesota	$0.31	$0.47	$0.78
Mississippi	$0.21	$0.25	$0.46
Missouri	$0.33	$0.69	$1.0
Montana	$0.06	$0.03	$0.08
Nebraska	$0.10	$0.13	$0.22
Nevada	$0.20	$0.33	$0.53
New Hampshire	$0.08	$0.16	$0.24
New Jersey	$0.50	$2.3	$2.8
New Mexico	$0.13	$0.10	$0.23
New York	$1.03	$4.8	$5.8
North Carolina	$0.65	$1.9	$2.6
North Dakota	$0.04	$0.02	$0.05
Ohio	$0.61	$2.3	$2.9
Oklahoma	$0.20	$0.33	$0.53
Oregon	$0.22	$0.64	$0.86
Pennsylvania	$0.67	$3.5	$4.2
Rhode Island	$0.06	$0.18	$0.24
South Carolina	$0.32	$0.61	$0.93
South Dakota	$0.04	$0.03	$0.08
Tennessee	$0.44	$0.84	$1.3
Texas	$1.4	$2.7	$4.1
Utah	$0.18	$0.72	$0.90

STATE	RECREATIONAL BENEFITS	RESIDENTIAL BENEFITS	TOTAL BENEFITS
Vermont	$0.04	$0.03	$0.07
Virginia	$0.58	$1.9	$2.5
Washington	$0.38	$0.81	$1.2
West Virginia	$0.12	$0.32	$0.44
Wisconsin	$0.32	$0.67	$0.99
Wyoming	$0.03	$0.00	$0.03
TOTAL	**$19**	**$48**	**$67**

APPENDIX B | RELATIVE YIELD LOSS MAPS AND TABLES

This appendix provides relative yield loss maps for the crops and forest types included in the analysis. Relative yield losses are expressed as the percent reduction in the overall yield of a crop or forest type under the counterfactual (no CAAA) scenario.[58] Changes in crop yield are presented by FASOM subregion; while, changes in forest yield are presented by FASOM region. Relative yield losses are only presented for subregions and regions where the specific crop or forest type being considered is present as defined by FASOM. Exhibits B-1 through B-11 present relative yield losses for crops; Exhibits B-12 and B-13 present relative yield losses for hardwood and softwood forest types, respectively.

In addition to relative yield loss maps, this appendix provides tables presenting relative yield losses for each crop by subregion (Exhibits B-14 through B-24) and for hardwood and softwood forest types by region (Exhibits B-25 through B-32).[59] Exhibits B-14 through B-32 also present intermediate values used to calculate relative yield losses for crops and trees.

Relative yield loss tables for hardwood and softwood forest types (Exhibit B-25 through B-32) present relative yield losses for individual hardwood and softwood tree species found in each region, as well as, the average relative yield loss for all hardwood and softwood species found in each region (only average relative yield losses for hardwood and softwood forest types are used to estimate welfare effects).

None of the hardwood species, for which exposure-response functions exist, are present (as defined in FASOM) in the Great Plains, Pacific Northwest-Westside, Pacific Southwest, and Rocky Mountains regions. The average relative yield loss in hardwood forest types across all regions, for which hardwood relative yield losses are estimated, is applied as the best-estimate of hardwood relative yield losses in these regions (5.06 percent in 2000; 13.86 percent in 2010; and, 16.68 percent in 2020). None of the softwood species, for which exposure-response functions exist, are present (as defined in FASOM) in the Great Plains region. As with hardwoods, the average relative yield loss in softwood forest types across all regions, for which softwood relative yield losses are estimated, is applied as the best-estimate of softwood relative yield losses in the Great Plains region (1.77 percent in 2000; 4.88 percent in 2010; and, 6.11 percent in 2020).

[58] Note that relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

[59] Relative yield loss tables for crop are split by crop; while, relative yield loss tables for hardwood/softwood forest types are split by region.

There is no table for the Great Plains region, given that no hardwood or softwood species, for which relative yield losses are estimated, are present in this region. Further, timber management is not defined by FASOM in either the Southwest or the Pacific Northwest-Eastside, therefore, relative yield loss tables are not presented for these regions.

EXHIBIT B-1. RELATIVE YIELD LOSSES IN BARLEY UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

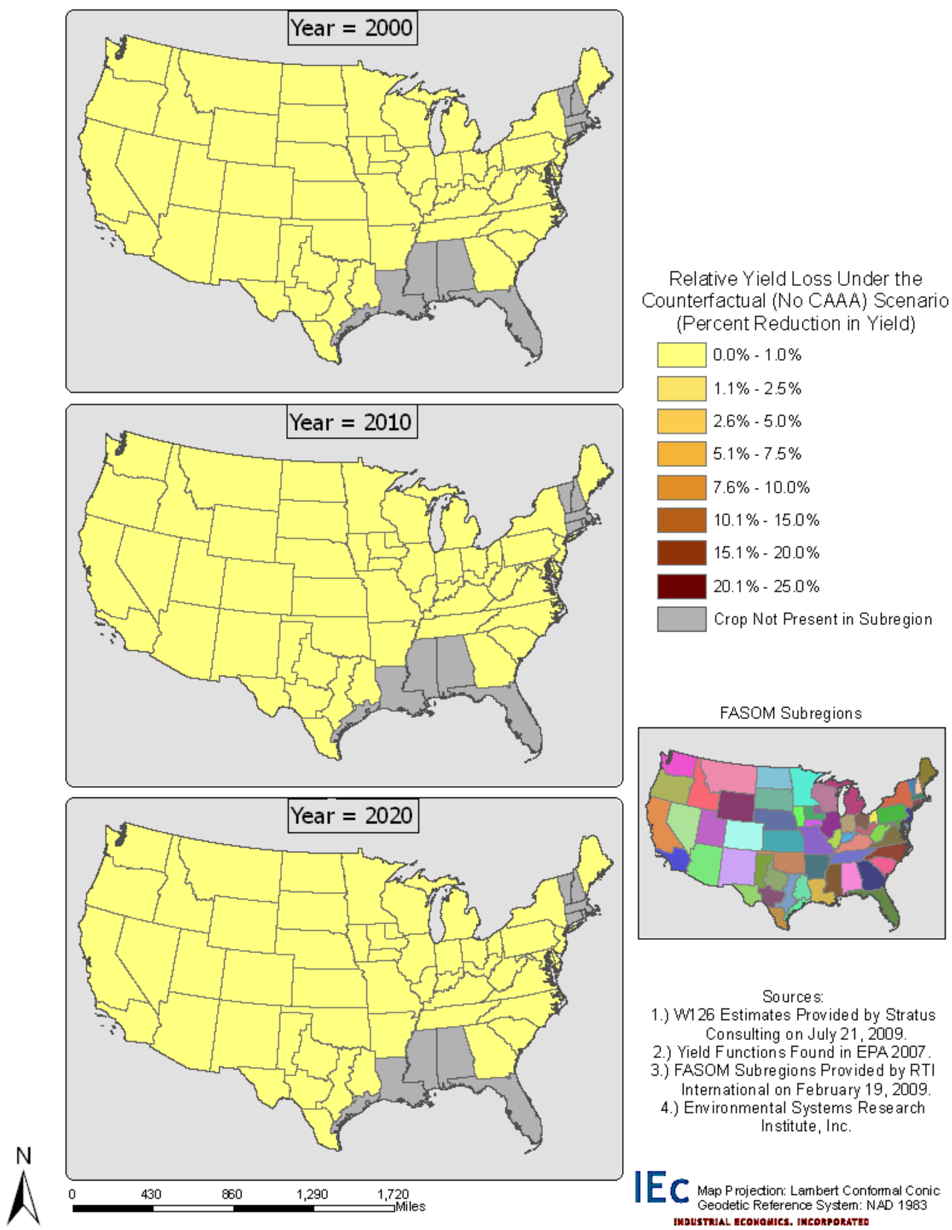

EXHIBIT B-2. RELATIVE YIELD LOSSES IN CORN UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

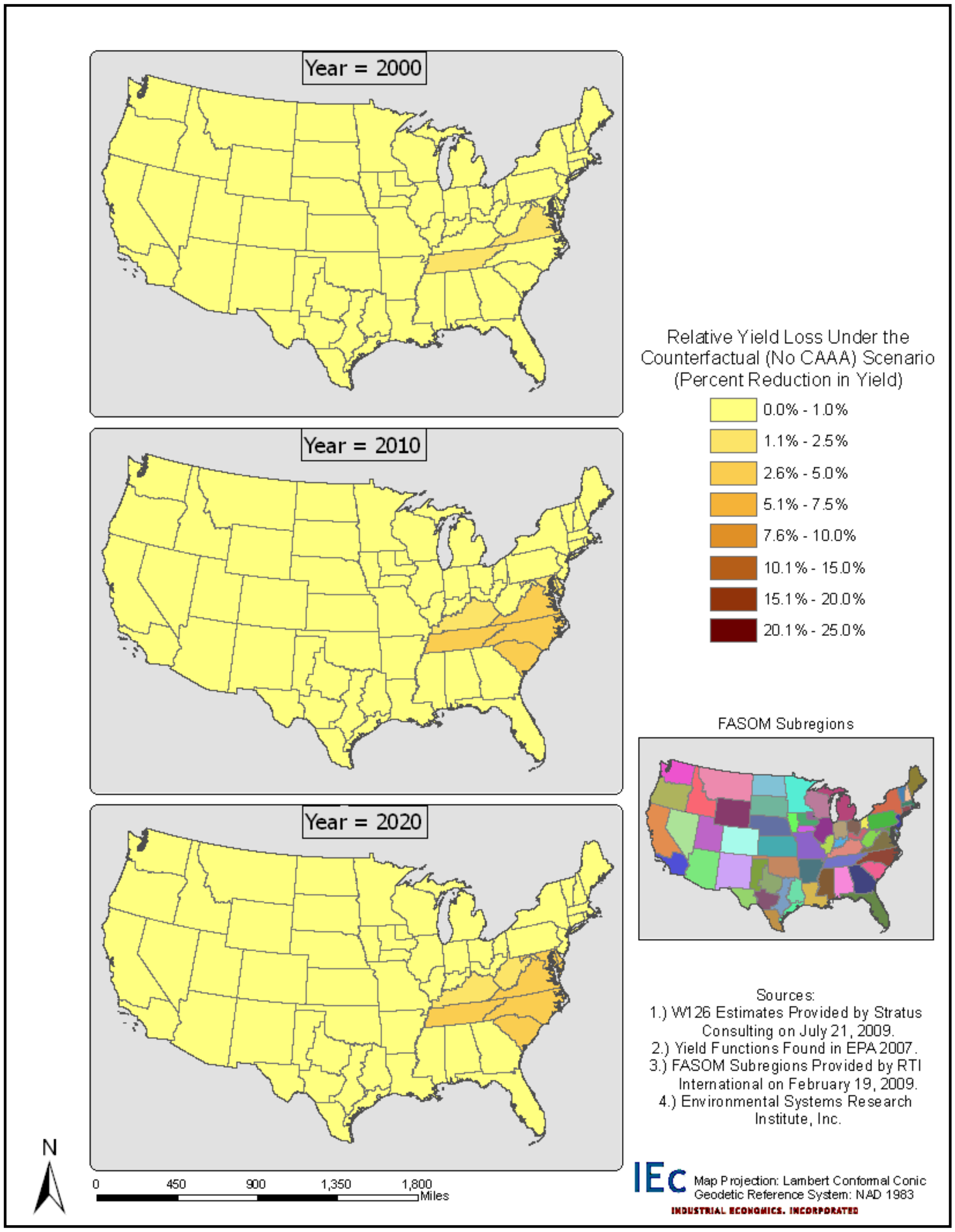

EXHIBIT B-3. RELATIVE YIELD LOSSES IN COTTON UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

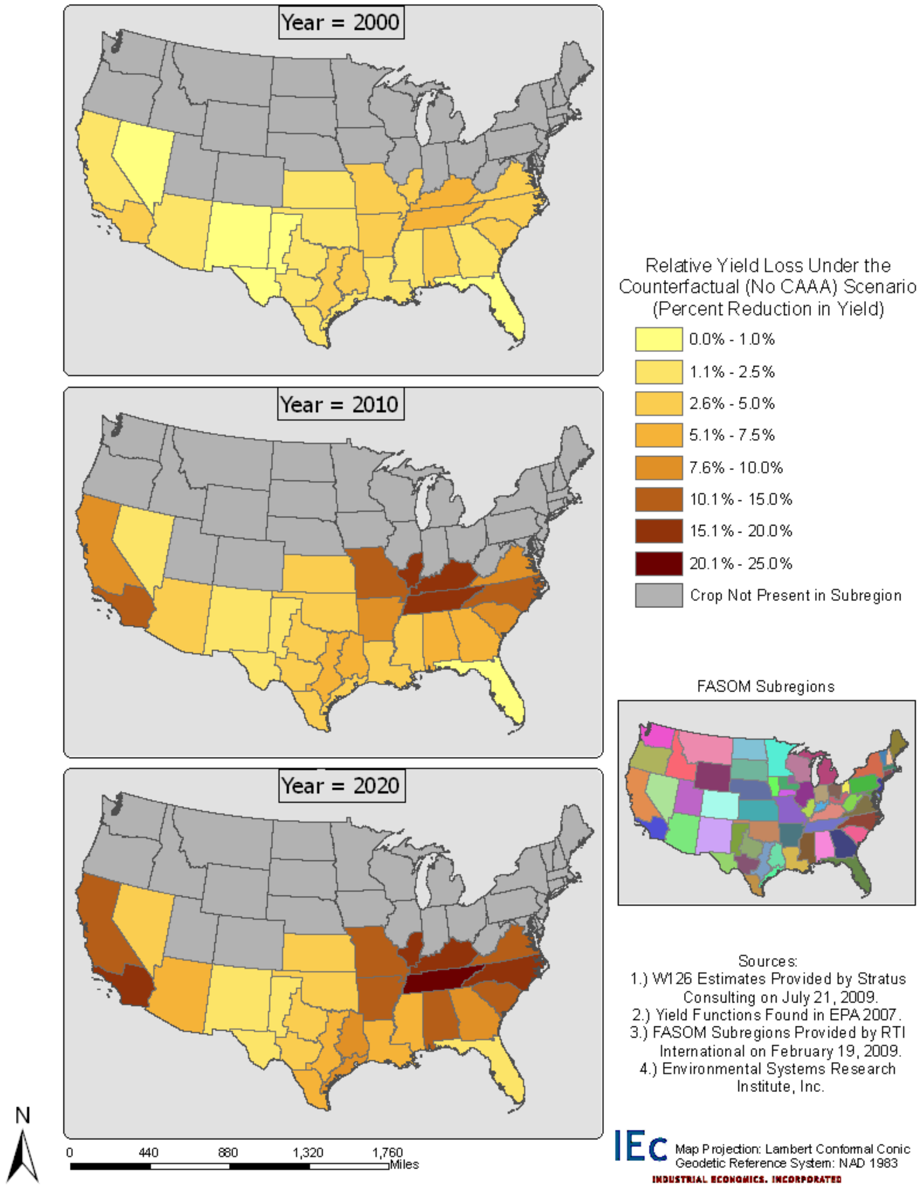

EXHIBIT B-4. RELATIVE YIELD LOSSES IN ORANGES UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

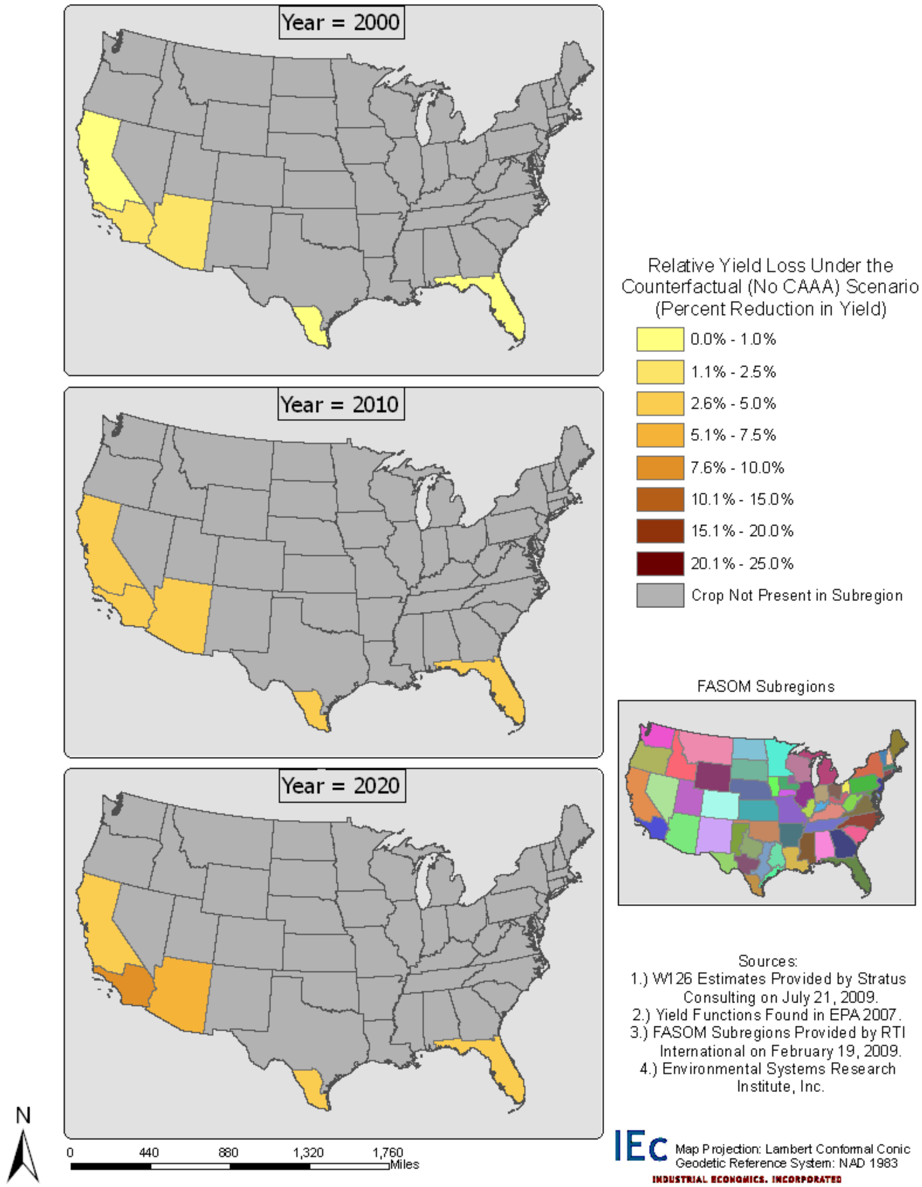

EXHIBIT B-5. RELATIVE YIELD LOSSES IN POTATOES UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

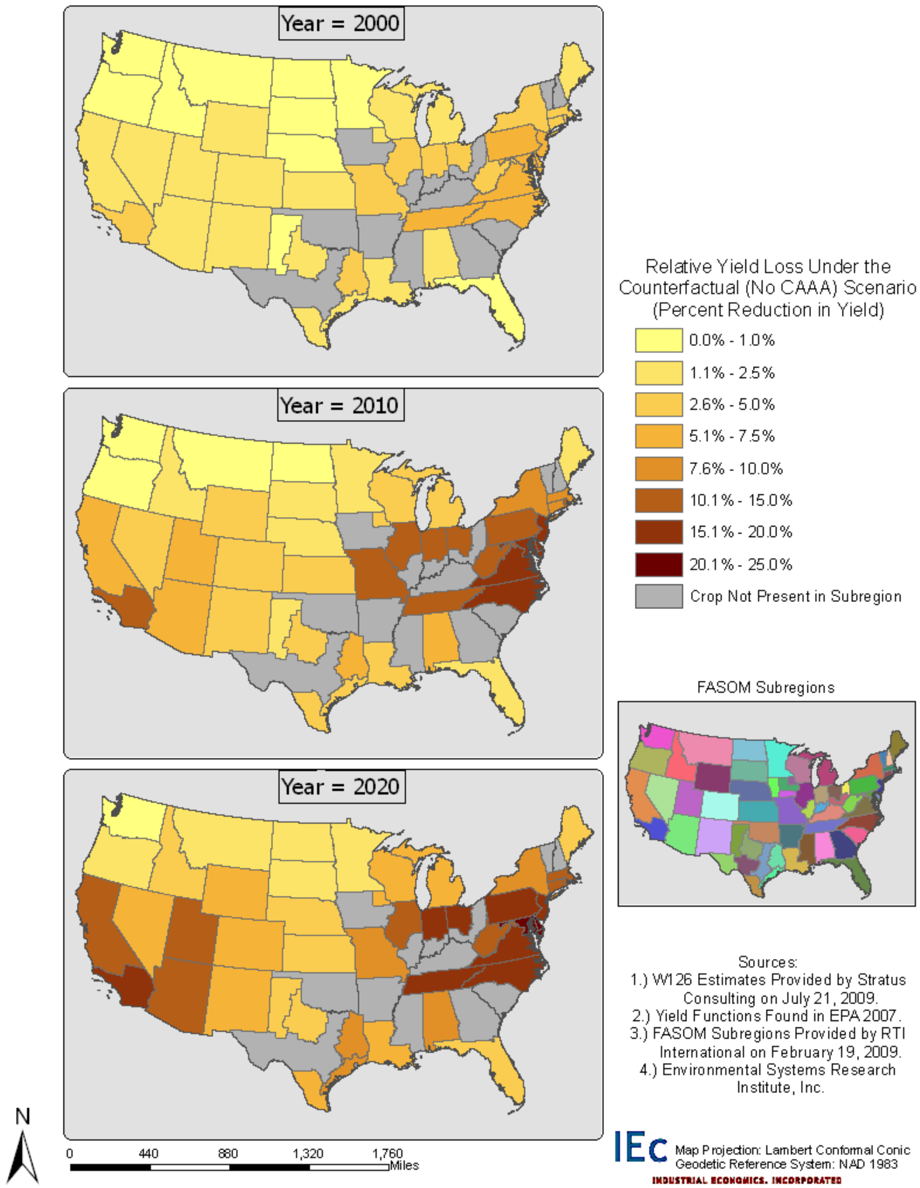

EXHIBIT B-6. RELATIVE YIELD LOSSES IN RICE UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

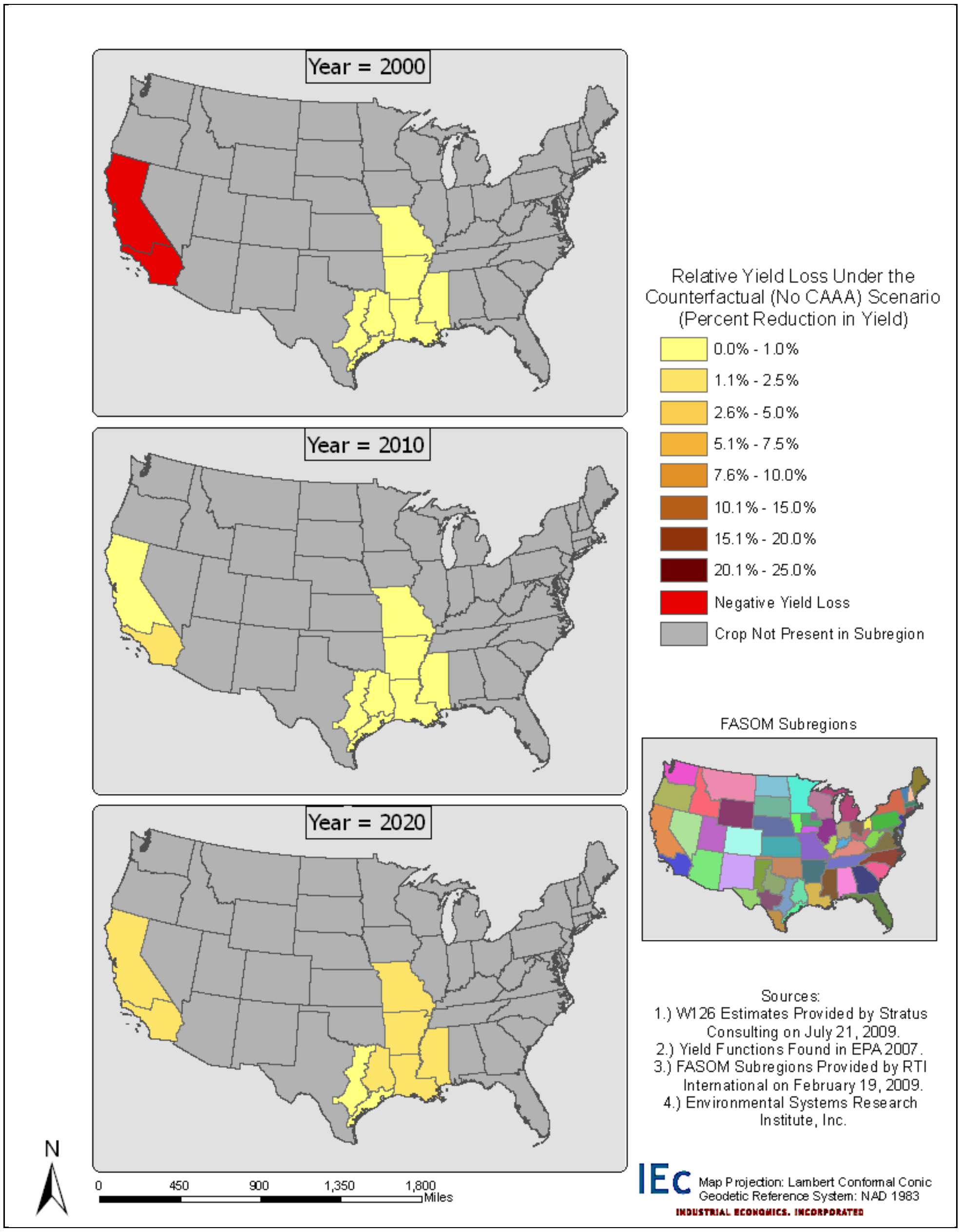

EXHIBIT B-7. RELATIVE YIELD LOSSES IN SORGHUM UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

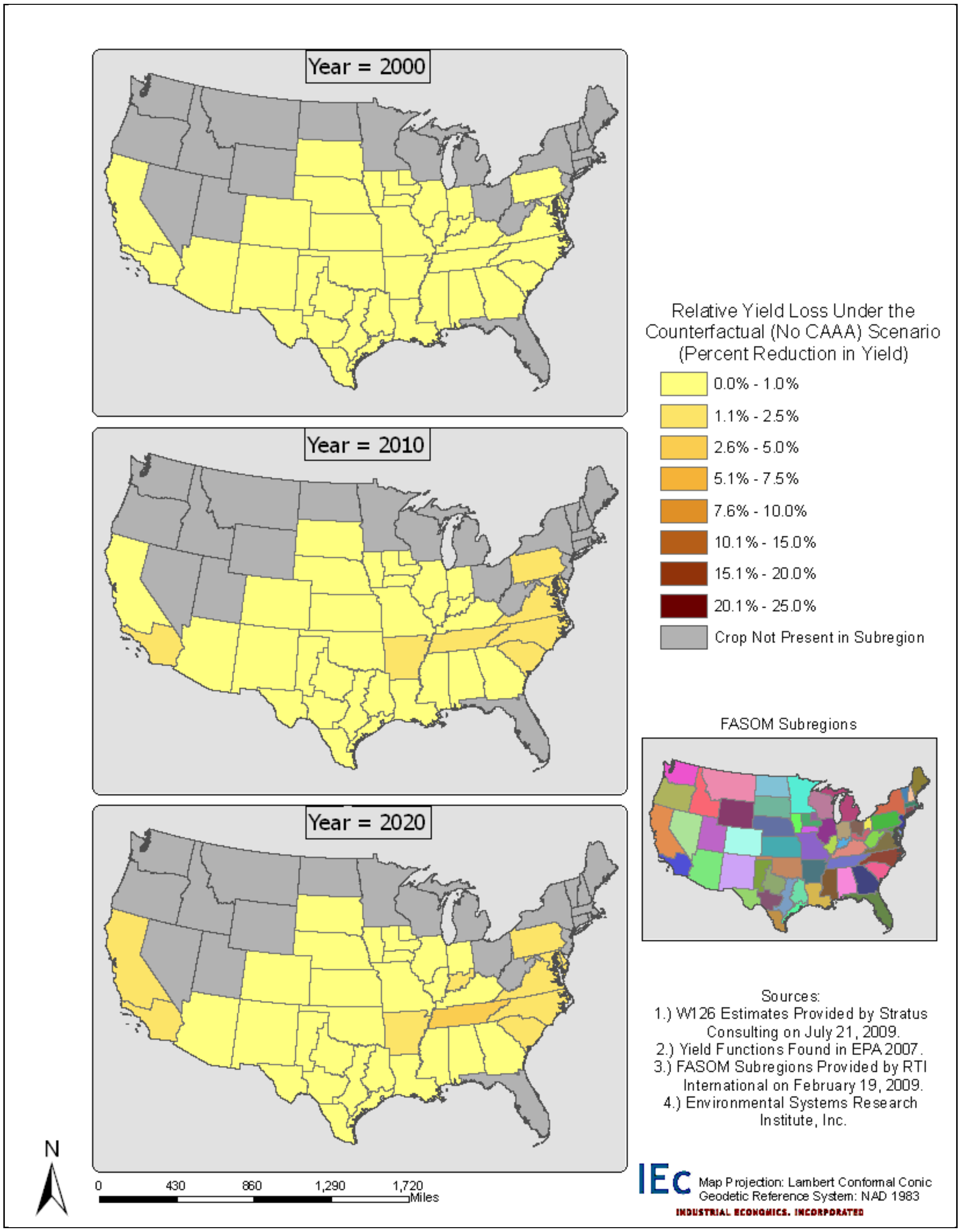

EXHIBIT B-8. RELATIVE YIELD LOSSES IN SOYBEANS UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

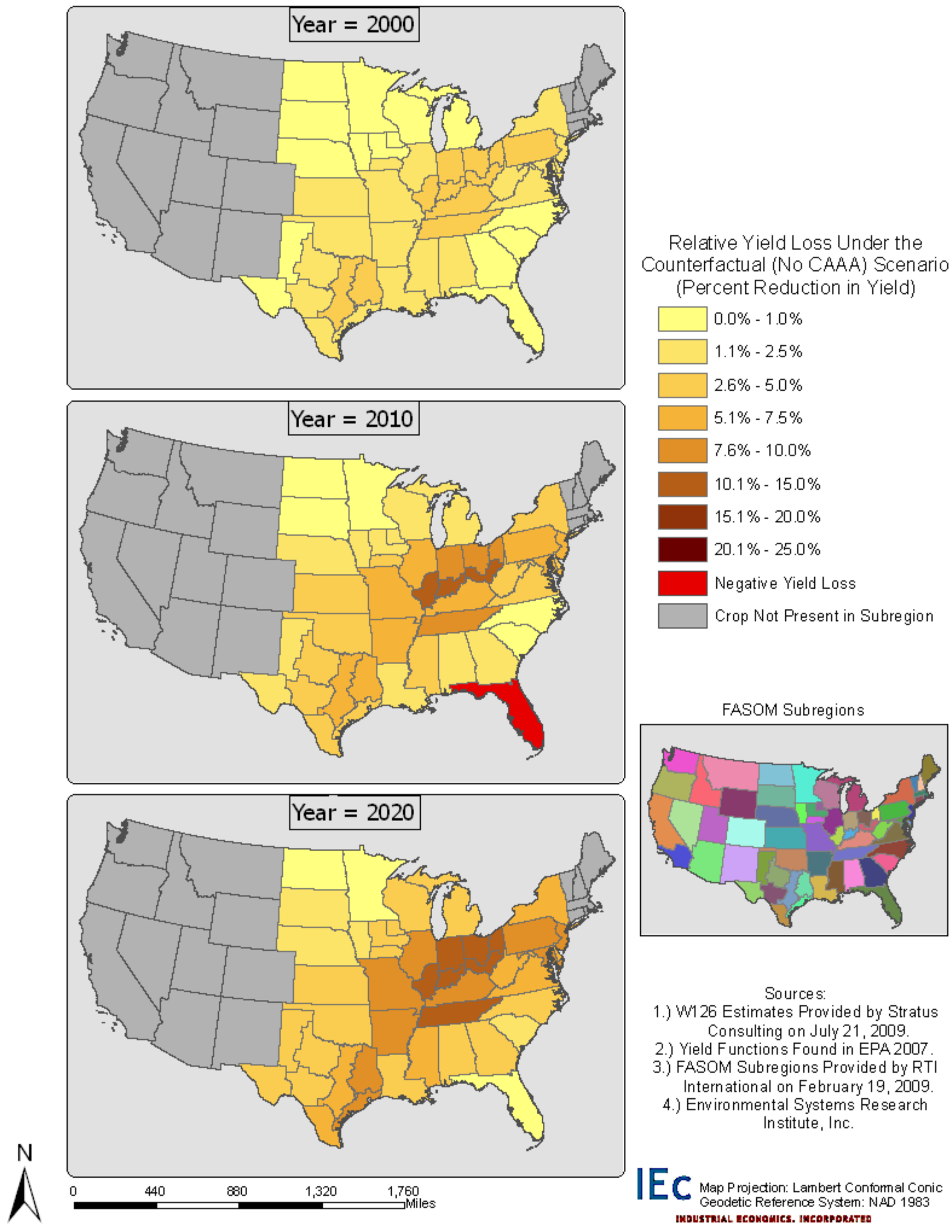

EXHIBIT B-9. RELATIVE YIELD LOSSES IN PROCESSING TOMATOES UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

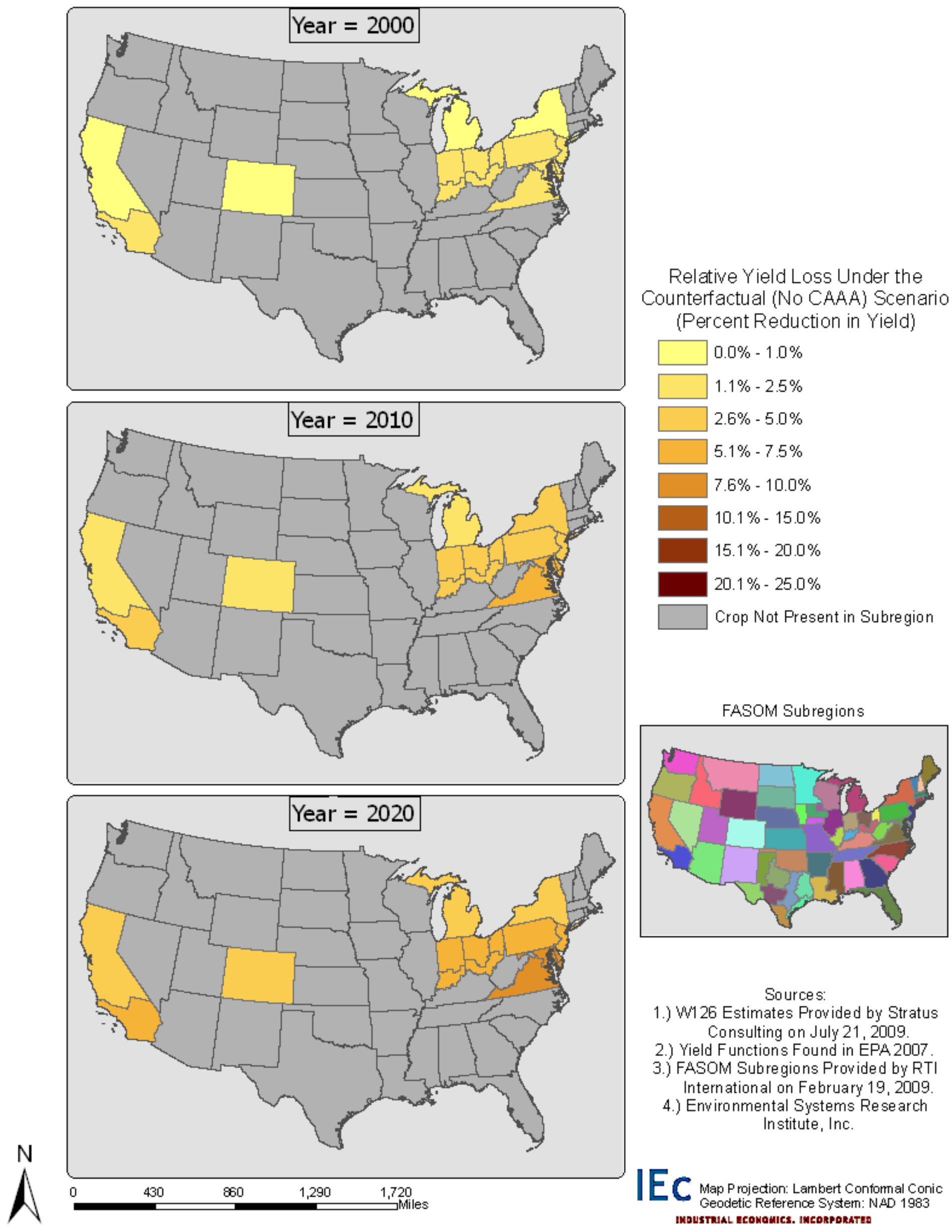

EXHIBIT B-10. RELATIVE YIELD LOSSES IN SPRING WHEAT UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

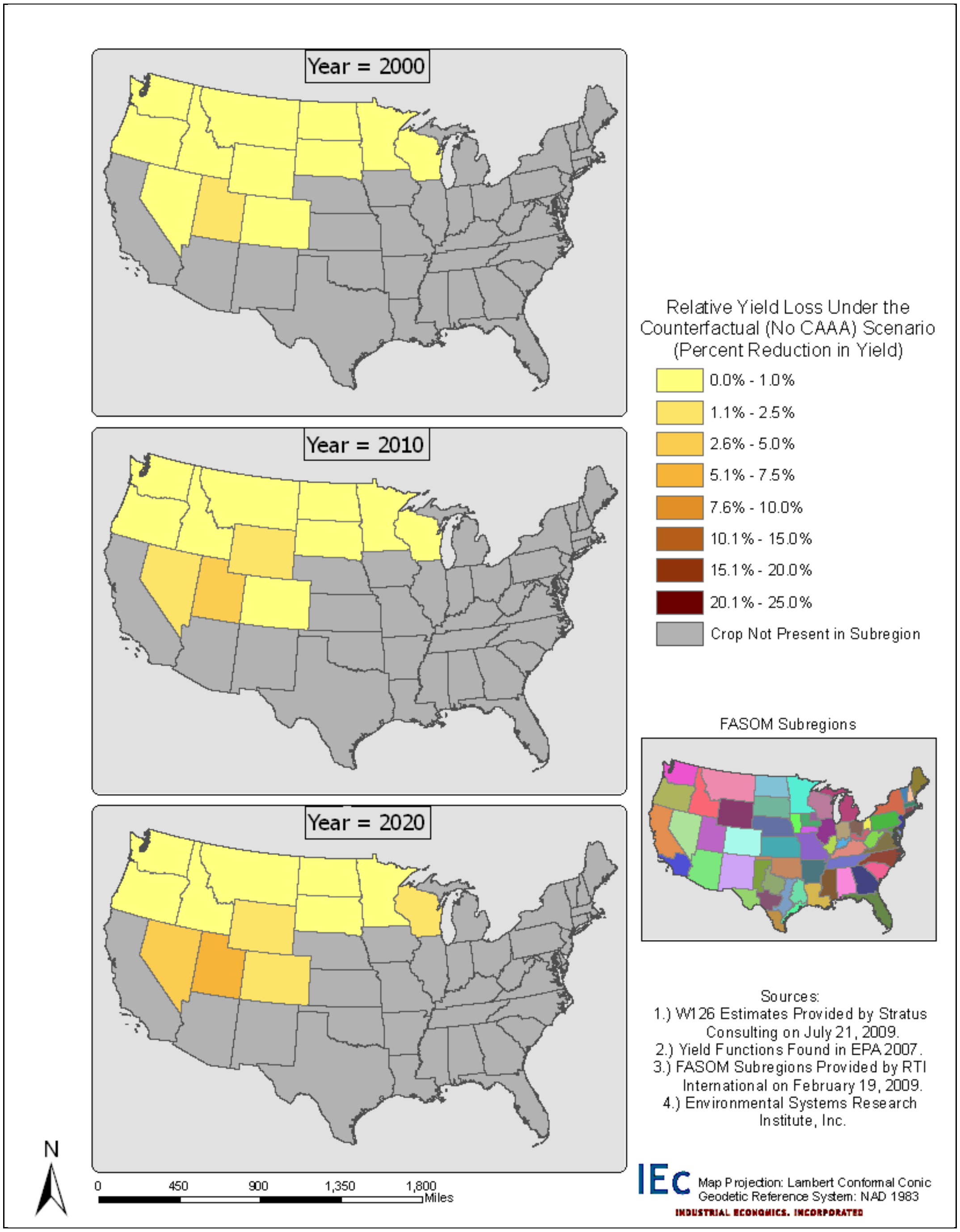

EXHIBIT B-11. RELATIVE YIELD LOSSES IN WINTER WHEAT UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM SUBREGION AND YEAR BASED ON SUBREGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

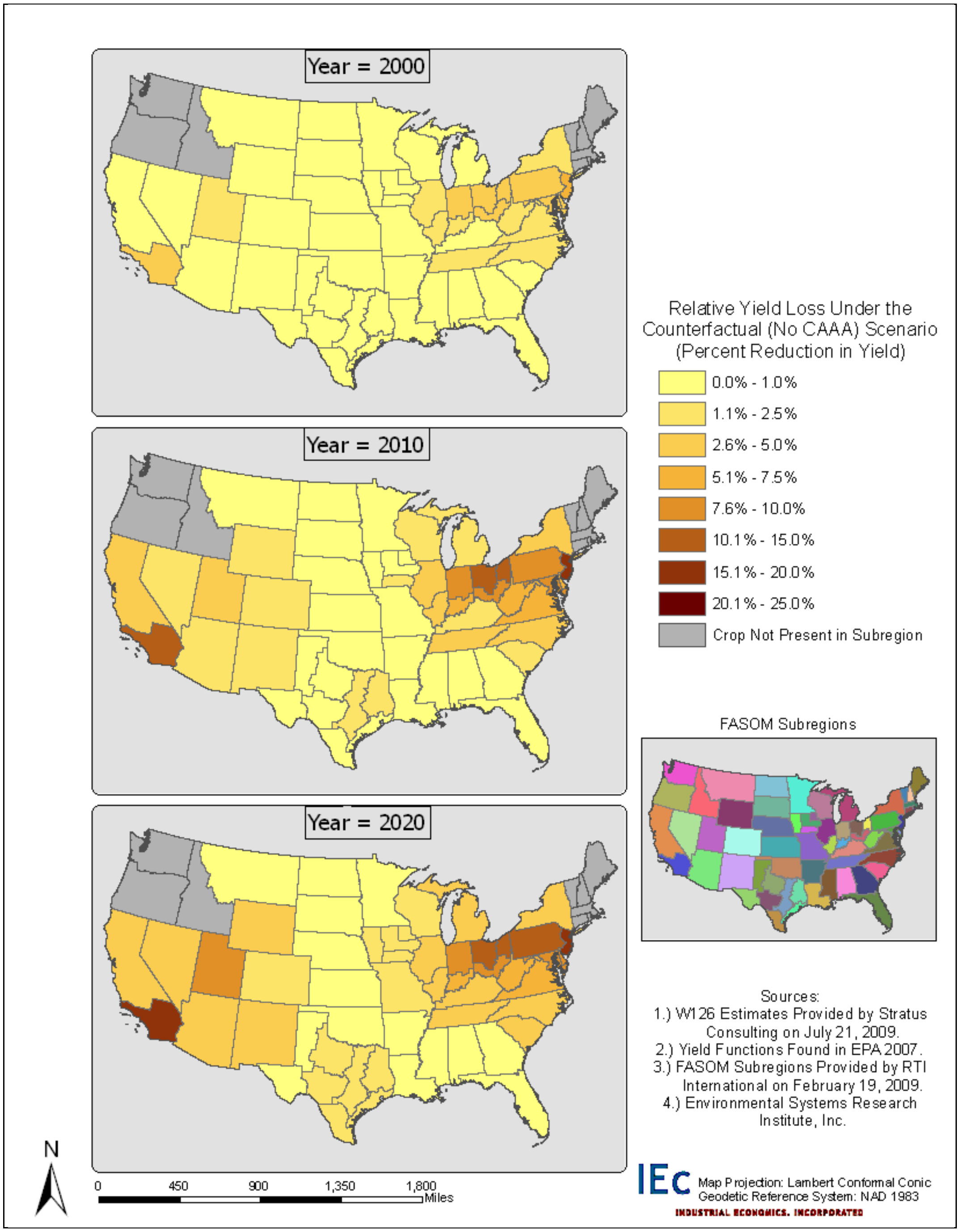

EXHIBIT B-12. RELATIVE YIELD LOSSES IN HARDWOOD FOREST TYPES UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM REGION AND YEAR BASED ON REGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

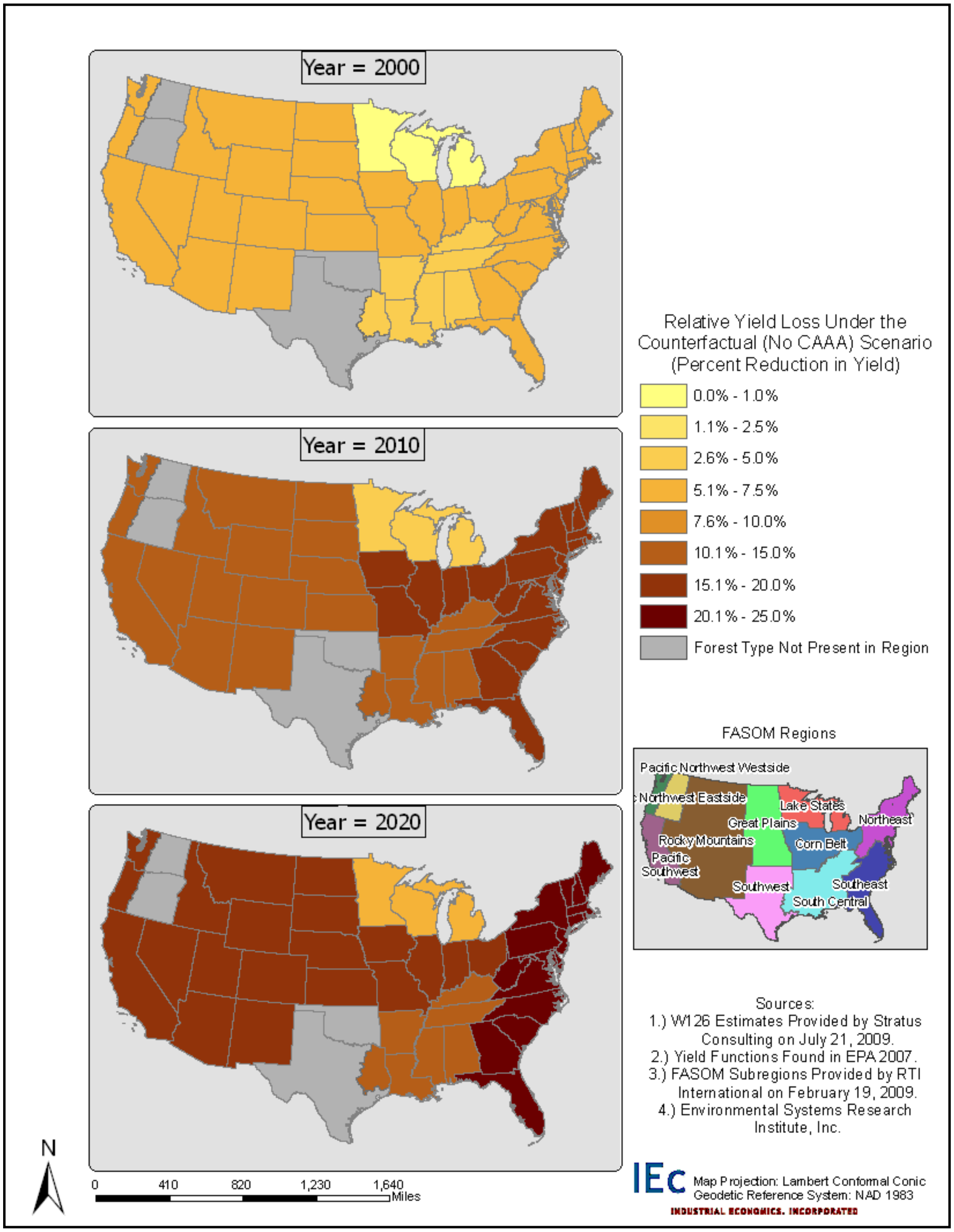

EXHIBIT B-13. RELATIVE YIELD LOSSES IN SOFTWOOD FOREST TYPES UNDER THE COUNTERFACTUAL (NO CAAA) SCENARIO BY FASOM REGION AND YEAR BASED ON REGIONAL-SPECIFIC OZONE CONCENTRATIONS AND GROWING PERIODS

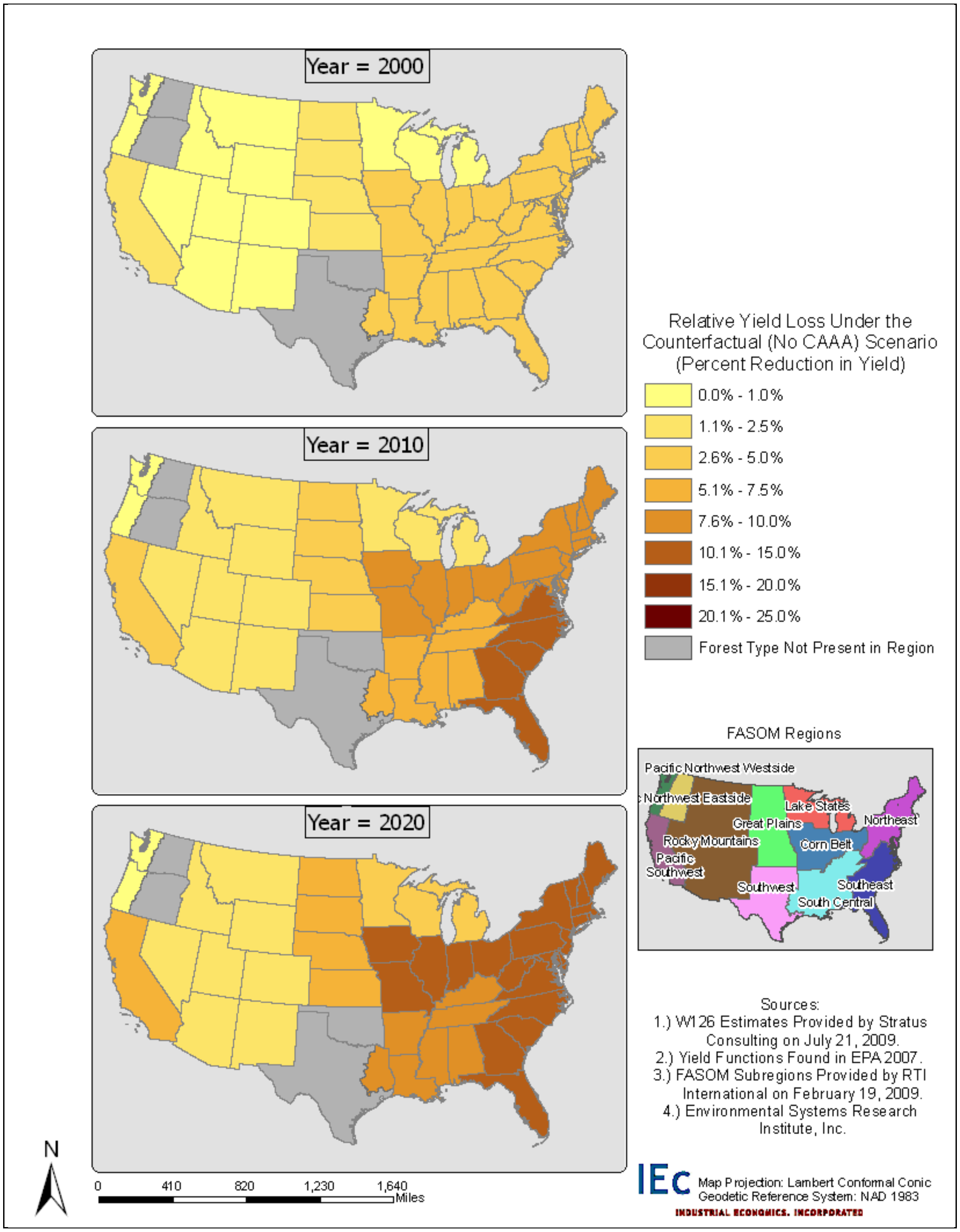

EXHIBIT B-14. DERIVATION OF RELATIVE YIELD LOSSES FOR BARLEY BY FASOM SUBREGION AND YEAR

SUBREGION	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Arizona	0.9997	0.9996	0.9995	0.9998	0.9998	0.9999	0.01%	0.02%	0.04%
Arkansas	0.9998	0.9997	0.9997	0.9999	1.0000	1.0000	0.01%	0.02%	0.02%
California North	0.9996	0.9995	0.9994	0.9997	0.9998	0.9998	0.01%	0.03%	0.05%
California South	0.9994	0.9993	0.9991	0.9996	0.9997	0.9998	0.02%	0.04%	0.07%
Colorado	0.9998	0.9998	0.9998	0.9999	0.9999	0.9999	0.00%	0.01%	0.02%
Delaware	0.9994	0.9993	0.9992	0.9996	0.9998	0.9999	0.02%	0.06%	0.07%
Georgia	0.9998	0.9997	0.9997	0.9999	0.9999	1.0000	0.01%	0.02%	0.03%
Idaho	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.00%	0.00%	0.01%
Illinois North	0.9997	0.9996	0.9996	0.9998	0.9999	0.9999	0.01%	0.03%	0.03%
Illinois South	0.9996	0.9995	0.9996	0.9998	0.9999	1.0000	0.01%	0.04%	0.04%
Indiana North	0.9995	0.9994	0.9994	0.9997	0.9999	0.9999	0.02%	0.04%	0.05%
Indiana South	0.9996	0.9994	0.9995	0.9997	0.9999	0.9999	0.01%	0.05%	0.05%
Iowa West	0.9999	0.9999	0.9998	0.9999	0.9999	1.0000	0.00%	0.01%	0.01%
Iowa Central	0.9999	0.9999	0.9999	0.9999	1.0000	1.0000	0.00%	0.01%	0.01%
Iowa Northeast	0.9999	0.9999	0.9998	0.9999	1.0000	1.0000	0.00%	0.01%	0.01%
Iowa South	0.9999	0.9998	0.9998	0.9999	1.0000	1.0000	0.00%	0.01%	0.01%
Kansas	1.0000	0.9999	0.9999	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%
Kentucky	0.9997	0.9995	0.9996	0.9998	0.9999	1.0000	0.01%	0.04%	0.04%
Maine	0.9999	0.9999	0.9999	1.0000	1.0000	1.0000	0.00%	0.00%	0.01%
Maryland	0.9993	0.9992	0.9992	0.9995	0.9998	0.9999	0.02%	0.06%	0.07%
Michigan	0.9998	0.9998	0.9998	0.9999	0.9999	1.0000	0.00%	0.01%	0.02%
Minnesota	0.9999	0.9999	0.9999	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%
Missouri	0.9998	0.9996	0.9997	0.9998	0.9999	1.0000	0.01%	0.03%	0.03%
Montana	0.9999	0.9999	0.9999	0.9999	1.0000	1.0000	0.00%	0.00%	0.00%
Nebraska	0.9999	0.9999	0.9999	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%
Nevada	0.9998	0.9997	0.9997	0.9998	0.9999	0.9999	0.00%	0.01%	0.02%
New Jersey	0.9994	0.9993	0.9993	0.9995	0.9998	0.9999	0.02%	0.05%	0.07%
New Mexico	0.9998	0.9998	0.9998	0.9999	0.9999	0.9999	0.00%	0.01%	0.02%
New York	0.9997	0.9997	0.9997	0.9998	0.9999	1.0000	0.01%	0.02%	0.03%
North Carolina	0.9995	0.9993	0.9993	0.9997	0.9999	1.0000	0.02%	0.06%	0.07%
North Dakota	1.0000	1.0000	0.9999	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%
Ohio Northwest	0.9995	0.9994	0.9994	0.9996	0.9998	0.9999	0.01%	0.05%	0.06%
Ohio South	0.9995	0.9994	0.9994	0.9997	0.9999	0.9999	0.01%	0.05%	0.05%
Ohio Northeast	0.9995	0.9994	0.9994	0.9996	0.9998	0.9999	0.01%	0.04%	0.06%
Oklahoma	0.9998	0.9998	0.9998	0.9999	0.9999	1.0000	0.00%	0.01%	0.02%
Oregon	0.9999	0.9999	0.9999	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%
Pennsylvania	0.9995	0.9995	0.9994	0.9997	0.9999	0.9999	0.02%	0.04%	0.05%
South Carolina	0.9996	0.9994	0.9994	0.9997	0.9999	1.0000	0.02%	0.05%	0.06%
South Dakota	0.9999	0.9999	0.9999	0.9999	1.0000	1.0000	0.00%	0.00%	0.00%
Tennessee	0.9996	0.9995	0.9994	0.9997	0.9999	1.0000	0.02%	0.04%	0.05%
Texas High Plains	0.9999	0.9999	0.9999	0.9999	0.9999	1.0000	0.00%	0.01%	0.01%

SUBREGION	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Texas Rolling Plains	0.9999	0.9998	0.9998	0.9999	0.9999	1.0000	0.00%	0.01%	0.02%
Texas Central Blacklands	0.9998	0.9998	0.9998	0.9999	0.9999	1.0000	0.01%	0.01%	0.02%
Texas East	0.9998	0.9998	0.9997	0.9999	1.0000	1.0000	0.01%	0.02%	0.02%
Texas Edwards Plateau	0.9999	0.9999	0.9999	0.9999	1.0000	1.0000	0.00%	0.01%	0.01%
Texas South	0.9999	0.9999	0.9998	0.9999	1.0000	1.0000	0.00%	0.01%	0.01%
Texas Trans Pecos	0.9999	0.9999	0.9999	0.9999	1.0000	1.0000	0.00%	0.01%	0.01%
Utah	0.9997	0.9996	0.9995	0.9998	0.9998	0.9999	0.01%	0.02%	0.03%
Virginia	0.9995	0.9993	0.9993	0.9997	0.9999	0.9999	0.02%	0.05%	0.06%
Washington	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%
West Virginia	0.9996	0.9995	0.9995	0.9998	0.9999	1.0000	0.01%	0.04%	0.04%
Wisconsin	0.9999	0.9999	0.9998	0.9999	0.9999	1.0000	0.00%	0.01%	0.01%
Wyoming	0.9998	0.9998	0.9997	0.9999	0.9999	0.9999	0.01%	0.01%	0.02%

Notes:

1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-15. DERIVATION OF RELATIVE YIELD LOSSES FOR CORN BY FASOM SUBREGION AND YEAR

SUBREGION	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Alabama	0.9974	0.9960	0.9946	0.9991	0.9999	1.0000	0.17%	0.40%	0.54%
Arizona	0.9994	0.9989	0.9984	0.9997	0.9999	0.9999	0.04%	0.10%	0.15%
Arkansas	0.9958	0.9914	0.9909	0.9986	0.9999	1.0000	0.27%	0.85%	0.90%
California North	0.9959	0.9936	0.9927	0.9970	0.9985	0.9986	0.11%	0.49%	0.59%
California South	0.9947	0.9925	0.9910	0.9973	0.9988	0.9992	0.26%	0.63%	0.82%
Colorado	0.9998	0.9998	0.9997	0.9999	1.0000	1.0000	0.01%	0.02%	0.02%
Connecticut	0.9972	0.9967	0.9960	0.9986	0.9996	1.0000	0.14%	0.29%	0.40%
Delaware	0.9849	0.9779	0.9744	0.9937	0.9983	0.9999	0.88%	2.04%	2.55%
Florida	0.9998	0.9997	0.9995	0.9999	1.0000	1.0000	0.01%	0.03%	0.05%
Georgia	0.9958	0.9927	0.9905	0.9983	0.9998	1.0000	0.25%	0.71%	0.95%
Idaho	0.9999	0.9999	0.9999	1.0000	1.0000	1.0000	0.00%	0.00%	0.01%
Illinois North	0.9988	0.9985	0.9979	0.9995	0.9999	1.0000	0.07%	0.14%	0.21%
Illinois South	0.9961	0.9954	0.9939	0.9984	0.9998	1.0000	0.22%	0.44%	0.60%
Indiana North	0.9980	0.9976	0.9968	0.9991	0.9998	1.0000	0.11%	0.22%	0.32%
Indiana South	0.9972	0.9968	0.9959	0.9986	0.9997	1.0000	0.14%	0.30%	0.41%
Iowa West	0.9999	0.9999	0.9998	1.0000	1.0000	1.0000	0.00%	0.01%	0.01%
Iowa Central	0.9999	0.9998	0.9997	0.9999	1.0000	1.0000	0.01%	0.02%	0.03%
Iowa Northeast	0.9998	0.9998	0.9996	0.9999	1.0000	1.0000	0.01%	0.02%	0.04%
Iowa South	0.9995	0.9993	0.9990	0.9998	1.0000	1.0000	0.03%	0.07%	0.10%
Kansas	0.9990	0.9987	0.9984	0.9995	0.9999	0.9999	0.05%	0.12%	0.15%
Kentucky	0.9895	0.9833	0.9828	0.9959	0.9995	0.9999	0.64%	1.62%	1.71%
Louisiana	0.9990	0.9981	0.9976	0.9997	0.9999	1.0000	0.06%	0.18%	0.24%
Maine	0.9998	0.9997	0.9997	0.9999	0.9999	1.0000	0.01%	0.02%	0.03%
Maryland	0.9837	0.9775	0.9735	0.9926	0.9981	0.9999	0.90%	2.06%	2.63%
Massachusetts	0.9974	0.9970	0.9964	0.9988	0.9996	1.0000	0.14%	0.26%	0.36%
Michigan	0.9997	0.9996	0.9995	0.9998	1.0000	1.0000	0.01%	0.03%	0.05%
Minnesota	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%
Mississippi	0.9987	0.9976	0.9970	0.9996	0.9999	1.0000	0.09%	0.23%	0.29%
Missouri	0.9961	0.9931	0.9927	0.9985	0.9998	1.0000	0.24%	0.68%	0.73%
Montana	0.9999	0.9999	0.9998	0.9999	1.0000	1.0000	0.00%	0.01%	0.01%
Nebraska	0.9999	0.9999	0.9999	1.0000	1.0000	1.0000	0.00%	0.01%	0.01%
Nevada	0.9994	0.9991	0.9988	0.9996	0.9998	0.9998	0.02%	0.07%	0.10%
New Hampshire	0.9993	0.9992	0.9989	0.9997	0.9999	1.0000	0.04%	0.07%	0.11%
New Jersey	0.9984	0.9981	0.9977	0.9991	0.9996	1.0000	0.07%	0.15%	0.23%
New Mexico	0.9998	0.9997	0.9995	0.9999	1.0000	1.0000	0.01%	0.03%	0.04%
New York	0.9990	0.9989	0.9986	0.9996	0.9999	1.0000	0.06%	0.10%	0.14%
North Carolina	0.9845	0.9680	0.9654	0.9942	0.9987	1.0000	0.97%	3.07%	3.45%
North Dakota	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%
Ohio Northwest	0.9969	0.9964	0.9953	0.9985	0.9997	1.0000	0.16%	0.33%	0.46%
Ohio South	0.9966	0.9962	0.9952	0.9983	0.9997	1.0000	0.16%	0.35%	0.48%
Ohio Northeast	0.9973	0.9968	0.9960	0.9986	0.9998	0.9999	0.13%	0.30%	0.39%
Oklahoma	0.9968	0.9955	0.9943	0.9985	0.9997	0.9998	0.17%	0.42%	0.54%
Oregon	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%

SUBREGION	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Pennsylvania	0.9978	0.9974	0.9966	0.9991	0.9998	1.0000	0.13%	0.24%	0.34%
Rhode Island	0.9973	0.9968	0.9961	0.9987	0.9996	1.0000	0.14%	0.28%	0.39%
South Carolina	0.9852	0.9709	0.9657	0.9947	0.9994	1.0000	0.96%	2.85%	3.43%
South Dakota	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%
Tennessee	0.9825	0.9737	0.9671	0.9936	0.9992	1.0000	1.12%	2.55%	3.29%
Texas High Plains	0.9993	0.9992	0.9986	0.9997	0.9999	1.0000	0.03%	0.07%	0.13%
Texas Rolling Plains	0.9985	0.9980	0.9969	0.9993	0.9999	1.0000	0.08%	0.19%	0.31%
Texas Central Blacklands	0.9978	0.9972	0.9953	0.9991	0.9998	1.0000	0.13%	0.26%	0.46%
Texas East	0.9976	0.9965	0.9947	0.9992	0.9999	1.0000	0.16%	0.34%	0.53%
Texas Edwards Plateau	0.9994	0.9993	0.9987	0.9997	0.9999	1.0000	0.03%	0.07%	0.13%
Texas Coastal Bend	0.9979	0.9977	0.9959	0.9991	0.9999	1.0000	0.12%	0.22%	0.40%
Texas South	0.9994	0.9994	0.9988	0.9998	1.0000	1.0000	0.03%	0.06%	0.11%
Texas Trans Pecos	0.9995	0.9993	0.9988	0.9997	0.9999	1.0000	0.02%	0.06%	0.12%
Utah	0.9993	0.9989	0.9984	0.9996	0.9998	0.9999	0.03%	0.09%	0.14%
Vermont	0.9993	0.9991	0.9988	0.9997	0.9999	1.0000	0.05%	0.08%	0.12%
Virginia	0.9840	0.9722	0.9691	0.9941	0.9984	0.9999	1.02%	2.62%	3.08%
Washington	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%
West Virginia	0.9927	0.9899	0.9875	0.9972	0.9995	1.0000	0.45%	0.96%	1.24%
Wisconsin	0.9998	0.9998	0.9997	0.9999	1.0000	1.0000	0.01%	0.02%	0.03%
Wyoming	0.9998	0.9997	0.9996	0.9999	0.9999	0.9999	0.01%	0.02%	0.03%

Notes:

1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-16. DERIVATION OF RELATIVE YIELD LOSSES FOR COTTON BY FASOM SUBREGION AND YEAR

SUBREGION	X: $e^{-\left(\frac{O_3 NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3 WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Alabama	0.9249	0.9086	0.8944	0.9544	0.9785	0.9955	3.08%	7.15%	10.16%
Arizona	0.9538	0.9404	0.9238	0.9701	0.9823	0.9874	1.68%	4.26%	6.44%
Arkansas	0.9157	0.8846	0.8783	0.9498	0.9825	0.9932	3.59%	9.96%	11.57%
California North	0.8839	0.8550	0.8334	0.9022	0.9332	0.9408	2.04%	8.38%	11.42%
California South	0.8554	0.8290	0.8029	0.8974	0.9335	0.9533	4.67%	11.19%	15.78%
Florida	0.9894	0.9856	0.9818	0.9932	0.9885	0.9990	0.38%	0.30%	1.72%
Georgia	0.9438	0.9261	0.9154	0.9643	0.9795	0.9965	2.12%	5.45%	8.13%
Illinois South	0.8680	0.8130	0.8366	0.9128	0.9712	0.9869	4.91%	16.29%	15.23%
Kansas	0.9605	0.9553	0.9505	0.9719	0.9857	0.9875	1.18%	3.08%	3.75%
Kentucky	0.8629	0.8183	0.8276	0.9125	0.9695	0.9888	5.44%	15.59%	16.31%
Louisiana	0.9522	0.9375	0.9281	0.9719	0.9767	0.9944	2.03%	4.02%	6.67%
Mississippi	0.9551	0.9416	0.9344	0.9734	0.9856	0.9972	1.88%	4.46%	6.30%
Missouri	0.9051	0.8590	0.8731	0.9390	0.9783	0.9890	3.61%	12.19%	11.71%
Nevada	0.9657	0.9573	0.9487	0.9719	0.9796	0.9836	0.64%	2.27%	3.54%
New Mexico	0.9827	0.9787	0.9749	0.9886	0.9929	0.9931	0.59%	1.43%	1.84%
North Carolina	0.8783	0.8314	0.8231	0.9236	0.9581	0.9932	4.91%	13.23%	17.13%
Oklahoma	0.9503	0.9428	0.9371	0.9664	0.9859	0.9837	1.66%	4.37%	4.73%
South Carolina	0.9078	0.8744	0.8614	0.9442	0.9682	0.9948	3.86%	9.69%	13.41%
Tennessee	0.8425	0.8050	0.7900	0.9021	0.9660	0.9914	6.60%	16.67%	20.31%
Texas High Plains	0.9726	0.9686	0.9656	0.9808	0.9902	0.9887	0.84%	2.18%	2.33%
Texas Rolling Plains	0.9507	0.9434	0.9397	0.9672	0.9860	0.9821	1.71%	4.32%	4.32%
Texas Central Blacklands	0.9336	0.9255	0.9131	0.9578	0.9800	0.9844	2.53%	5.56%	7.24%
Texas East	0.9400	0.9290	0.9142	0.9656	0.9805	0.9929	2.64%	5.25%	7.93%
Texas Edwards Plateau	0.9640	0.9588	0.9499	0.9773	0.9876	0.9920	1.36%	2.92%	4.24%
Texas Coastal Bend	0.9381	0.9330	0.9156	0.9589	0.9800	0.9912	2.17%	4.79%	7.63%
Texas South	0.9611	0.9564	0.9433	0.9757	0.9847	0.9951	1.49%	2.88%	5.20%
Texas Trans Pecos	0.9726	0.9678	0.9641	0.9805	0.9898	0.9884	0.81%	2.22%	2.46%
Virginia	0.9025	0.8786	0.8665	0.9398	0.9655	0.9928	3.97%	9.00%	12.72%

Notes:

1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-17. DERIVATION OF RELATIVE YIELD LOSSES FOR ORANGES BY FASOM SUBREGION AND YEAR

SUBREGION	X: $A-(B*O_3NoCAAA)$			Y: $A-(B*O_3WithCAAA)$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Arizona	39.55	39.24	38.76	40.06	40.61	41.24	1.28%	3.37%	6.02%
California North	40.12	39.76	39.33	40.39	40.85	41.25	0.68%	2.69%	4.67%
California South	38.23	37.81	37.19	38.99	39.67	40.37	1.95%	4.68%	7.87%
Florida	44.06	43.88	43.60	44.36	45.10	45.63	0.67%	2.71%	4.44%
Texas South	42.56	42.40	42.13	42.92	43.54	43.93	0.85%	2.60%	4.10%

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-18. DERIVATION OF RELATIVE YIELD LOSSES FOR POTATOES BY FASOM SUBREGION AND YEAR

SUBREGION	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Alabama	0.9396	0.9308	0.9187	0.9606	0.9881	0.9947	2.18%	5.79%	7.65%
Arizona	0.9106	0.8945	0.8673	0.9325	0.9513	0.9684	2.35%	5.98%	10.44%
California North	0.8840	0.8594	0.8330	0.9002	0.9287	0.9488	1.80%	7.46%	12.21%
California South	0.8267	0.8028	0.7669	0.8686	0.9067	0.9425	4.82%	11.46%	18.63%
Colorado	0.9385	0.9324	0.9192	0.9538	0.9630	0.9715	1.61%	3.18%	5.39%
Connecticut	0.8738	0.8665	0.8564	0.9050	0.9607	0.9877	3.44%	9.80%	13.30%
Delaware	0.8136	0.7811	0.7739	0.8672	0.9472	0.9770	6.17%	17.54%	20.79%
Florida	0.9749	0.9694	0.9611	0.9815	0.9915	0.9937	0.68%	2.22%	3.28%
Idaho	0.9656	0.9609	0.9528	0.9702	0.9753	0.9796	0.48%	1.48%	2.74%
Illinois North	0.8933	0.8645	0.8706	0.9207	0.9624	0.9784	2.99%	10.17%	11.01%
Indiana North	0.8392	0.8097	0.8081	0.8825	0.9469	0.9728	4.91%	14.49%	16.93%
Iowa Northeast	0.9564	0.9520	0.9392	0.9684	0.9838	0.9906	1.24%	3.23%	5.19%
Kansas	0.9554	0.9496	0.9415	0.9665	0.9804	0.9874	1.16%	3.14%	4.64%
Louisiana	0.9563	0.9456	0.9383	0.9724	0.9867	0.9934	1.66%	4.17%	5.55%
Maine	0.9681	0.9660	0.9628	0.9785	0.9897	0.9960	1.06%	2.39%	3.33%
Maryland	0.8061	0.7753	0.7687	0.8569	0.9379	0.9706	5.93%	17.33%	20.80%
Massachusetts	0.8865	0.8718	0.8711	0.9158	0.9625	0.9844	3.20%	9.42%	11.51%
Michigan	0.9311	0.9314	0.9167	0.9458	0.9700	0.9819	1.55%	3.98%	6.64%
Minnesota	0.9785	0.9759	0.9731	0.9828	0.9888	0.9926	0.43%	1.31%	1.97%
Missouri	0.9156	0.8706	0.8921	0.9421	0.9754	0.9869	2.81%	10.74%	9.61%
Montana	0.9749	0.9734	0.9700	0.9788	0.9816	0.9844	0.39%	0.83%	1.46%
Nebraska	0.9697	0.9673	0.9620	0.9768	0.9852	0.9897	0.73%	1.81%	2.79%
Nevada	0.9319	0.9195	0.9008	0.9422	0.9557	0.9675	1.09%	3.78%	6.90%
New Jersey	0.8067	0.7785	0.7781	0.8509	0.9328	0.9725	5.19%	16.54%	19.99%
New Mexico	0.9482	0.9398	0.9250	0.9611	0.9710	0.9787	1.34%	3.21%	5.48%
New York	0.9016	0.8890	0.8862	0.9286	0.9667	0.9841	2.90%	8.04%	9.95%
North Carolina	0.8485	0.7968	0.7962	0.8955	0.9642	0.9850	5.25%	17.36%	19.17%
North Dakota	0.9867	0.9858	0.9844	0.9894	0.9922	0.9943	0.27%	0.64%	1.00%
Ohio Northwest	0.8321	0.8088	0.8026	0.8733	0.9429	0.9715	4.71%	14.22%	17.38%
Oregon	0.9810	0.9775	0.9728	0.9829	0.9860	0.9881	0.20%	0.86%	1.55%
Pennsylvania	0.8488	0.8367	0.8207	0.8937	0.9588	0.9801	5.03%	12.73%	16.26%
Rhode Island	0.8670	0.8506	0.8483	0.8988	0.9583	0.9861	3.54%	11.25%	13.97%
South Dakota	0.9717	0.9726	0.9658	0.9772	0.9858	0.9878	0.56%	1.34%	2.23%
Tennessee	0.8613	0.8286	0.8220	0.9083	0.9711	0.9891	5.17%	14.68%	16.89%
Texas High Plains	0.9653	0.9611	0.9531	0.9743	0.9853	0.9872	0.92%	2.45%	3.45%
Texas Rolling Plains	0.9433	0.9363	0.9421	0.9596	0.9803	0.9902	1.70%	4.49%	4.86%
Texas East	0.9324	0.9221	0.9083	0.9577	0.9762	0.9893	2.64%	5.54%	8.19%
Texas Coastal Bend	0.9323	0.9277	0.9119	0.9522	0.9751	0.9871	2.09%	4.87%	7.61%
Texas South	0.9570	0.9439	0.9410	0.9710	0.9760	0.9923	1.44%	3.28%	5.17%
Utah	0.9000	0.8853	0.8595	0.9213	0.9390	0.9568	2.31%	5.72%	10.17%
Virginia	0.8482	0.8038	0.8051	0.8976	0.9628	0.9832	5.50%	16.51%	18.11%
Washington	0.9911	0.9897	0.9877	0.9919	0.9936	0.9950	0.09%	0.40%	0.73%
West Virginia	0.8826	0.8585	0.8548	0.9212	0.9756	0.9880	4.19%	12.00%	13.47%

SUBREGION	X: $e^{-\left(\frac{O_3 NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3 WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Wisconsin	0.9472	0.9446	0.9318	0.9598	0.9778	0.9866	1.31%	3.39%	5.56%
Wyoming	0.9326	0.9261	0.9131	0.9489	0.9578	0.9670	1.72%	3.31%	5.58%

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-19. DERIVATION OF RELATIVE YIELD LOSSES FOR RICE BY FASOM SUBREGION AND YEAR

SUBREGION	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Arkansas	0.9696	0.9681	0.9653	0.9700	0.9775	0.9814	0.04%	0.97%	1.64%
California North	0.9625	0.9589	0.9567	0.9623	0.9655	0.9681	-0.02%	0.68%	1.18%
California South	0.9597	0.9538	0.9524	0.9589	0.9637	0.9684	-0.08%	1.03%	1.66%
Louisiana	0.9772	0.9763	0.9744	0.9779	0.9819	0.9844	0.07%	0.57%	1.02%
Mississippi	0.9761	0.9749	0.9727	0.9762	0.9823	0.9858	0.00%	0.75%	1.33%
Missouri	0.9671	0.9659	0.9636	0.9674	0.9745	0.9787	0.03%	0.89%	1.54%
Texas Central Blacklands	0.9787	0.9773	0.9761	0.9787	0.9824	0.9846	0.01%	0.53%	0.86%
Texas East	0.9752	0.9740	0.9721	0.9763	0.9813	0.9839	0.11%	0.74%	1.20%
Texas Coastal Bend	0.9801	0.9796	0.9784	0.9815	0.9841	0.9856	0.14%	0.46%	0.73%

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-20. DERIVATION OF RELATIVE YIELD LOSSES FOR SORGHUM BY FASOM SUBREGION AND YEAR

SUBREGION	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Alabama	0.9966	0.9957	0.9945	0.9983	0.9992	0.9999	0.17%	0.35%	0.54%
Arizona	0.9990	0.9985	0.9982	0.9994	0.9997	0.9997	0.05%	0.12%	0.15%
Arkansas	0.9932	0.9892	0.9887	0.9967	0.9993	0.9998	0.35%	1.01%	1.11%
California North	0.9900	0.9863	0.9839	0.9920	0.9952	0.9957	0.21%	0.89%	1.18%
California South	0.9870	0.9835	0.9803	0.9918	0.9954	0.9969	0.49%	1.20%	1.67%
Colorado	0.9992	0.9990	0.9989	0.9995	0.9997	0.9997	0.03%	0.06%	0.08%
Delaware	0.9876	0.9843	0.9824	0.9930	0.9969	0.9996	0.54%	1.26%	1.72%
Georgia	0.9952	0.9930	0.9915	0.9974	0.9988	0.9999	0.22%	0.58%	0.83%
Illinois North	0.9973	0.9970	0.9962	0.9985	0.9996	0.9998	0.11%	0.26%	0.36%
Illinois South	0.9943	0.9936	0.9923	0.9968	0.9993	0.9997	0.25%	0.57%	0.74%
Indiana North	0.9929	0.9917	0.9903	0.9959	0.9987	0.9996	0.30%	0.70%	0.93%
Indiana South	0.9912	0.9894	0.9886	0.9944	0.9983	0.9995	0.33%	0.89%	1.09%
Iowa West	0.9994	0.9993	0.9992	0.9996	0.9998	0.9999	0.02%	0.04%	0.07%
Iowa Central	0.9993	0.9991	0.9988	0.9996	0.9998	0.9999	0.03%	0.06%	0.11%
Iowa Northeast	0.9992	0.9990	0.9986	0.9996	0.9997	0.9999	0.04%	0.07%	0.13%
Iowa South	0.9983	0.9978	0.9974	0.9991	0.9997	0.9999	0.08%	0.19%	0.25%
Kansas	0.9984	0.9982	0.9979	0.9990	0.9996	0.9996	0.06%	0.15%	0.17%
Kentucky	0.9933	0.9924	0.9907	0.9963	0.9990	0.9998	0.31%	0.66%	0.91%
Louisiana	0.9974	0.9961	0.9954	0.9987	0.9995	0.9998	0.13%	0.34%	0.45%
Maryland	0.9848	0.9812	0.9790	0.9910	0.9963	0.9993	0.63%	1.52%	2.03%
Mississippi	0.9971	0.9957	0.9950	0.9986	0.9996	0.9999	0.15%	0.39%	0.49%
Missouri	0.9942	0.9917	0.9913	0.9969	0.9993	0.9997	0.27%	0.75%	0.84%
Nebraska	0.9994	0.9993	0.9992	0.9996	0.9998	0.9998	0.02%	0.05%	0.06%
New Mexico	0.9995	0.9993	0.9993	0.9997	0.9999	0.9998	0.02%	0.05%	0.06%
North Carolina	0.9908	0.9865	0.9842	0.9952	0.9974	0.9998	0.44%	1.08%	1.56%
Oklahoma	0.9974	0.9968	0.9966	0.9985	0.9995	0.9993	0.11%	0.27%	0.27%
Pennsylvania	0.9883	0.9868	0.9844	0.9935	0.9980	0.9996	0.53%	1.13%	1.52%
South Carolina	0.9912	0.9866	0.9844	0.9956	0.9978	0.9998	0.44%	1.12%	1.55%
South Dakota	0.9996	0.9996	0.9995	0.9997	0.9999	0.9999	0.01%	0.03%	0.04%
Tennessee	0.9824	0.9762	0.9732	0.9910	0.9979	0.9997	0.87%	2.17%	2.65%
Texas High Plains	0.9981	0.9977	0.9968	0.9987	0.9994	0.9997	0.07%	0.17%	0.28%
Texas Rolling Plains	0.9966	0.9960	0.9945	0.9980	0.9993	0.9997	0.13%	0.33%	0.51%
Texas Central Blacklands	0.9956	0.9949	0.9929	0.9976	0.9992	0.9997	0.20%	0.43%	0.68%
Texas East	0.9956	0.9942	0.9924	0.9979	0.9995	0.9998	0.24%	0.52%	0.74%
Texas Edwards Plateau	0.9982	0.9979	0.9968	0.9989	0.9996	0.9998	0.08%	0.17%	0.30%
Texas Coastal Bend	0.9959	0.9955	0.9936	0.9976	0.9993	0.9997	0.18%	0.38%	0.61%
Texas South	0.9982	0.9980	0.9971	0.9990	0.9997	0.9998	0.08%	0.17%	0.28%
Texas Trans Pecos	0.9984	0.9980	0.9972	0.9989	0.9995	0.9997	0.05%	0.14%	0.25%
Virginia	0.9863	0.9805	0.9788	0.9929	0.9969	0.9996	0.67%	1.65%	2.08%

Notes:

1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-21. DERIVATION OF RELATIVE YIELD LOSSES FOR SOYBEANS BY FASOM SUBREGION AND YEAR

SUBREGION	X: $e^{-\left(\frac{O_3 NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3 WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Alabama	0.9710	0.9670	0.9605	0.9814	0.9864	0.9978	1.06%	1.96%	3.74%
Arkansas	0.9418	0.9309	0.9176	0.9644	0.9863	0.9946	2.34%	5.62%	7.75%
Delaware	0.9397	0.9329	0.9227	0.9589	0.9707	0.9939	2.01%	3.89%	7.16%
Florida	0.9958	0.9948	0.9931	0.9972	0.9894	0.9995	0.13%	-0.55%	0.64%
Georgia	0.9763	0.9720	0.9656	0.9842	0.9858	0.9979	0.80%	1.40%	3.24%
Illinois North	0.9306	0.9125	0.9124	0.9511	0.9799	0.9886	2.16%	6.88%	7.71%
Illinois South	0.8951	0.8601	0.8721	0.9285	0.9743	0.9875	3.60%	11.73%	11.68%
Indiana North	0.8940	0.8765	0.8705	0.9259	0.9665	0.9853	3.45%	9.31%	11.65%
Indiana South	0.8865	0.8569	0.8658	0.9166	0.9633	0.9842	3.29%	11.05%	12.02%
Iowa West	0.9766	0.9749	0.9708	0.9827	0.9888	0.9928	0.62%	1.41%	2.21%
Iowa Central	0.9762	0.9733	0.9670	0.9837	0.9901	0.9958	0.75%	1.69%	2.89%
Iowa Northeast	0.9753	0.9722	0.9634	0.9834	0.9887	0.9957	0.82%	1.67%	3.25%
Iowa South	0.9602	0.9457	0.9460	0.9737	0.9884	0.9938	1.38%	4.32%	4.81%
Kansas	0.9640	0.9599	0.9560	0.9738	0.9860	0.9871	1.00%	2.65%	3.15%
Kentucky	0.9225	0.9140	0.9033	0.9485	0.9792	0.9923	2.74%	6.66%	8.96%
Louisiana	0.9652	0.9575	0.9497	0.9789	0.9796	0.9956	1.39%	2.26%	4.61%
Maryland	0.9219	0.9138	0.9024	0.9451	0.9665	0.9905	2.46%	5.45%	8.90%
Michigan	0.9635	0.9618	0.9542	0.9727	0.9862	0.9921	0.95%	2.47%	3.82%
Minnesota	0.9910	0.9898	0.9883	0.9932	0.9941	0.9973	0.23%	0.43%	0.90%
Mississippi	0.9543	0.9420	0.9353	0.9718	0.9836	0.9965	1.80%	4.23%	6.14%
Missouri	0.9348	0.9163	0.9142	0.9570	0.9838	0.9912	2.32%	6.87%	7.77%
Nebraska	0.9784	0.9765	0.9735	0.9840	0.9901	0.9918	0.57%	1.38%	1.85%
New Jersey	0.9212	0.9140	0.9069	0.9404	0.9647	0.9900	2.04%	5.25%	8.39%
New York	0.9461	0.9418	0.9356	0.9633	0.9807	0.9927	1.78%	3.96%	5.75%
North Carolina	0.9752	0.9708	0.9643	0.9841	0.9776	0.9980	0.91%	0.69%	3.38%
North Dakota	0.9908	0.9902	0.9893	0.9928	0.9947	0.9958	0.20%	0.46%	0.65%
Ohio Northwest	0.8814	0.8660	0.8575	0.9139	0.9612	0.9827	3.55%	9.90%	12.74%
Ohio South	0.8819	0.8628	0.8610	0.9129	0.9636	0.9843	3.39%	10.45%	12.53%
Ohio Northeast	0.8813	0.8670	0.8611	0.9106	0.9618	0.9791	3.22%	9.85%	12.05%
Oklahoma	0.9499	0.9432	0.9380	0.9650	0.9843	0.9816	1.57%	4.17%	4.44%
Pennsylvania	0.9271	0.9209	0.9116	0.9512	0.9768	0.9924	2.54%	5.73%	8.14%
South Carolina	0.9822	0.9787	0.9738	0.9888	0.9832	0.9985	0.67%	0.46%	2.47%
South Dakota	0.9846	0.9833	0.9814	0.9882	0.9920	0.9933	0.37%	0.87%	1.20%
Tennessee	0.9085	0.8976	0.8790	0.9410	0.9749	0.9938	3.45%	7.93%	11.55%
Texas High Plains	0.9675	0.9632	0.9598	0.9765	0.9872	0.9857	0.92%	2.43%	2.63%
Texas Rolling Plains	0.9458	0.9386	0.9348	0.9626	0.9828	0.9789	1.74%	4.50%	4.51%
Texas Central Blacklands	0.9293	0.9216	0.9094	0.9533	0.9764	0.9813	2.51%	5.61%	7.33%
Texas East	0.9346	0.9233	0.9091	0.9607	0.9769	0.9907	2.71%	5.49%	8.24%
Texas Edwards Plateau	0.9600	0.9550	0.9458	0.9738	0.9850	0.9899	1.41%	3.05%	4.46%
Texas Coastal Bend	0.9335	0.9291	0.9117	0.9543	0.9764	0.9888	2.18%	4.85%	7.80%
Texas South	0.9574	0.9530	0.9398	0.9723	0.9818	0.9935	1.53%	2.94%	5.40%
Texas Trans Pecos	0.9676	0.9625	0.9582	0.9763	0.9868	0.9855	0.89%	2.47%	2.77%
Virginia	0.9466	0.9392	0.9279	0.9660	0.9731	0.9950	2.01%	3.48%	6.74%

SUBREGION	X: $e^{-\left(\frac{O_3 NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3 WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
West Virginia	0.9373	0.9313	0.9200	0.9588	0.9785	0.9941	2.24%	4.82%	7.45%
Wisconsin	0.9766	0.9745	0.9687	0.9833	0.9889	0.9953	0.68%	1.46%	2.67%

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-22. DERIVATION OF RELATIVE YIELD LOSSES FOR PROCESSING TOMATOES BY FASOM SUBREGION AND YEAR

SUBREGION	X: $A-(B*O_3NoCAAA)$			Y: $A-(B*O_3WithCAAA)$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
California North	7,290.13	7,232.09	7,164.21	7,332.20	7,406.13	7,469.18	0.57%	2.35%	4.08%
California South	7,096.73	7,032.19	6,938.08	7,209.71	7,313.33	7,431.04	1.57%	3.84%	6.63%
Colorado	7,415.28	7,390.86	7,344.74	7,478.11	7,532.51	7,591.02	0.84%	1.88%	3.24%
Delaware	7,054.53	7,034.34	6,984.21	7,177.10	7,423.04	7,584.43	1.71%	5.24%	7.91%
Indiana North	7,167.08	7,138.69	7,094.80	7,269.14	7,456.14	7,585.62	1.40%	4.26%	6.47%
Indiana South	7,188.07	7,161.13	7,114.87	7,294.13	7,506.79	7,644.14	1.45%	4.60%	6.92%
Maryland	7,022.28	6,982.46	6,933.75	7,152.79	7,392.19	7,553.57	1.82%	5.54%	8.21%
Michigan	7,522.37	7,546.02	7,528.65	7,560.12	7,690.92	7,769.18	0.50%	1.88%	3.10%
New Jersey	7,067.04	7,029.99	7,003.71	7,160.55	7,356.54	7,533.69	1.31%	4.44%	7.03%
New York	7,398.89	7,382.07	7,385.19	7,465.67	7,594.68	7,718.73	0.89%	2.80%	4.32%
Ohio Northwest	7,110.99	7,083.27	7,045.09	7,211.10	7,408.55	7,548.21	1.39%	4.39%	6.67%
Ohio South	7,159.61	7,134.65	7,091.84	7,256.56	7,489.78	7,622.76	1.34%	4.74%	6.97%
Ohio Northeast	7,097.34	7,073.26	7,045.48	7,190.71	7,390.46	7,531.13	1.30%	4.29%	6.45%
Pennsylvania	7,201.80	7,176.27	7,150.19	7,308.58	7,518.60	7,656.11	1.46%	4.55%	6.61%
Virginia	7,143.70	7,102.29	7,047.07	7,267.16	7,510.62	7,653.34	1.70%	5.44%	7.92%

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-23. DERIVATION OF RELATIVE YIELD LOSSES FOR SPRING WHEAT BY FASOM SUBREGION AND YEAR

SUBREGION	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Colorado	0.9893	0.9868	0.9802	0.9944	0.9967	0.9982	0.51%	0.99%	1.80%
Idaho	0.9962	0.9950	0.9925	0.9972	0.9982	0.9988	0.09%	0.31%	0.63%
Minnesota	0.9992	0.9990	0.9988	0.9995	0.9998	0.9999	0.03%	0.08%	0.12%
Montana	0.9980	0.9977	0.9970	0.9986	0.9990	0.9993	0.06%	0.13%	0.23%
Nevada	0.9833	0.9762	0.9631	0.9882	0.9933	0.9965	0.50%	1.71%	3.35%
North Dakota	0.9990	0.9989	0.9986	0.9993	0.9996	0.9998	0.03%	0.07%	0.12%
Oregon	0.9982	0.9975	0.9965	0.9985	0.9990	0.9993	0.03%	0.15%	0.28%
South Dakota	0.9958	0.9953	0.9940	0.9972	0.9984	0.9991	0.14%	0.31%	0.50%
Utah	0.9639	0.9514	0.9246	0.9785	0.9876	0.9940	1.50%	3.67%	6.98%
Washington	0.9996	0.9995	0.9993	0.9997	0.9998	0.9999	0.01%	0.03%	0.06%
Wisconsin	0.9906	0.9899	0.9840	0.9945	0.9983	0.9994	0.39%	0.85%	1.54%
Wyoming	0.9857	0.9824	0.9747	0.9922	0.9950	0.9971	0.66%	1.26%	2.25%

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-24. DERIVATION OF RELATIVE YIELD LOSSES FOR WINTER WHEAT BY FASOM SUBREGION AND YEAR

SUBREGION	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Alabama	0.9960	0.9951	0.9934	0.9979	0.9995	0.9998	0.19%	0.44%	0.64%
Arizona	0.9816	0.9772	0.9690	0.9873	0.9916	0.9952	0.58%	1.45%	2.63%
Arkansas	0.9948	0.9935	0.9903	0.9973	0.9992	0.9997	0.25%	0.57%	0.94%
California North	0.9716	0.9612	0.9442	0.9783	0.9874	0.9918	0.68%	2.64%	4.80%
California South	0.8857	0.8583	0.8109	0.9284	0.9586	0.9797	4.60%	10.47%	17.24%
Colorado	0.9839	0.9810	0.9741	0.9900	0.9931	0.9955	0.62%	1.22%	2.16%
Delaware	0.9425	0.9313	0.9166	0.9681	0.9923	0.9977	2.64%	6.14%	8.13%
Florida	0.9994	0.9992	0.9989	0.9996	0.9999	0.9999	0.02%	0.06%	0.10%
Georgia	0.9963	0.9954	0.9937	0.9979	0.9994	0.9998	0.15%	0.40%	0.61%
Illinois North	0.9758	0.9703	0.9661	0.9858	0.9959	0.9983	1.02%	2.57%	3.23%
Illinois South	0.9746	0.9660	0.9628	0.9865	0.9968	0.9989	1.21%	3.09%	3.61%
Indiana North	0.9326	0.9155	0.9062	0.9626	0.9905	0.9970	3.12%	7.58%	9.10%
Indiana South	0.9520	0.9294	0.9327	0.9734	0.9939	0.9982	2.20%	6.49%	6.57%
Iowa West	0.9908	0.9896	0.9863	0.9943	0.9976	0.9990	0.34%	0.80%	1.27%
Iowa Central	0.9919	0.9903	0.9868	0.9953	0.9985	0.9994	0.34%	0.82%	1.26%
Iowa Northeast	0.9918	0.9900	0.9856	0.9953	0.9985	0.9994	0.35%	0.85%	1.38%
Iowa South	0.9922	0.9870	0.9869	0.9960	0.9989	0.9996	0.38%	1.19%	1.27%
Kansas	0.9953	0.9946	0.9924	0.9972	0.9988	0.9994	0.19%	0.42%	0.70%
Kentucky	0.9824	0.9790	0.9725	0.9911	0.9980	0.9993	0.87%	1.91%	2.68%
Louisiana	0.9976	0.9973	0.9963	0.9986	0.9994	0.9997	0.10%	0.21%	0.33%
Maryland	0.9266	0.9113	0.8967	0.9570	0.9887	0.9964	3.18%	7.82%	10.00%
Michigan	0.9804	0.9799	0.9722	0.9875	0.9958	0.9983	0.72%	1.59%	2.62%
Minnesota	0.9983	0.9979	0.9974	0.9989	0.9996	0.9998	0.06%	0.16%	0.24%
Mississippi	0.9966	0.9959	0.9942	0.9981	0.9994	0.9998	0.15%	0.36%	0.55%
Missouri	0.9911	0.9893	0.9857	0.9951	0.9985	0.9994	0.40%	0.91%	1.37%
Montana	0.9976	0.9972	0.9964	0.9983	0.9987	0.9991	0.07%	0.15%	0.26%
Nebraska	0.9971	0.9967	0.9957	0.9982	0.9991	0.9995	0.11%	0.24%	0.38%
Nevada	0.9812	0.9737	0.9599	0.9866	0.9921	0.9958	0.54%	1.86%	3.61%
New Jersey	0.8505	0.8020	0.8048	0.9100	0.9808	0.9964	6.53%	18.23%	19.23%
New Mexico	0.9823	0.9779	0.9695	0.9884	0.9923	0.9952	0.61%	1.44%	2.58%
New York	0.9643	0.9549	0.9534	0.9797	0.9947	0.9985	1.58%	3.99%	4.51%
North Carolina	0.9695	0.9617	0.9500	0.9827	0.9957	0.9986	1.35%	3.42%	4.87%
North Dakota	0.9986	0.9985	0.9984	0.9989	0.9992	0.9995	0.03%	0.07%	0.11%
Ohio Northwest	0.9087	0.8864	0.8751	0.9468	0.9877	0.9965	4.03%	10.25%	12.18%
Ohio South	0.9327	0.9083	0.9080	0.9614	0.9931	0.9979	2.99%	8.54%	9.01%
Ohio Northeast	0.9033	0.8827	0.8755	0.9403	0.9854	0.9952	3.94%	10.42%	12.02%
Oklahoma	0.9940	0.9929	0.9899	0.9964	0.9985	0.9993	0.24%	0.57%	0.95%
Pennsylvania	0.9199	0.9090	0.8908	0.9585	0.9931	0.9982	4.03%	8.47%	10.75%
South Carolina	0.9845	0.9800	0.9733	0.9919	0.9979	0.9993	0.74%	1.79%	2.61%
South Dakota	0.9961	0.9957	0.9947	0.9973	0.9984	0.9990	0.12%	0.27%	0.43%
Tennessee	0.9753	0.9699	0.9596	0.9872	0.9974	0.9992	1.20%	2.75%	3.96%
Texas High Plains	0.9951	0.9943	0.9923	0.9966	0.9981	0.9988	0.15%	0.37%	0.65%
Texas Rolling Plains	0.9930	0.9917	0.9885	0.9957	0.9981	0.9990	0.27%	0.65%	1.06%

SUBREGION	X: $e^{-\left(\frac{O_3 NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3 WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
Texas Central Blacklands	0.9868	0.9843	0.9782	0.9928	0.9973	0.9987	0.60%	1.31%	2.05%
Texas East	0.9895	0.9875	0.9816	0.9950	0.9984	0.9992	0.55%	1.09%	1.76%
Texas Edwards Plateau	0.9934	0.9919	0.9887	0.9958	0.9982	0.9991	0.24%	0.62%	1.04%
Texas Coastal Bend	0.9896	0.9879	0.9839	0.9939	0.9977	0.9988	0.43%	0.98%	1.50%
Texas South	0.9906	0.9887	0.9845	0.9944	0.9976	0.9987	0.38%	0.90%	1.42%
Texas Trans Pecos	0.9979	0.9975	0.9966	0.9984	0.9989	0.9993	0.05%	0.14%	0.27%
Utah	0.9562	0.9426	0.9140	0.9730	0.9837	0.9917	1.72%	4.18%	7.84%
Virginia	0.9539	0.9407	0.9274	0.9756	0.9947	0.9981	2.23%	5.43%	7.09%
West Virginia	0.9525	0.9355	0.9300	0.9764	0.9970	0.9991	2.45%	6.17%	6.92%
Wisconsin	0.9882	0.9873	0.9804	0.9931	0.9978	0.9992	0.49%	1.06%	1.88%
Wyoming	0.9801	0.9762	0.9671	0.9886	0.9922	0.9952	0.86%	1.61%	2.82%

Notes:

1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by crop in Exhibit X-6.
2. Relative yield losses are only derived for subregions where the crop is present as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.

EXHIBIT B-25. DERIVATION OF AVERAGE RELATIVE YIELD LOSSES FOR HARDWOOD AND SOFTWOOD FOREST TYPES IN THE NORTHEAST FASOM REGION

FOREST TYPE	SPECIES	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)			AVERAGE RYL		
		2000	2010	2020	2000	2010	2020	2000	2010	2020	2000	2010	2020
Hardwoods	Black Cherry	0.5345	0.5059	0.4873	0.6227	0.7968	0.8837	14.17%	36.51%	44.86%	7.16%	17.13%	21.24%
	Tulip Poplar	0.8113	0.7791	0.7562	0.8904	0.9756	0.9932	8.88%	20.14%	23.86%			
	Sugar Maple	0.9100	0.8574	0.8103	0.9817	0.9997	1.0000	7.30%	14.24%	18.97%			
	Red Maple	0.9714	0.9679	0.9654	0.9805	0.9929	0.9969	0.93%	2.52%	3.16%			
	Aspen	0.8532	0.8386	0.8286	0.8935	0.9554	0.9786	4.51%	12.23%	15.34%			
Softwoods	Eastern White Pine	0.8149	0.7902	0.7729	0.8796	0.9631	0.9865	7.36%	17.96%	21.66%	3.85%	9.49%	11.50%
	Virginia Pine	0.9859	0.9847	0.9839	0.9894	0.9949	0.9972	0.35%	1.03%	1.34%			

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by tree species in Exhibit X-6.
2. Relative yield losses are only derived for tree species present in the region as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.
4. Average relative yield losses for hardwood and softwood forest types are estimated by taking the arithmetic average of relative yield losses for all hardwood or softwood species present in the region.
5. If no hardwood or softwood species, for which relative yield losses are estimated, are present in the region, the average relative yield loss of hardwoods or softwoods from all other regions is applied as a proxy estimate of average relative yield losses.

EXHIBIT B-26. DERIVATION OF AVERAGE RELATIVE YIELD LOSSES FOR HARDWOOD AND SOFTWOOD FOREST TYPES IN THE SOUTHEAST FASOM REGION

FOREST TYPE	SPECIES	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)			AVERAGE RYL		
		2000	2010	2020	2000	2010	2020	2000	2010	2020	2000	2010	2020
Hardwoods	Black Cherry	0.5648	0.4961	0.4765	0.6601	0.8326	0.9097	14.44%	40.41%	47.62%	6.49%	19.12%	23.04%
	Tulip Poplar	0.8418	0.7673	0.7423	0.9157	0.9844	0.9961	8.08%	22.06%	25.48%			
	Sugar Maple	0.9463	0.8340	0.7777	0.9914	0.9999	1.0000	4.55%	16.59%	22.23%			
	Red Maple	0.9747	0.9666	0.9640	0.9837	0.9947	0.9979	0.91%	2.83%	3.40%			
	Aspen	0.8678	0.8334	0.8226	0.9086	0.9656	0.9846	4.49%	13.69%	16.45%			
Softwoods	Eastern White Pine	0.8391	0.7812	0.7625	0.9021	0.9741	0.9913	6.99%	19.81%	23.08%	3.67%	10.49%	12.27%
	Virginia Pine	0.9872	0.9843	0.9834	0.9907	0.9959	0.9979	0.35%	1.17%	1.46%			

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by tree species in Exhibit X-6.
2. Relative yield losses are only derived for tree species present in the region as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.
4. Average relative yield losses for hardwood and softwood forest types are estimated by taking the arithmetic average of relative yield losses for all hardwood or softwood species present in the region.
5. If no hardwood or softwood species, for which relative yield losses are estimated, are present in the region, the average relative yield loss of hardwoods or softwoods from all other regions is applied as a proxy estimate of average relative yield losses.

EXHIBIT B-27. DERIVATION OF AVERAGE RELATIVE YIELD LOSSES FOR HARDWOOD AND SOFTWOOD FOREST TYPES IN THE LAKE STATES FASOM REGION

FOREST TYPE	SPECIES	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)			AVERAGE RYL		
		2000	2010	2020	2000	2010	2020	2000	2010	2020	2000	2010	2020
Hardwoods	Black Cherry	0.7571	0.7493	0.7164	0.7975	0.8677	0.9094	5.06%	13.64%	21.23%	1.60%	4.20%	6.61%
	Tulip Poplar	0.9628	0.9599	0.9460	0.9758	0.9909	0.9961	1.33%	3.12%	5.02%			
	Sugar Maple	0.9992	0.9990	0.9976	0.9997	1.0000	1.0000	0.06%	0.10%	0.24%			
	Red Maple	0.9906	0.9901	0.9879	0.9929	0.9963	0.9979	0.23%	0.62%	1.00%			
	Aspen	0.9431	0.9406	0.9295	0.9556	0.9748	0.9845	1.31%	3.50%	5.59%			
Softwoods	Eastern White Pine	0.9487	0.9455	0.9311	0.9634	0.9830	0.9913	1.53%	3.82%	6.07%	0.82%	2.07%	3.30%
	Virginia Pine	0.9938	0.9935	0.9925	0.9949	0.9968	0.9979	0.12%	0.33%	0.54%			

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by tree species in Exhibit X-6.
2. Relative yield losses are only derived for tree species present in the region as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.
4. Average relative yield losses for hardwood and softwood forest types are estimated by taking the arithmetic average of relative yield losses for all hardwood or softwood species present in the region.
5. If no hardwood or softwood species, for which relative yield losses are estimated, are present in the region, the average relative yield loss of hardwoods or softwoods from all other regions is applied as a proxy estimate of average relative yield losses.

EXHIBIT B-28. DERIVATION OF AVERAGE RELATIVE YIELD LOSSES FOR HARDWOOD AND SOFTWOOD FOREST TYPES IN THE CORN BELT FASOM REGION

FOREST TYPE	SPECIES	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)			AVERAGE RYL		
		2000	2010	2020	2000	2010	2020	2000	2010	2020	2000	2010	2020
Hardwoods	Black Cherry	0.5734	0.5111	0.5165	0.6540	0.8035	0.8773	12.33%	36.39%	41.13%	5.48%	16.76%	17.96%
	Tulip Poplar	0.8498	0.7853	0.7914	0.9119	0.9774	0.9923	6.82%	19.66%	20.24%			
	Sugar Maple	0.9539	0.8686	0.8793	0.9903	0.9998	1.0000	3.67%	13.12%	12.07%			
	Red Maple	0.9757	0.9685	0.9692	0.9832	0.9933	0.9967	0.77%	2.49%	2.76%			
	Aspen	0.8718	0.8413	0.8441	0.9063	0.9574	0.9771	3.80%	12.12%	13.62%			
Softwoods	Eastern White Pine	0.8455	0.7948	0.7995	0.8987	0.9653	0.9852	5.91%	17.66%	18.84%	3.11%	9.34%	10.02%
	Virginia Pine	0.9875	0.9849	0.9852	0.9905	0.9951	0.9971	0.30%	1.02%	1.20%			

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by tree species in Exhibit X-6.
2. Relative yield losses are only derived for tree species present in the region as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.
4. Average relative yield losses for hardwood and softwood forest types are estimated by taking the arithmetic average of relative yield losses for all hardwood or softwood species present in the region.
5. If no hardwood or softwood species, for which relative yield losses are estimated, are present in the region, the average relative yield loss of hardwoods or softwoods from all other regions is applied as a proxy estimate of average relative yield losses.

EXHIBIT B-29. DERIVATION OF AVERAGE RELATIVE YIELD LOSSES FOR HARDWOOD AND SOFTWOOD FOREST TYPES IN THE SOUTH CENTRAL FASOM REGION

FOREST TYPE	SPECIES	X: $e^{-\left(\frac{O_3 NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3 WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)			AVERAGE RYL		
		2000	2010	2020	2000	2010	2020	2000	2010	2020	2000	2010	2020
Hardwoods	Black Cherry	0.6403	0.5900	0.5698	0.7302	0.8722	0.9265	12.32%	32.36%	38.50%	4.58%	12.08%	14.56%
	Tulip Poplar	0.9029	0.8644	0.8465	0.9522	0.9916	0.9975	5.18%	12.82%	15.14%			
	Sugar Maple	0.9871	0.9659	0.9509	0.9983	1.0000	1.0000	1.13%	3.41%	4.91%			
	Red Maple	0.9820	0.9774	0.9753	0.9889	0.9965	0.9984	0.69%	1.92%	2.32%			
	Aspen	0.9008	0.8793	0.8701	0.9342	0.9759	0.9881	3.58%	9.89%	11.94%			
Softwoods	Eastern White Pine	0.8905	0.8576	0.8429	0.9374	0.9841	0.9940	5.00%	12.85%	15.20%	2.65%	6.87%	8.15%
	Virginia Pine	0.9900	0.9882	0.9874	0.9930	0.9969	0.9983	0.30%	0.88%	1.10%			

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by tree species in Exhibit X-6.
2. Relative yield losses are only derived for tree species present in the region as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.
4. Average relative yield losses for hardwood and softwood forest types are estimated by taking the arithmetic average of relative yield losses for all hardwood or softwood species present in the region.
5. If no hardwood or softwood species, for which relative yield losses are estimated, are present in the region, the average relative yield loss of hardwoods or softwoods from all other regions is applied as a proxy estimate of average relative yield losses.

EXHIBIT B-30. DERIVATION OF AVERAGE RELATIVE YIELD LOSSES FOR HARDWOOD AND SOFTWOOD FOREST TYPES IN THE ROCKY MOUNTAINS FASOM REGION

FOREST TYPE	SPECIES	X: $e^{-\left(\frac{O_3 NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3 WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)			AVERAGE RYL		
		2000	2010	2020	2000	2010	2020	2000	2010	2020	2000	2010	2020
Softwoods	Ponderosa Pine	0.9488	0.9415	0.9288	0.9595	0.9683	0.9764	1.11%	2.77%	4.88%	0.56%	1.38%	2.44%
	Douglas Fir	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%			

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by tree species in Exhibit X-6.
2. Relative yield losses are only derived for tree species present in the region as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.
4. Average relative yield losses for hardwood and softwood forest types are estimated by taking the arithmetic average of relative yield losses for all hardwood or softwood species present in the region.
5. If no hardwood or softwood species, for which relative yield losses are estimated, are present in the region, the average relative yield loss of hardwoods or softwoods from all other regions is applied as a proxy estimate of average relative yield losses.

EXHIBIT B-31. DERIVATION OF AVERAGE RELATIVE YIELD LOSSES FOR HARDWOOD AND SOFTWOOD FOREST TYPES IN THE PACIFIC NORTHWEST-WESTSIDE FASOM REGION

FOREST TYPE	SPECIES	X: $e^{-\left(\frac{O_3 NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3 WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)			AVERAGE RYL		
		2000	2010	2020	2000	2010	2020	2000	2010	2020	2000	2010	2020
Softwoods	Ponderosa Pine	0.9892	0.9873	0.9852	0.9907	0.9922	0.9936	0.15%	0.49%	0.85%	0.07%	0.25%	0.42%
	Douglas Fir	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.00%	0.00%	0.00%			

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by tree species in Exhibit X-6.
2. Relative yield losses are only derived for tree species present in the region as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.
4. Average relative yield losses for hardwood and softwood forest types are estimated by taking the arithmetic average of relative yield losses for all hardwood or softwood species present in the region.
5. If no hardwood or softwood species, for which relative yield losses are estimated, are present in the region, the average relative yield loss of hardwoods or softwoods from all other regions is applied as a proxy estimate of average relative yield losses.

EXHIBIT B-32. DERIVATION OF AVERAGE RELATIVE YIELD LOSSES FOR HARDWOOD AND SOFTWOOD FOREST TYPES IN THE PACIFIC SOUTHWEST FASOM REGION

FOREST TYPE	SPECIES	X: $e^{-\left(\frac{O_3NoCAAA}{A}\right)^B}$			Y: $e^{-\left(\frac{O_3WithCAAA}{A}\right)^B}$			RYL: (X/Y) * (100%)			AVERAGE RYL		
		2000	2010	2020	2000	2010	2020	2000	2010	2020	2000	2010	2020
Softwoods	Ponderosa Pine	0.8803	0.8595	0.8312	0.9006	0.9280	0.9485	2.25%	7.38%	12.37%	1.14%	3.73%	6.30%
	Douglas Fir	0.9996	0.9991	0.9977	0.9999	1.0000	1.0000	0.02%	0.08%	0.23%			

Notes:
1. Parameter values for A and B in the equations for X and Y are presented along with the appropriate ozone metric to apply by tree species in Exhibit X-6.
2. Relative yield losses are only derived for tree species present in the region as defined in FASOM.
3. Relative yield losses are based on ozone concentrations during the growing period for each crop and forest type, not ozone concentrations for the entire May through September period. Growing periods are specific to individual crops and subregions, and to individual regions for hardwood and softwood forest types.
4. Average relative yield losses for hardwood and softwood forest types are estimated by taking the arithmetic average of relative yield losses for all hardwood or softwood species present in the region.
5. If no hardwood or softwood species, for which relative yield losses are estimated, are present in the region, the average relative yield loss of hardwoods or softwoods from all other regions is applied as a proxy estimate of average relative yield losses.