United States
Environmental Protection
Agency

Office of Water
Washington, DC 20460

EPA-821-R-24-006
April 18, 2024

Benefit and Cost Analysis for Supplemental Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category

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U.S. Environmental Protection Agency
Office of Water (4303T)
Engineering and Analysis Division
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Abbreviations

ACS	American Community Survey
ADD	Average daily dose
ALE	Action level exceedance
As	Arsenic
ATSDR	Agency for Toxic Substances and Disease Registry
BA	Bottom ash
BAT	Best available technology economically achievable
BCA	Benefit-cost analysis
BEA	Bureau of Economic Analysis
BenMAP-CE	Environmental Benefits Mapping and Analysis Program—Community Edition
BLL	Blood lead level
BLS	Bureau of Labor Statistics
BMP	Best management practices
BOD	Biochemical oxygen demand
BW	Body weight
CAMx	Comprehensive Air Quality Model with Extensions
CBG	Census Block Group
CCI	Construction Cost Index
CCME	Canadian Council of Ministers of the Environment
CCR	Coal combustion residuals
CDC	Center for Disease Control
CFR	Code of Federal Regulations
CIL	Climate Impact Lab
CO_2	Carbon dioxide
COD	Chemical oxygen demand
COI	Cost-of-illness
COPD	Chronic obstructive pulmonary disease
CPI	Consumer Price Index
CWA	Clean Water Act
CWS	Community Water System
CWWS	Community Water System Survey
D-FATE	Downstream Fate and Transport Equations
DBP	Disinfection byproduct
DBPR	Disinfectants and Disinfection Byproduct Rule
DCN	Document Control Number
DICE	Dynamic Integrated Climate and Economy
DO	Dissolved oxygen
DSCIM	Data-driven Spatial Climate Impact Model
E2RF1	Enhanced River File 1
EA	Environmental Assessment
EC	Elemental carbon
ECI	Employment Cost Index

ECOS	Environmental Conservation Online System
EG	Emissions guidelines
EGU	Electricity generating unit
EJ	Environmental justice
ELGs	Effluent limitations guidelines and standards
EO	Executive Order
EPA	United States Environmental Protection Agency
EROM	Enhanced Runoff Method
ESA	Endangered Species Act
FaIR	Finite Amplitude Impulse Response
FC	Fecal coliform
FCA	Fish consumption advisories
FGD	Flue gas desulfurization
FUND	Climate Framework for Uncertainty, Negotiation, and Distribution
FR	Federal Register
FrEDI	Framework for Evaluating Damages and Impacts
GDP	Gross Domestic Product
GHG	Greenhouse gas
GIS	Geographic Information System
GIVE	Greenhouse Gas Impact Value Estimator
GMSL	Global mean sea level
GWP	Global warming potential
HAP	Hazardous air pollutant
HCl	Hydrogen chloride
Hg	Mercury
HRTR	High Residence Time Reduction
HUC	Hydrologic unit code
IAM	Integrated assessment model
IBI	Index of biotic integrity
IEUBK	Integrated Exposure, Uptake, and Biokinetics
IPCC	Intergovernmental Panel on Climate Change
IPM	Integrated Planning Model
ISA	Integrated science assessment
ISI	Influential Scientific Information
IRIS	Integrated Risk Information System
IQ	Intelligence quotient
LADD	Lifetime average daily dose
LML	Lowest measured level
LRTR	Low Residence Time Reduction
MATS	Mercury and Air Toxics Standards
MCL	Maximum contaminant level
MCLG	Maximum contaminant level goal
MDA1	Maximum daily 1-hour average
MDA8	Maximum daily 8-hour average

MGD	Million gallons per day
MRM	Meta-regression model
NAAQS	National Ambient Air Quality Standards
NARS	National Aquatic Resources Survey
NEI	National Emissions Inventory
NERC	North American Electric Reliability Corporation
NHD	National Hydrography Dataset
NLCD	National Land Cover Dataset
NLFA	National Listing Fish Advisory
NOAA	National Oceanic and Atmospheric Administration
NOAEL	No observed adverse effect level
NO_X	Nitrogen oxides
NPDES	National Pollutant Discharge Elimination System
NRSA	National Rivers and Streams Assessment
NRWQC	National Recommended Water Quality Criteria
NSPS	New source performance standard
NTU	Nephelometric turbidity units
NWIS	National Water Information System
O3	Ozone
O3V	Ozone formed in VOC-limited chemical regimes
O3N	Ozone formed in NO_X-limited chemical regimes
OA	Organic aerosol
O&M	Operation and maintenance
OMB	Office of Management and Budget
OSAT/APCA	Ozone Source Apportionment Technique/Anthropogenic Precursor Culpability Assessment
OWTP	Willingness-to-pay for a one-point WQI improvement (one-point WTP)
PACE	Policy Analysis of the Greenhouse Gas Effect
Pb	Lead
$PM_{2.5}$	Particulate matter (fine inhalable particles with diameters 2.5 μm and smaller)
PM_{10}	Particulate matter (inhalable particles with diameters 10 μm and smaller)
ppm	parts per million
PSAT	Particulate Source Apportionment Technique
PSES	Pretreatment Standards for Existing Sources
PV	Present value
PWS	Public water system
QA	Quality assurance
QC	Quality control
RIA	Regulatory Impact Analysis
RFF	Resources for the Future
SAB-HES	Science Advisory Board Health Effect Subcommittee
SBREFA	Small Business Regulatory Enforcement Fairness Act
$SC\text{-}CO_2$	Social cost of carbon
SDWIS	Safe Drinking Water Information System
Se	Selenium

SO_2	Sulfur dioxide
SPARROW	SPAtially Referenced Regressions On Watershed attributes
SSC	Suspended solids concentration
SWFSC	Southwest Fisheries Science Center
T&E	Threatened and endangered
TDD	Technical Development Document
TDS	Total dissolved solids
TEC	Threshold effect concentration
TN	Total nitrogen
TP	Total phosphorus
TRI	Toxics Release Inventory
TSD	Technical support document
TSS	Total suspended solids
TTHM	Total trihalomethanes
TWTP	Total willingness-to-pay
U.S. FWS	United States Fish and Wildlife Service
USGS	United States Geological Survey
VIP	Voluntary Incentive Program
VOC	Volatile organic compounds
VSL	Value of a statistical life
WBD	Watershed Boundary Dataset
WQ	Water quality
WQI	Water quality index
WQI-BL	Baseline water quality index
WQI-PC	Post-technology implementation water quality index
WQL	Water quality ladder
WTP	Willingness-to-pay

Executive Summary

The U.S. Environmental Protection Agency (EPA) is finalizing revisions to the technology-based effluent limitations guidelines and standards (ELGs) for the steam electric power generating point source category, 40 Code of Federal Regulations (CFR) part 423, which EPA promulgated in October 2020 (85 FR 64650). The final rule revises certain best available technology economically achievable (BAT) effluent limitations and pretreatment standards for existing sources (PSES) for three wastestreams: flue gas desulfurization (FGD) wastewater, bottom ash (BA) transport water, and combustion residual leachate (CRL). EPA also sets new source performance standards and pretreatment standards for new sources for CRL.[1]

Regulatory Options

EPA analyzed three regulatory options, summarized in Table ES-1. The options are labeled Option A through Option C according to increasing stringency. All options include the same general technology basis for FGD wastewater and BA transport water (zero discharge) and for CRL (chemical precipitation) but differ in terms of the technology basis applicable to certain subcategories. For example, all three options use surface impoundments as the basis for units retiring by 2028, and options A and B use chemical precipitation with biological treatment for FGD wastewater or High Recycle Rate Systems (HRR) for BA transport water as the bases for units retiring by 2034. Options B and C also use chemical precipitation as the basis for legacy wastewater. EPA is finalizing ELGs based on Option B.

The baseline for the benefit and social cost analyses reflects existing ELG requirements in absence of this EPA action, *i.e.*, the 2020 ELG. As detailed in this report, EPA calculated the difference between the baseline and regulatory Options A through C to determine the net incremental effect of the regulatory options. In general, the regulatory options are estimated to result in smaller pollutant loads, improved environmental conditions, and net benefits.

Benefits of Regulatory Options

EPA estimated the potential social welfare effects of the regulatory options and, where possible, quantified and monetized the benefits (see Chapters 3 through 9 for details of the methodology and results). Table ES-2 summarizes the benefits that EPA quantified and monetized.

EPA quantified but did not monetize other welfare effects of the regulatory options and discusses other effects only qualitatively. Chapter 2 presents additional information on these welfare effects

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[1] EPA does not expect, and is not aware of, any planned new sources that would be subject to the requirements of this final rule.

Table ES-1: Regulatory Options Analyzed for the Final Rule

Wastestream	Subcategory	Technology Basis for BAT/PSES Regulatory Options[a]			
		Baseline (2020 Rule)	Option A	Option B (Final Rule)	Option C
FGD Wastewater	NA (default unless in subcategory)[b]	CP + Bio	ZLD	ZLD	ZLD
	Boilers permanently ceasing the combustion of coal by 2028	SI	SI	SI	SI
	Boilers permanently ceasing the combustion of coal by 2034	NS	CP + Bio	CP + Bio	NS
	High FGD Flow Facilities or Low Utilization Boilers	CP	NS	NS	NS
BA Transport Water	NA (default unless in subcategory)[b]	HRR	ZLD	ZLD	ZLD
	Boilers permanently ceasing the combustion of coal by 2028	SI	SI	SI	SI
	Boilers permanently ceasing the combustion of coal by 2034	NS	HRR	HRR	NS
	Low Utilization Boilers	BMP Plan	NS	NS	NS
CRL	NA (default)[b]	BPJ	CP	ZLD	ZLD
	Discharges of unmanaged CRL	NA	NS	CP	CP
	Boilers permanently ceasing the combustion of coal by 2034	NA	CP	CP	NS
Legacy Wastewater	Operate after 2024	NA	NS	CP	CP

Abbreviations: BMP = Best Management Practice; CP = Chemical Precipitation; HRR = High Recycle Rate Systems; SI = Surface Impoundment; ZLD = Zero Liquid Discharge; NS = Not subcategorized (default technology basis applies); NA = Not applicable

a. See TDD for a description of these technologies (U.S. EPA, Agency for Toxic Substances and Disease Registry, 2009; Grandjean et al., 2014; Hollingsworth & Rudik, 2021; Mergler et al., 2007; 2024f).

b. The table does not present existing subcategories included in the 2015 and 2020 rules as EPA did not reopen the existing subcategorization of oil-fired units or units with a nameplate capacity of 50 MW or less.

Source: U.S. EPA Analysis, 2024

Table ES-2: Summary of Total Annualized Benefits for Regulatory Options, Compared to Baseline (Millions of 2023$; 2 Percent Discount)

Benefit Category	Option A	Option B (Final Rule)	Option C
Human Health			
Changes in IQ losses in children from exposure to lead via fish ingestion[a]	<$0.01	<$0.01	<$0.01
Changes in cardiovascular disease premature mortality from exposure to lead via fish ingestion	$0.16 – $0.43	$0.16 – $0.43	$0.16 – $0.45
Changes in IQ losses in children from exposure to mercury via fish ingestion	$1.71	$1.98	$2.00
Changes in cancer risk from disinfection by-products in drinking water	$13.37	$13.37	$14.27
Ecological Conditions and Recreational Uses Changes			
Use and nonuse values for water quality changes[b]	$0.79	$1.24	$1.68
Market and Productivity Effects[a]			
Changes in drinking water treatment costs	$0.45 – $0.54	$0.46 – $0.55	$0.59 – $0.71
Changes in dredging costs[a]	<$0.01	<$0.01	<$0.01
Air Quality-Related Effects			
Climate change effects from changes in greenhouse gas emissions[c]	$1,200	$1,600	$1,900
Human health effects from changes in NO_X, SO_2, and $PM_{2.5}$ emissions[c,d]	$1,200	$1,600	$2,000
Total[e]	**$2,417**	**$3,217**	**$3,919**
Additional non-monetized benefits	Other avoided adverse health effects (cancer and non-cancer) from reduced exposure to pollutants discharged to receiving waters; improvements in T&E species habitat and potential effects on T&E species populations; changes in property value from water quality improvements; changes in ecosystem effects, visibility impairment, and human health effects from direct exposure to NO_2, SO_2, and hazardous air pollutants.		

a. "<$0.01" indicates that monetary values are greater than $0 but less than $0.01 million.

b. Value reflects the main willingness-to-pay estimates. See Chapter 6 for details.

c. Values for air-quality related effects are rounded to two significant figures. EPA estimated the air quality-related benefits for Option B. EPA extrapolated estimates of air quality-related benefits for Options A and C from the estimate for Option B that is based on IPM outputs. See Chapter 8 for details.

d. The values reflect the LT estimates of human health effects from changes in $PM_{2.5}$ and ozone levels. See Chapter 8 for details.

e. Values for individual benefit categories may not sum to the total due to independent rounding.

Source: U.S. EPA Analysis, 2024

Social Costs of Regulatory Options

Table ES-3 (below) presents the incremental social costs attributable to the regulatory options, calculated as the difference between each option and the baseline. The regulatory options generally result in additional costs across regulatory options and discount rates. Chapter 11 describes the social cost analysis. The compliance costs of the regulatory options are detailed in the Regulatory Impact Analysis (RIA) (U.S. EPA, 2023k).

Comparison of Benefits and Social Costs of Regulatory Options

In accordance with the requirements of Executive Order (E.O.) 12866: *Regulatory Planning and Review*, as amended by E.O. 13563: *Improving Regulation and Regulatory Review* and E.O. 14094: *Modernizing Regulatory Review*. EPA compared the benefits and costs of each regulatory option. Table ES-4 presents the monetized benefits and social costs attributable to the regulatory options, calculated as the difference between each option and the baseline. The total social costs are presented as a range to reflect uncertainty regarding the costs to meet limits for unmanaged CRL.

Table ES-3: Total Annualized Benefits and Social Costs by Regulatory Option and Discount Rate (Millions of 2023$; 2 Percent Discount)

Regulatory Option	Total Monetized Benefits[a, b]	Total Social Costs[a]	
		Lower Bound	Upper Bound
Option A	$2,417	$433.2	$960.9
Option B (Final Rule)	$3,217	$536.2	$1,063.9
Option C	$3,919	$622.4	$1,150.1

a. EPA's benefits analysis did not account for the effects of loading reductions associated with limits for unmanaged CRL and legacy wastewater, whereas the total costs account for outlays for meeting these limits. See Chapter 11 for details on the lower and upper bound cost scenarios.

b. EPA estimated the air quality-related benefits for the final rule (Option B) only. EPA extrapolated estimates of air quality-related benefits for Options A and C from the estimate for Option B that is based on IPM outputs. See Chapter 8 for details.

Source: U.S. EPA Analysis, 2024.

1 Introduction

EPA is finalizing revisions to the technology-based ELGs for the steam electric power generating point source category, 40 CFR part 423, which EPA previously proposed in March 29, 2023 (88 FR 18824). The final rule revises certain effluent limitations promulgated in October 2020 (85 FR 64650) based on BAT and pretreatment standards for existing sources for four wastestreams: flue gas desulphurization (FGD) wastewater, bottom ash (BA) transport water, combustion residual leachate (CRL), and legacy wastewater. EPA also sets new source performance standards and pretreatment standards for new sources for CRL.[2]

This document presents an analysis of the benefits and social costs of the regulatory options and complements other analyses EPA conducted in support of this final rule, described in separate documents:

- *Environmental Assessment for Supplemental Effluent Guidelines and Standards for the Steam Electric Power Generating Point Source Category* (EA; U.S. EPA, 2024b). The EA summarizes the potential environmental and human health impacts that are estimated to result from the regulatory options.

- *Technical Development Document for Supplemental Effluent Guidelines and Standards for the Steam Electric Power Generating Point Source Category* (TDD; U.S. EPA, 2024f). The TDD summarizes the technical and engineering analyses supporting the final rule. The TDD presents EPA's updated analyses supporting the revisions to limitations and standards applicable to discharges of FGD wastewater, BA transport water, leachate, and legacy wastewater. These updates include additional data collection that has occurred since publication of the 2023 proposed rule, updates to the industry (*e.g.*, retirements, treatment updates), cost methodologies, pollutant removal estimates, and explanations for the calculation of the effluent limitations and standards.

- *Regulatory Impact Analysis for Supplemental Revisions to the Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category* (RIA; U.S. EPA, 2024e). The RIA describes EPA's analysis of the costs and economic impacts of the regulatory options. This analysis provides the basis for social cost estimates presented in Chapter 11 of this document. The RIA also provides information pertinent to meeting several legislative and administrative requirements, including the Regulatory Flexibility Act of 1980 (as amended by the Small Business Regulatory Enforcement Fairness Act [SBREFA] of 1996), the Unfunded Mandates Reform Act of 1995, Executive Order (E.O.) 13211 on *Actions Concerning Regulations That Significantly Affect Energy Supply, Distribution, or Use*, and others.

- *Environmental Justice Analysis for Supplemental Revisions to the Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category (*EJA; U.S. EPA, 2024c). This report presents a profile of the communities and populations potentially impacted by this final rule and an analysis of the distribution of impacts in the baseline and final rule changes.

The rest of this chapter discusses aspects of the regulatory options that are salient to EPA's analysis of the benefits and social costs of the final rule and summarizes key analytic inputs used throughout this document.

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[2] EPA does not expect, and is not aware of, any planned new sources that would be subject to the requirements of this final rule.

The analyses of the regulatory options are based on data generated or obtained in accordance with EPA's Quality Policy and Information Quality Guidelines. EPA's quality assurance (QA) and quality control (QC) activities for this rulemaking include the development, approval and implementation of Quality Assurance Project Plans for the use of environmental data generated or collected from all sampling and analyses, existing databases and literature searches, and for the development of any models which used environmental data. Unless otherwise stated within this document, the data used and associated data analyses were evaluated as described in these quality assurance documents to ensure they are of known and documented quality, meet EPA's requirements for objectivity, integrity and utility, and are appropriate for the intended use.

1.1 Steam Electric Power Plants

The ELGs for the Steam Electric Power Generating Point Source Category apply to a subset of the electric power industry, namely those plants "with discharges resulting from the operation of a generating unit by an establishment whose generation of electricity is the predominant source of revenue or principal reason for operation, and whose generation of electricity results primarily from a process utilizing fossil-type fuel (coal, oil, or gas), fuel derived from fossil fuel (*e.g.*, petroleum coke, synthesis gas), or nuclear fuel in conjunction with a thermal cycle employing the steam water system as the thermodynamic medium" (40 Code of Federal Regulations [CFR] 423.10).

As described in the RIA, of the 858 steam electric power plants in the universe identified by EPA, only those coal-fired power plants that discharge FGD wastewater, BA transport water, CRL or legacy wastewater may incur compliance costs under the regulatory options analyzed for this final rule. After accounting for planned retirements and fuel conversions, EPA estimated that 185 power plants will have coal-fired generating units operating after December 31, 2028 and/or generate FGD wastewater, BA transport water, CRL or legacy wastewater. Of those plants, an estimated 110 steam electric power plants generate the relevant wastestreams and may incur costs to meet the effluent limits under one or more regulatory options. See TDD and RIA for details (U.S. EPA, 2024e; 2024f).

1.2 Baseline and Regulatory Options Analyzed

EPA presents three regulatory options (see Table 1-1). These options differ in the stringency of controls and applicability of these controls to generating units or plants based on generation capacity utilization, and retirement or repowering status (see TDD for a detailed discussion of the options and the associated treatment technology bases).

The baseline for this analysis reflects applicable requirements (in absence of the rule). The baseline includes the 2020 rule (85 FR 64650). As discussed further in Section 2.2.2 of the RIA, the baseline for this analysis also includes the effects of the 2020 CCR Part A rule.

The Agency estimated and presents in this report the water quality and other environmental effects of FGD wastewater, BA transport water, leachate, and legacy wastewater discharges under both the 2020 rule baseline and regulatory options A through C presented in Table 1-1. The Agency calculated the difference between the baseline and the regulatory options to determine the net effect of each regulatory option. EPA is finalizing Option B.

Table 1-1: Regulatory Options Analyzed for the Final Rule

Wastestream	**Subcategory**	**Technology Basis for BAT/PSES Regulatory Options**[a]			
		Baseline (2020 Rule)	**Option A**	**Option B (Final Rule)**	**Option C**
FGD Wastewater	NA (default unless in subcategory)[b]	CP + Bio	ZLD	ZLD	ZLD
	Boilers permanently ceasing the combustion of coal by 2028	SI	SI	SI	SI
	Boilers permanently ceasing the combustion of coal by 2034	NS	CP + Bio	CP + Bio	NS
	High FGD Flow Facilities or Low Utilization Boilers	CP	NS	NS	NS
BA Transport Water	NA (default unless in subcategory)[b]	HRR	ZLD	ZLD	ZLD
	Boilers permanently ceasing the combustion of coal by 2028	SI	SI	SI	SI
	Boilers permanently ceasing the combustion of coal by 2034	NS	HRR	HRR	NS
	Low Utilization Boilers	BMP Plan	NS	NS	NS
CRL	NA (default)[b]	BPJ	CP	ZLD	ZLD
	Discharges of unmanaged CRL	NA	NS	CP	CP
	Boilers permanently ceasing the combustion of coal by 2034	NA	CP	CP	NS
Legacy wastewater	Operate after 2024	NA	NS	CP	CP

Abbreviations: BMP = Best Management Practice; CP = Chemical Precipitation; HRR = High Recycle Rate Systems; SI = Surface Impoundment; ZLD = Zero Liquid Discharge; NS = Not subcategorized (default technology basis applies); NA = Not applicable

a. See TDD for a description of these technologies (U.S. EPA, 2024f).

b. The table does not present existing subcategories included in the 2015 and 2020 rules as EPA did not reopen the existing subcategorization of oil-fired units or units with a nameplate capacity of 50 MW or less.

Source: U.S. EPA Analysis, 2024

1.3 Analytic Framework

The analytic framework of this benefit-cost analysis (BCA) includes basic components used consistently throughout the analysis of benefits and social costs[3] of the regulatory options:

1. All values are presented in 2023 dollars;
2. Future benefits and costs are discounted at 2 percent back to 2024;
3. Benefits and costs are analyzed over a 25-year period (2025 to 2049) which covers the years when plants implement wastewater treatment technologies to meet the revised ELGs (2025-2029) and the subsequent life of these technologies (20 years);
4. Technology installation and the resulting pollutant loading changes occur at the end of the estimated wastewater treatment technology implementation year;
5. Benefits and costs are annualized over 25 years, based on the period of analysis described above;
6. Positive values represent net benefits (*e.g.*, improvements in environmental conditions or social welfare) compared to baseline; and
7. Future values account for annual U.S. population and income growth, unless noted otherwise.

These components are discussed in the sections below.

As was the case for the 2023 proposed rule, EPA's analysis of the regulatory options generally follows the methodology the Agency used previously to analyze the 2015 and 2020 rules and the 2023 proposed rule (U.S. EPA, 2015a, 2020b, 2024a). In analyzing the regulatory options, however, EPA made several changes relative to the analysis of the 2020 rule and 2023 proposed rule:

- EPA used revised inputs that reflect the costs and loads estimated for each of the three regulatory options (see TDD and RIA for details; U.S. EPA, 2024e; 2024f). Like the analysis of the 2020 final rule and 2023 proposed rule, EPA estimated loading reductions for two periods (2025-2029 and 2030-2049) during the overall period of analysis (2025-2049) to account for transitional conditions when different plants are in the process of installing technologies to meet the ELGs.
- EPA updated the baseline industry information to incorporate changes in the universe and operational characteristics of steam electric power plants such as electricity generating unit retirements and fuel conversions since the analysis of the 2020 final rule and 2023 proposed rule. EPA also incorporated updated information on the technologies and other controls that plants employ. See the TDD for details on the changes (U.S. EPA, 2024f).
- Finally, EPA made certain changes to the methodologies to be consistent with approaches used by the Agency for other rules and/or incorporate recent advances in environmental assessment, health risk, and resource valuation research.

These changes are described in the relevant sections of this document, and summarized in Appendix A.

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[3] Unless otherwise noted, costs represented in this document are social costs.

1.3.1 Constant Prices

This BCA applies a year 2023 constant price level to all future monetary values of benefits and costs. Some monetary values of benefits and costs are based on actual past market price data for goods or services, while others are based on other measures of values, such as household willingness-to-pay (WTP) surveys used to monetize ecological changes resulting from surface water quality changes. This BCA updates market and non-market prices using the Consumer Price Index (CPI), Gross Domestic Product (GDP) implicit price deflator, or Construction Cost Index (CCI). To update the value of a Statistical Life (VSL), EPA used the GDP deflator and the elasticity of VSL with respect to income of 0.4, as recommended in EPA's Guidelines for preparing Economic Analysis (U.S. EPA, 2010, updated 2014). EPA used the GDP deflator to update the value of an IQ point, the CPI to update the WTP for surface water quality improvements and cost of illness (COI) estimates, and the CCI to update the cost of dredging navigational waterways and reservoirs.

1.3.2 Discount Rate and Year

This BCA estimates the annualized value of future benefits and costs using a discount rate of 2 percent, following current Office of Management and Budget (OMB) guidance in Circular A-4 (U.S. Office of Management and Budget, 2023).[4] Climate benefits are monetized using social cost of greenhouse gas (SC-GHG) estimates calculated with near-term Ramsey discount rates of 1.5 percent, 2 percent, and 2.5 percent. To calculate the annualized value of climate benefits, EPA uses the same discount rate as the near-term Ramsey rate used to discount the climate benefits from future GHG changes. That is, future climate benefits estimated with the SC-GHG at the near-term 2 percent Ramsey rate are discounted to the base year of the analysis using a 2 percent rate. Section 8.2 provides additional details on the discounting of climate benefits.

All future cost and benefit values are discounted back to 2024, the rule promulgation year.[5]

In Appendix B, EPA presents the benefits and costs of the final rule using the discount rates used in the proposal BCA, which followed the guidance applicable at the time the prior analysis was conducted (OMB, 2003).[6]

1.3.3 Period of Analysis

The rule benefits are projected to begin accruing when each plant implements the control technologies needed to comply with any applicable BAT effluent limitations or pretreatment standards. As described in greater

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[4] The social costs presented in this BCA differ from the annualized pre-tax compliance costs described in Chapter 3 of the RIA or the compliance costs modeled in IPM (Chapter 5 of the RIA) which use the estimated weighted average cost of capital for the power sector of 3.76 percent to discount and annualize costs.

[5] In its analysis of the 2015 rule, EPA presented benefits in 2013 dollars and discounted these benefits and costs to 2015 (see U.S. Environmental Protection Agency. (2015a). *Benefit and Cost Analysis for the Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category*. (EPA-821-R-15-005).), whereas the analysis of the 2020 rule used 2018 dollars and discounted benefits and costs to 2020 (see U.S. Environmental Protection Agency. (2020b). *Benefit and Cost Analysis for Revisions to the Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category*. (EPA-821-R-20-003).).

[6] In the prior version of Circular A-4, the OMB recommended that 3 percent be used when a regulation affects private consumption, and 7 percent in evaluating a regulation that would mainly displace or alter the use of capital in the private sector (U.S. Office of Management and Budget. (2003). *Circular A-4: Regulatory Analysis*. Retrieved from https://www.whitehouse.gov/sites/whitehouse.gov/files/omb/circulars/A4/a-4.pdf). OMB has long recognized that climate effects should be discounted only at appropriate consumption-based discount rates. Because the SC-GHG estimates reflect net climate change damages in terms of reduced consumption (or monetary consumption equivalents), the use of the social rate of return on capital (7 percent under ibid.) to discount damages estimated in terms of reduced consumption would inappropriately underestimate the impacts of climate change for the purposes of estimating the SC-GHG.

detail in the NPRM, EPA is establishing availability timing for BAT limitations that is "as soon as possible" after the effective date of any final rule but "no later than" five years from the effective date (*i.e.*, a 2029 deadline). As discussed in the RIA (in Chapter 3), for the purpose of the economic impact and benefit analysis, EPA generally estimates that plants will implement control technologies to meet the applicable rule limitations and standards as their permits are renewed, and no later than December 31, 2029. This schedule recognizes that control technology implementation is likely to be staggered over time across the universe of steam electric power plants.

The period of analysis extends to 2049 to capture the estimated life of the compliance technology at any steam electric power plant (20 or more years), starting from the year of technology implementation, which can be as late as 2029.

The different compliance years between options, wastestreams, and plants means that environmental changes may occur in a staggered fashion over the analysis period as plants implement control technologies to meet applicable limits under each option. To analyze environmental changes from the baseline and resulting benefits, EPA used the annual average of loadings or other environmental changes (*e.g.*, air emissions, water withdrawals) projected during two distinct periods (2025-2029 and 2030-2049) within the overall analysis period (2025-2049). Section 3.2 provides further details on the breakout of the analysis periods.

1.3.4 Timing of Technology Installation and Loading Reductions

For the purpose of the analysis of benefits and social costs, EPA estimates that plants meet revised applicable limitations and standards by the end of their estimated technology implementation year and that any resulting changes in loadings will be in effect at the start of the following year.

1.3.5 Annualization of future costs and benefits

Consistent with the timing of technology installation and loading reductions described above which is modeled to occur at the end of the year, EPA uses the following equation to annualize the future stream of costs and benefits:

Equation 1-1.

$$AV = \frac{r(PV)}{(1+r)[1-(1+r)^{-n}]}$$

Where AV is the annualized value, PV is the present value, r is the discount rate (2 percent), and n is the number of years (25 years) over which non-zero costs and benefits are modeled.

1.3.6 Population and Income Growth

To account for future population growth or decline, EPA used Woods & Poole population forecasts for the United States (Woods & Poole Economics Inc., 2021). EPA used the growth projections for each year to adjust affected population estimates for future years (*i.e.*, from 2025 to 2049).

Because WTP is expected to increase as income increases, EPA accounted for income growth for estimating the value of avoided premature mortality based on the value of a statistical life (VSL) and WTP for water quality improvements. To develop income adjustment factors, EPA calculated income growth factors using historical and projected "real disposable personal income" estimates (U.S. Energy Information Administration, 2021). For the VSL calculations, EPA used the VSL value in 1990 dollars ($4.8 million) and adjusted for inflation using the U.S. Bureau of Labor Statistics' (2023) CPI and adjusted for income growth using real GDP per capita and an income elasticity of 0.4 (U.S. EPA, 2010, updated 2014). Adjusted VSL values ranged from $13.5 million in 2025 to $16.4 million in 2049. For the WTP for water quality improvements, EPA multiplied income estimates by the income growth rate, relative to 2021, for the applicable analysis period year (*i.e.*, from 2025 to 2049).[7]

1.4 Organization of the Benefit and Cost Analysis Report

This BCA report presents EPA's analysis of the benefits of the regulatory options, assessment of the total social costs, and comparison of the social costs and monetized benefits.

The remainder of this report is organized as follows:

- Chapter 2 provides an overview of the main benefits expected to result from the implementation of the three regulatory options analyzed for this proposal.
- Chapter 3 describes EPA's estimates of the environmental changes resulting from the regulatory options, including water quality modeling that underlays the Agency's estimates of several categories of benefits.
- Chapters 4 and 5 details the methods and results of EPA's analysis of human health benefits from changes in pollutant exposure via the drinking water and fish ingestion pathways, respectively.
- Chapter 6 discusses EPA's analysis of the nonmarket benefits of changes in surface water quality resulting from the regulatory options.
- Chapter 7 discusses EPA's analysis of benefits to threatened and endangered (T&E) species.
- Chapter 8 describes EPA's analysis of benefits associated with changes in emissions of air pollutants associated with energy use, transportation, and the profile of electricity generation for the regulatory options.
- Chapter 9 describes benefits from changes in costs for drinking water treatment and dredging costs to maintain navigational channels and reservoirs.
- Chapter 10 summarizes monetized benefits across benefit categories.
- Chapter 11 summarizes the social costs of the regulatory options.
- Chapter 12 compares the benefits and social costs of its actions in accordance with executive order E.O. 12866: Regulatory Planning and Review (58 FR 51735, October 4, 1993), as amended by E.O. 13563: Improving Regulation and Regulatory Review (76 FR 3821, January 21, 2011) and E.O. 14094: Modernizing Regulatory Review (88 FR 21879, April 11, 2023).
- Chapter 13 provides references cited in the text.

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[7] There is a relatively strong consensus in economic literature that income elasticities of approximately "1" are appropriate for adjusting WTP for water quality improvements in future years (Johnston, R. J., Besedin, E. Y., & Holland, B. M. (2019). Modeling Distance Decay within Valuation Meta-Analysis. *Environmental and resource economics*, *72*(3), 657-690. https://doi.org/https://doi.org/10.1007/s10640-018-0218-z ; Tyllianakis, E., & Skuras, D. (2016). The income elasticity of Willingness-To-Pay (WTP) revisited: A meta-analysis of studies for restoring Good Ecological Status (GES) of water bodies under the Water Framework Directive (WFD). *Journal of environmental management*, *182*, 531-541. https://doi.org/10.1016/j.jenvman.2016.08.012). Therefore, EPA used an income elasticity of "1" in this analysis.

Several appendices provide additional details on selected aspects of analyses described in the main text of the report.

2 Benefits Overview

This chapter provides an overview of the estimated welfare effects to society resulting from changes in pollutant loadings due to implementation of the main regulatory options analyzed for the final rule. EPA expects the regulatory options to change discharge loads of various categories of pollutants when fully implemented. The categories of pollutants include conventional pollutants (such as suspended solids, biochemical oxygen demand (BOD), and oil and grease), priority pollutants (such as mercury [Hg], arsenic [As], and selenium [Se]), and non-conventional pollutants (such as total nitrogen [TN], total phosphorus [TP], chemical oxygen demand [COD] and total dissolved solids [TDS]).

Table 2-1 presents estimated annual pollutant loads in the baseline and changes in pollutant loads under full implementation of the effluent limitations and standards for the regulatory options. The TDD provides further detail on the loading changes (U.S. EPA, 2024f). As described in Section 3.2, EPA anticipates a transition period and estimated loadings during interim years before all plants have implemented control technologies to meet the applicable final ELGs under the regulatory options may differ from these values. EPA also anticipates loading reductions for legacy wastewater to occur only when facilities dewater and close their existing ponds, which may happen after the end of the period of analysis.

Table 2-1: Estimated Baseline Annual Pollutant Loadings and Changes in Loadings for Regulatory Options Under Technology Implementation

Pollutant	Estimated Baseline Total Pollutant Loadings[a] (pounds per year)	Estimated Changes in Pollutant Loadings[a] from Baseline (pounds per year)		
		Option A	Option B (Final Rule)	Option C
Antimony	245	-179	-225	-245
Arsenic	742	-480	-667	-691
Barium	7,260	-4,500	-5,680	-6,180
Beryllium	31	-27	-27	-31
Boron	6,270,000	-4,590,000	-4,910,000	-5,620,000
Bromide	6,160,000	-5,730,000	-5,730,000	-6,160,000
Cadmium	534	-134	-494	-510
Chemical oxygen demand	117,000	-112,000	-112,000	-117,000
Chromium	20,500	-20,300	-20,400	-20,400
Copper	379	-164	-331	-346
Cyanide	21,900	-18,900	-18,900	-21,900
Lead	215	-124	-172	-185
Manganese	600,000	-253,000	-516,000	-557,000
Mercury	40	-11	-38	-38
Nickel	3,390	-654	-3,280	-3,310
Total nitrogen	492,000	-165,000	-165,000	-189,000
Total phosphorus	10,800	-7,670	-7,670	-8,710
Selenium	4,750	-181	-1,930	-2,020
Thallium	743	-207	-626	-657
Total dissolved solids	712,000,000	-496,000,000	-563,000,000	-640,000,000
Total suspended solids	878,000	-547,000	-767,000	-803,000
Zinc	6,440	-1,920	-6,180	-6,270

Note: Pollutant loadings and removals are rounded to three significant figures. See TDD for additional details on estimated loads (U.S. EPA, 2024f).

Table 2-1: Estimated Baseline Annual Pollutant Loadings and Changes in Loadings for Regulatory Options Under Technology Implementation

Pollutant	Estimated Baseline Total Pollutant Loadings[a] (pounds per year)	Estimated Changes in Pollutant Loadings[a] from Baseline (pounds per year)		
		Option A	Option B (Final Rule)	Option C

a. Industry-wide pollutant loadings reflect full implementation of ELGs. Values shown in this table do not account for generating unit retirements or conversions during the period of analysis which are estimated to reduce total industry loadings under the baseline and regulatory options.

Source: U.S. EPA Analysis, 2024

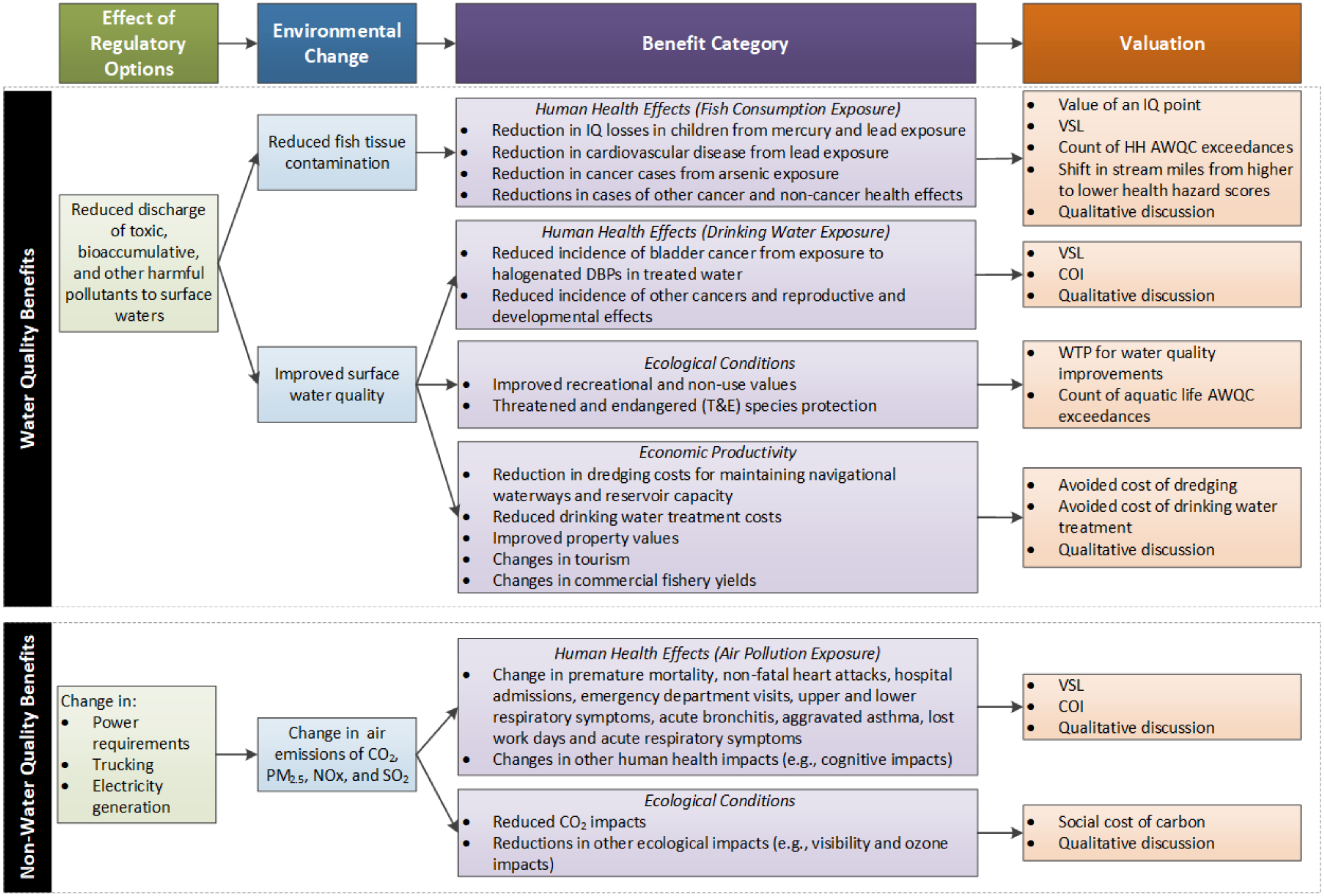
In addition to water quality changes, effects of the regulatory options in comparison to the 2020 rule also include other effects of the implementation of control technologies and changes in plant operations, such as changes in emissions of air pollutants (*e.g.*, carbon dioxide [CO_2], fine particulate matter [$PM_{2.5}$], nitrogen oxides [NO_X], and sulfur dioxide [SO_2]) which result in benefits to society in the form of changes in morbidity and mortality and CO_2 impacts on environmental quality and economic activities.

This chapter also briefly discusses the effects of pollutants found in FGD wastewater, BA transport water, CRL, and legacy wastewater and provides a framework for understanding the benefits expected to be achieved under by the regulatory options. For a more detailed description of steam electric wastewater pollutants, their fate, transport, and impacts on human health and environment, see the EA (U.S. EPA, 2024b).

Figure 2-1 summarizes the potential effects of the regulatory options, the expected environmental changes, and categories of social welfare effects as well as EPA's approach to analyzing those welfare effects.

EPA was not able to bring the same depth of analysis to all categories of social welfare effects because of imperfect understanding of the link between discharge changes or other environmental effects of the regulatory options and welfare effect categories, and how society values some of these effects. EPA was able to quantify and monetize some welfare effects, quantify but not monetize other welfare effects, and assess still other welfare effects only qualitatively. The remainder of this chapter provides a qualitative discussion of the social welfare effects applicable to the final rule, including human health effects, ecological effects, economic productivity, and changes in air pollution. Some estimates of the monetary value of social welfare changes presented in this document rely on models with a variety of limitations and uncertainties, as discussed in more detail in Chapters 3 through 9 for the relevant benefit categories.

Figure 2-1: Summary of Estimated Benefits Resulting from the Regulatory Options.



DBP = Disinfection byproducts; VSL = Value of Statistical Life; HH AWQC= human health ambient water quality criteria; COI = Cost of illness; WTP = Willingness to Pay; AWQC= ambient water quality criteria

Source: U.S. EPA Analysis, 2024.

2.1 Human Health Impacts Associated with Changes in Surface Water Quality

Pollutants present in steam electric power plant wastewater discharges can cause a variety of adverse human health effects. Chapter 3 describes the approach EPA used to estimate changes in pollutant levels in waters. More details on the fate, transport, and exposure risks of steam electric pollutants are provided in the EA (U.S. EPA, 2024b).

Human health effects are typically analyzed by estimating the change in the expected number of adverse human health events in the exposed population resulting from changes in effluent discharges. While some health effects (*e.g.*, cancer) are relatively well understood and can be quantified in a benefits analysis, others are less well characterized and cannot be assessed with the same rigor, or at all.

The regulatory options affect human health risk by changing exposure to pollutants in water via two principal exposure pathways discussed below: (1) treated water sourced from surface waters affected by steam electric power plant discharges and (2) fish and shellfish taken from waterways affected by steam electric power plant discharges. The regulatory options also affect human health risk by changing air emissions of pollutants via shifts in the profile of electricity generation, changes in auxiliary electricity use, and transportation; these effects are discussed separately in Section 2.5.

2.1.1 Drinking Water

Pollutants discharged by steam electric power plants to surface waters may affect the quality of water used for public drinking supplies. People may then be exposed to harmful constituents in treated water through ingestion, as well as inhalation and dermal absorption (*e.g.*, showering, bathing). The pollutants may not be removed adequately during treatment at a drinking water treatment plant, or constituents found in steam electric power plant discharges may interact with drinking water treatment processes and contribute to the formation of disinfection byproducts (DBPs).

Public drinking water supplies are subject to legally enforceable maximum contaminant levels (MCLs) established by EPA (U.S. EPA, 2018b). As the term implies, an MCL for drinking water specifies the highest level of a contaminant that is allowed in drinking water. The MCL is based on the MCL Goal (MCLG), which is the level of a contaminant in drinking water below which there is no known or expected risk to human health. EPA sets the MCL as close to the MCLG as possible, with consideration for the best available treatment technologies and costs. Table 2-2 shows the MCL and MCLG for selected constituents or constituent derivatives of steam electric power plant effluent.

Table 2-2: Drinking Water Maximum Contaminant Levels and Goals for Selected Pollutants in Steam Electric FGD Wastewater, BA Transport Water, CRL, and Legacy Wastewater Discharges

Pollutant	MCL (mg/L)	MCLG (mg/L)
Antimony	0.006	0.006
Arsenic	0.01	0
Barium	2.0	2.0
Beryllium	0.004	0.004
Bromate	0.010	0
Cadmium	0.005	0.005
Chromium (total)	0.1	0.1
Copper[a]	1.3	1.3
Cyanide (free cyanide)	0.2	0.2
Lead[a]	0.015	0

Table 2-2: Drinking Water Maximum Contaminant Levels and Goals for Selected Pollutants in Steam Electric FGD Wastewater, BA Transport Water, CRL, and Legacy Wastewater Discharges

Pollutant	MCL (mg/L)	MCLG (mg/L)
Mercury	0.002	0.002
Nitrate-Nitrite as N	10 (Nitrate); 1 (Nitrite)	10 (Nitrate); 1 (Nitrite)
Selenium	0.05	0.05
Thallium	0.002	0.0005
Total trihalomethanes[b]	0.080	Not applicable
bromodichloromethane	Not applicable	0
bromoform	Not applicable	0
dibromochloromethane	Not applicable	0.06
chloroform	Not applicable	0.07

a. MCL value is based on action level.

b. Bromide, a constituent found in steam electric power plant effluent, is a precursor for Total Trihalomethanes and three of its subcomponents. Additional trihalomethanes may also be formed in the presence of iodine, a constituent also found in steam electric power plant wastewater discharges.

Source: 40 CFR 141.53 as summarized in U.S. EPA (2018b): National Primary Drinking Water Regulation, EPA 816-F-09-004

Pursuant to MCLs, public drinking water supplies are tested and treated for pollutants that pose human health risks. In analyzing the human health benefits of the regulatory options, EPA assumes that treated water meets applicable MCLs in the baseline. Table 2-2 shows that for arsenic, bromate, lead, and certain trihalomethanes, the MCLG is zero. For these pollutants and for those that have an MCL above the MCLG (thallium), there may be incremental benefits from reducing concentrations even where they are below the MCL.

EPA used a mass balance approach to estimate the changes in halogen (bromide) levels in surface waters downstream from steam electric power plant outfalls. Halogens can be precursors for halogenated disinfection byproduct formation in treated drinking water, including trihalomethanes addressed by the total trihalomethanes (TTHM) MCL. The occurrence of TTHM and other halogenated disinfection byproducts in downstream drinking water depends on a number of environmental factors and site-specific processes at drinking water treatment plants. There is some evidence of associations between adverse human health effects, including bladder cancer, and exposure to sufficient levels of halogenated disinfection byproducts in drinking water (Hrudey et al., 2015; Regli et al., 2015; U.S. EPA, 2005b; 2016c; Villanueva et al., 2004; Villanueva et al., 2003). EPA quantitatively estimated the marginal effect of changes in surface water bromide levels on drinking water TTHM levels and bladder cancer incidence in exposed populations. EPA also monetized associated changes in human mortality and morbidity. EPA relied on the COI approach to monetize the estimated reduction in non-fatal bladder cancer cases and the VSL to monetize benefits from avoided fatal cancer cases (see Section 4.3.3). The COI approach allows valuation of a particular type of non-fatal illness by placing monetary values on measures, such as lost productivity and the cost of health care and medications, that can be monetized.

To assess potential for changes in health risk from exposure to arsenic, lead, and thallium in drinking water, EPA estimated changes in pollutant levels in source waters downstream from steam electric power plants under each regulatory option. This analysis is discussed in Section 4.3.2.3. EPA did not quantify or monetize benefits from reduced exposure to arsenic, lead, and thallium via drinking water due to the relatively small concentration changes in source waters downstream from steam electric plants. EPA however notes that coal ash effluents can make water more corrosive by increasing the conductivity of source waters used by downstream water systems and, as a result, increase lead leaching from water distribution infrastructure.

2.1.2 Fish Consumption

Recreational and subsistence fishers (and their household members) who consume fish caught in the reaches downstream of steam electric power plants may be affected by changes in pollutant concentrations in fish tissue. EPA analyzed the following direct measures of change in risk to human health from exposure to contaminated fish tissue:

- Neurological effects to children ages 0 to 7 from exposure to lead;
- Incidence of premature cardiovascular mortality in adults from exposure to lead;
- Neurological effects to infants from in-utero exposure to mercury;
- Incidence of skin cancer from exposure to arsenic[8]; and
- Reduced risk of other cancer and non-cancer toxic effects.

The Agency evaluated potential changes in intellectual impairment, or intelligence quotient (IQ), resulting from changes in childhood and in-utero exposures to lead and mercury. EPA also estimated changes in the incidence of cardiovascular premature mortality from exposure to lead and the number of avoided skin cancer cases exposure to arsenic.

For constituents with human health ambient water quality criteria or oral reference dose (RfD),[9] the change in the risk of other cancer and non-cancer toxic effects from fish consumption is addressed indirectly in EPA's assessment of changes in exceedances of these thresholds (see Section 5.8 and Section 4 and Appendix A of the EA; U.S. EPA, 2024b).

EPA relied on VSL to estimate the value of avoided cardiovascular premature mortality and a COI approach to estimate the value of changes in the incidence of skin cancer, which are generally non-fatal (see Section 5.6). Some health effects of changes in exposure to steam electric pollutants, such as neurological effects to children and infants exposed to lead and mercury, are measured based on avoided IQ losses. Changes in IQ cannot be valued based on WTP approaches because the available economic research provides little empirical data on society's WTP to avoid IQ losses. Instead, EPA calculated monetary values for changes in neurological and cognitive damages based on the impact of an additional IQ point on an individual's future earnings and the cost of compensatory education for children with learning disabilities. These estimates represent only one component of society's WTP to avoid adverse neurological effects and therefore produce a partial measure of the monetary value from changes in exposure to lead and mercury. Employed alone, these monetary values would underestimate society's WTP to avoid adverse neurological effects. See Sections 5.3 and 5.4 for applications of this method to valuing health effects in children and infants from changes in

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[8] In 2023, EPA released an update to the IRIS inorganic arsenic protocol. "U.S. EPA. IRIS Toxicological Review of Inorganic Arsenic (Public Comment and External Review Draft)" to reflect new data on internal cancers including bladder, liver, kidney, and lung cancers associated with arsenic exposure via ingestion (U.S. Environmental Protection Agency. (2023i). *IRIS Toxicological Review of Inorganic Arsenic (Public Comment and External Review Draft)*. (EPA/635/R-23/166). Retrieved from https://iris.epa.gov/Document/&deid=253756). Because cancer slope factors for internal organs have not been finalized, the Agency did not consider these effects in the analysis of the final rule.

[9] An RfD is defined as an estimate of a daily oral exposure that likely would not result in the occurrence of adverse health effects in humans, including sensitive individuals, during a lifetime. An RfD is typically established by applying uncertainty factors to the lowest- or no observed adverse effect level (NOAEL) for the critical toxic effect of a pollutant.

exposure to lead and mercury. This is the same approach EPA used in its analysis of the 2023 Proposed Lead and Copper Rule Improvements (U.S. EPA, 2023f).

EPA received comments on the analysis of the 2023 proposed supplemental ELG that it did not evaluate potential health impacts via the fish consumption pathway arising from changes in discharges of other steam electric pollutants, such as aluminum, boron, cadmium, hexavalent chromium, manganese, selenium, thallium, and zinc. Analyses of these health effects require data and information on the relationships between ingestion rate and potential adverse health effects and on the economic value of potential adverse health effects. Following a review of the available data, for the final rule EPA again did not quantify, nor was it able to monetize, changes in health effects associated with exposure to these pollutants under the regulatory options due to data limitations and uncertainty in the quantitative relationships. Despite numerous studies conducted by EPA and other researchers, dose-response functions are available for only a subset of health endpoints associated with steam electric wastewater pollutants. In addition, the available research does not always allow complete economic evaluation, even for quantifiable health effects. For example, sufficient data are not available to evaluate and monetize the following potential health effects from fish consumption: neonatal mortality from in-utero exposure to lead and other impacts to children from exposure to lead, such as decreased postnatal growth in children ages one to 16, delayed puberty, immunological effects, and decreased hearing and motor function (Cleveland et al., 2008; NTP, 2012; U.S. EPA, 2024d; 2019e); effects to adults from exposure to lead such as decreased kidney function, reproductive effects, immunological effects, cancer and nervous system disorders (Aoki et al., 2016; Chowdhury et al., 2018; Clay, Portnykh & Severnini, 2021; Grossman & Slusky, 2019; Lanphear et al., 2018; Navas-Acien, 2021; NTP, 2012; U.S. EPA, 2024d; 2019e; 2023f); neurological effects to children from exposure to mercury after birth (Grandjean et al., 2014); effects to adults from exposure to mercury, including vision defects, hand-eye coordination, hearing loss, tremors, cerebellar changes, premature mortality, and others (Hollingsworth & Rudik, 2021; Mergler et al., 2007; Center for Disease Control and Prevention (CDC), 2009); and other cancer and non-cancer effects from exposure to other steam electric pollutants (*e.g.,* kidney, liver, and lung damage from exposure to cadmium,[10] reproductive and developmental effects from exposure to arsenic, boron, and thallium, liver and blood effects from exposure to hexavalent chromium, and neurological effects from exposure to manganese) (California EPA, 2011; Oulhote et al., 2014; Roels et al., 2012; U.S. Department of Health and Human Services, 2012; U.S. EPA, 2020g; Ginsberg, 2012).

In some cases, EPA did not quantify or monetize health effects because the estimated changes in pollutant loadings and fish tissue concentrations are small and, combined with the available concentration-response or valuation functions, unlikely to result in tangible benefits. For example, concentration-response functions are available to characterize reductions in blood lead levels (caused by changes in lead exposure) and to translate these reductions into changes in birth weight and avoided cases of attention deficit hyperactivity disorder (ADHD). The corresponding COI estimates are also available. However, past analyses have shown that these benefits account for a small portion of total benefits associated with reducing adult and children exposure to

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[10] Although dose response relationships between a dietary exposure to cadmium and adverse effects in kidney functions have been developed for a cadmium exposure range of 0.003 to 0.014 mg/kg BW/d) (Ginsberg, G. L. (2012). Cadmium risk assessment in relation to background risk of chronic kidney disease. *Journal of Toxicology and Environmental Health, Part A, 75*(7), 374-390.), dose response relationships are not available for lower exposure ranges. Since exposure to cadmium associated with fish consumption caught in the reaches affected by steam electric discharges is below 0.001 mg/kg BW/d (RfD for cadmium) in 99.8 percent of the affected reaches (11,078 out of 11,080 reaches) in the baseline, EPA did not quantify changes in adverse health effects associated with reduced exposure to cadmium via fish consumption.

lead (*e.g.*, see U.S. EPA, 2023f). EPA therefore focused its quantitative analysis on the health effects that have been associated with the largest share of the benefits.

EPA recognizes that there may be cumulative or synergistic effects of pollutants that share the same toxicity mechanism, affect the same body organ or system, or result in the same health endpoint. For example, exposure to several pollutants discharged by steam electric plants (*i.e.*, lead, mercury, manganese, and aluminum) is associated with adverse neurological effects, in particular in fetuses and small children (Agency for Toxic Substances and Disease Registry (ATSDR), 2009; Grandjean et al., 2014; NTP, 2012; Oulhote et al., 2014; U.S. EPA, 2024d). However, data and resource limitations preclude a full analysis of such cumulative or synergistic effects. A weight of evidence approach is typically used in qualitatively evaluating the cumulative effect of a chemical mixture. Cumulative effects often depend on exposure doses as well as potential threshold effects (ATSDR, 2004; 2009). While there are no existing methods to fully analyze and monetize these effects, EPA quantified some of these effects in the EA (U.S. EPA, 2024b).

Due to these limitations, the total monetary value of changes in human health effects included in this analysis represents only a subset of the potential health benefits that are expected to result from the regulatory options.

2.1.3 Complementary Measure of Human Health Impacts

EPA quantified, but did not monetize, changes in pollutant concentrations in excess of human health-based national recommended water quality criteria (NRWQC). This analysis provides an approximate indication of the change in cancer and non-cancer health risk by comparing the number of receiving reaches exceeding health-based NRWQC for steam electric pollutants in the baseline to the number exceeding NRWQC under the regulatory options (Section 5.8).

Because the NRWQC in this analysis are set at levels to protect human health through ingestion of water and aquatic organisms, changes in the frequency at which human health-based NRWQC are exceeded could translate into changes in risk to human health. This analysis should be viewed as an indirect indicator of changes in risk to human health because it does not reflect the magnitude of human health risk changes or the population over which those changes would occur.

In addition, EPA assessed the risk of non-cancer health effects from exposure to steam electric pollutants by comparing the estimated exposure to the pollutant to the pollutant's RfD. To estimate a hazard quotient for a given pollutant EPA divided an individual's oral exposure to the pollutant by the pollutant's oral RfD. A hazard quotient less than one means that the pollutant dose to which an individual is exposed is less than the RfD. For assessing exposures to mixtures of pollutants, EPA developed distributions of non-cancer health hazard indices (HI) under the baseline and regulatory options by summing the individual hazard quotients for those pollutants in the mixture that affect the same target organ or system (*e.g.*, the kidneys, the respiratory system).[11] The shift in the affected stream miles from higher to lower hazard score values between the baseline and regulatory options is the measure of benefit from reduced non-cancer health hazards (See Section 4 of the EA; U.S. EPA, 2024b).

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[11] HI values are interpreted similarly to hazard quotients. Values below one are generally considered to suggest that exposures are not likely to result in appreciable risk of adverse health effects during a lifetime, and values above one are generally cause for concern,

2.2 Ecological and Recreational Impacts Associated with Changes in Surface Water Quality

The regulatory options may affect the value of ecosystem services provided by surface waters through changes in the habitats or ecosystems (aquatic and terrestrial) that receive steam electric power plant discharges.

The composition of steam electric power plant wastewater depends on a variety of factors, such as fuel properties, air pollution control technologies, and wastewater management techniques. Wastewater often contains toxic pollutants such as aluminum, arsenic, boron, cadmium, chromium, copper, iron, lead, manganese, mercury, nickel, selenium, thallium, vanadium, molybdenum, and zinc (U.S. EPA, 2024b). Discharges of these pollutants to surface water can have a wide variety of environmental effects, including fish kills, reduction in the survival and growth of aquatic organisms, behavioral and physiological effects in wildlife, and degradation of aquatic habitat in the vicinity of steam electric power plant discharges (U.S. EPA, 2024b). As presented in Table 2-1, steam electric plants discharge an estimated 492,000 pounds of nitrogen and 10,800 pounds of phosphorus each year in the baseline. Excess nutrients in surface water contribute to eutrophication which can also cause algal blooms and depress oxygen levels, further reducing the habitability for game fish and other aquatic life (U.S. EPA, 2000; U.S. EPA, 2001; Li et al., 2013; Mallin & Cahoon, 2020). The adverse effects associated with releases of steam electric pollutants depend on many factors such as the chemical-specific properties of the effluent, the mechanism, medium, and timing of releases, and site-specific environmental conditions. The modeled changes in environmental impacts are small relative to the changes estimated for the 2015 rule. Still, EPA expects the ecological impacts from the regulatory options could include improved habitat conditions for fresh- and saltwater plants, invertebrates, fish, and amphibians, as well as terrestrial wildlife and birds that prey on aquatic organisms exposed to steam electric pollutants. The change in pollutant loadings has the potential to enhance ecosystem productivity in waterways and the health of resident species, including T&E species. Loading reductions projected under the regulatory options have the potential to impact the general health of fish and invertebrate populations, their propagation to waters, and fisheries for both commercial and recreational purposes. Water quality improvements also have the potential to enhance recreational activities such as swimming, boating, fishing, and water skiing. Finally, the final rule has the potential to impact nonuse values (*e.g.*, option, existence, and bequest values) of the waters that receive steam electric power plant discharges.

Society values changes in ecosystem services by a number of mechanisms, including increased frequency of use and improved quality of recreational activities (*e.g.*, fishing, swimming, and boating). Individuals also value the protection of habitats and species that may reside in waters that receive steam electric plant discharges, even when those individuals do not use or anticipate future use of such waters for recreational or other purposes, resulting in nonuse values. The sections below discuss selected categories of benefits associated with changes in ecosystem services (additional economic productivity benefits associated with changes in ecosystem services are discussed in Section 2.4).

EPA’s analysis is intended to isolate possible effects of the regulatory options on aquatic ecosystems and organisms, including T&E species; however, it does not account for the fact that the National Pollutant Discharge Elimination System (NPDES) permit for each steam electric power plant, like all NPDES permits, is required to have limits more stringent than the technology-based limits established by an ELG wherever necessary to protect water quality standards. In cases where a NPDES permit would already provide for more stringent limits in the baseline than those that would be required under the final ELG, the improvements attributable to the rule will be less than estimated in this analysis.

2.2.1 Changes in Surface Water Quality

EPA quantified potential environmental impacts from the regulatory options by estimating in-waterway concentrations of FGD wastewater, BA transport water and CRL pollutants and translating water quality estimates into a single numerical indicator, a water quality index (WQI). EPA used the estimated change in WQI as a quantitative estimate of changes in aquatic ecosystem conditions for this regulatory analysis. Section 3.4 of this report provides details on the parameters used in formulating the WQI and the WQI methodology and calculations. In addition to estimating changes using the WQI, EPA compared estimated pollutant concentrations to freshwater NRWQC for aquatic life (see Section 3.4.1.1). The EA details comparisons of the estimated concentrations in immediate receiving and downstream reaches to the freshwater acute and chronic NRWQC for aquatic life for individual pollutants (U.S. EPA, 2024b).

A variety of primary methods exist for estimating recreational use values, including both revealed and stated preference methods (Freeman III, 2003). Where appropriate data are available or can be collected, revealed preference methods can represent a preferred set of methods for estimating use values. Revealed preference methods use observed behavior to infer users' values for environmental goods and services. Examples of revealed preference methods include travel cost, hedonic pricing, and random utility (or site choice) models.

In contrast to direct use values, nonuse values are considered more difficult to estimate. Stated preference methods, or benefit transfer based on stated preference studies, are the generally accepted techniques for estimating these values (U.S. EPA, 2010, updated 2014; OMB, 2023; Johnston, Boyle, et al., 2017). Stated preference methods rely on carefully designed surveys, which either (1) ask people about their WTP for particular environmental improvements, such as increased protection of aquatic species or habitats with particular attributes, or (2) ask people to choose between competing hypothetical "packages" of environmental improvements and household cost (Bateman et al., 2006; Johnston, Boyle, et al., 2017). In either case, values are estimated by statistical analysis of survey responses.

Although the use of primary research to estimate values is generally preferred because it affords the opportunity for the valuation questions to closely match the policy scenario, the realities of the regulatory process often dictate that benefit transfer is the only option for assessing certain types of non-market values (Rosenberger & Johnston, 2008; Johnston et al., 2021). Benefit transfer is described as the "practice of taking and adapting value estimates from past research … and using them … to assess the value of a similar, but separate, change in a different resource" (Smith, Van Houtven & Pattanayak, 2002, p. 134). It involves adapting research conducted for another purpose to estimate values within a particular policy context (Bergstrom & De Civita, 1999; Johnston et al., 2021). Among benefit transfer methods, meta-analyses are often more accurate compared to other types of transfer approaches due to the data synthesis from multiple source studies (Rosenberger and Phipps, 2007; Johnston et al., 2021). However, EPA acknowledges that there is still a potential for transfer errors (Shrestha, Rosenberger & Loomis, 2007) and no transfer method is always superior (Johnston et al., 2021).

EPA followed the same methodology used in analyzing the 2015 and 2020 rules and the 2023 proposal (U.S. EPA, 2015a, 2020b, 2023b) and relied on a benefit transfer approach based on an updated meta-analysis of surface water valuation studies to estimate the use and non-use benefits of improved surface water quality under the regulatory options. The updates consisted of incorporating WTP estimates from more recent peer reviewed studies into EPA's existing econometric model.[12] This analysis is presented in Chapter 6.

2.2.2 Impacts on Threatened and Endangered Species

For T&E species, even minor changes to reproductive rates and small mortality levels may represent a substantial portion of annual population growth. By reducing discharges of steam electric pollutants to aquatic habitats, the regulatory options have the potential to impact the survivability of some T&E species living in these habitats. These T&E species may have both use and nonuse values. However, given the protected nature of T&E species and the fact that use activities, such as fishing or hunting, generally constitute "take" which is illegal unless permitted, the majority of the economic value for T&E species comes from nonuse values.[13]

EPA quantified but did not monetize the potential benefits of the regulatory options on T&E species. EPA constructed databases to determine which species have habitat ranges that intersect waters downstream from steam electric power plants. EPA then queried these databases to identify "affected areas" of those habitats where 1) receiving waters do not meet aquatic life-based NRWQC under the baseline conditions; and 2) receiving waters do meet aquatic life-based NRWQC under the regulatory options.[14] Because NRWQC are set at levels to protect aquatic organisms, reducing the frequency at which aquatic life-based NRWQC are exceeded should translate into reduced effects to T&E species and potential improvement in species populations. EPA's analysis does not account for the potential for the NPDES permit issuance process to establish more stringent site-specific controls to meet applicable water quality standards (*i.e.*, water quality-based effluent limits issued under Section 301(b)(1)(C)). The analysis may therefore overestimate any potential impacts to T&E species and associated benefits.

EPA was unable to monetize the final rule's benefits on T&E species due to challenges in quantifying the response of T&E populations to changes in water quality. Although numerous economic studies have estimated WTP for T&E protection, these studies focused on estimating WTP to avoid species loss or extinction, increase in the probability of survival, or an increase in species population levels (Subroy et al., 2019; Richardson & Loomis, 2009). These studies, as summarized in Subroy et al. (2019), suggest that people attach economic value to protection of T&E species ranging from $12.6 per household (in 2023$) for Colorado pikeminnow to $208.5 (in 2023$) for lake sturgeon (both fish species).[15] In addition, T&E species may serve as a focus for eco-tourism and provide substantive economic benefit to local communities. For example, Solomon, Corey-Luse and Halvorsen (2004) estimate that manatee viewing provides a net benefit (tourism revenue minus the cost of manatee protection) of $14.1 million to $15.5 million (in 2023$) per year for Citrus County, Florida.[16]

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[12] See ICF. (2022b). *Revisions to the Water Quality Meta-Data and Meta-Regression Models after the 2020 Steam Electric Analysis through December 2021* [Memorandum]. for additional detail on updating the meta-analysis.

[13] The U.S. Endangered Species Act (ESA) defines "take" to mean "to harass, harm, pursue, hunt, shoot, wound, kill, trap, capture, or collect, or to attempt to engage in any such conduct." 16 U.S. Code § 1532

[14] Because the regulatory options reduce pollutant loads, the opposite (receiving waters meet aquatic life-based NRWQC under the baseline conditions but do not meet the NRWQC under the regulatory options) does not apply to this analysis.

[15] Values adjusted from $8.32 and $138 per household per year (in 2006$), respectively, using the CPI.

[16] Range adjusted from $8.2 million to $9 million (in 2001$), using the CPI.

2.2.3 Changes in Sediment Contamination

Effluent discharges from steam electric power plants can also contaminate waterbody sediments. For example, sediment adsorption of arsenic, selenium, and other pollutants found in FGD wastewater, BA transport water, CRL and legacy wastewater discharges can result in accumulation of contaminated sediment on stream and lake beds (Ruhl et al., 2012), posing a particular threat to benthic (*i.e.*, bottom-dwelling) organisms. These pollutants can later be re-released into the water column and enter organisms at different trophic levels. Concentrations of selenium and other pollutants in fish tissue of organisms of lower trophic levels can bio-magnify through higher trophic levels, posing a threat to the food chain at large (Ruhl et al., 2012).

In waters receiving direct discharges from steam electric power plants, EPA examined potential exposures of ecological receptors (*i.e.*, sediment biota) to pollutants in contaminated sediment. Benthic organisms can be affected by pollutant discharges such as mercury, nickel, selenium, and cadmium (U.S. EPA, 2024b). The pollutants in steam electric power plant discharges may accumulate in living benthic organisms that obtain their food from sediments and pose a threat to both the organism and humans consuming the organism. As discussed in the EA, EPA modeled sediment pollutant concentrations in immediate receiving waters and compared those concentrations to threshold effect concentrations (TECs) for sediment biota (U.S. EPA, 2024b). In 2015, EPA also evaluated potential risks to fish and waterfowl that feed on aquatic organisms with elevated selenium levels and found that steam electric power plant selenium discharges elevated the risk of adverse reproduction impacts among fish and mallards in immediate receiving waters (U.S. EPA, 2015b).

By reducing discharges of pollutants to receiving reaches, the final rule may reduce the contamination of waterbody sediments, impacts to benthic organisms, and the probability that pollutants could later be released into the water column and affect surface water quality and the waterbody food chain. Due to data limitations, EPA did not quantify or monetize the associated benefits.

2.3 Water Supply and Use

The regulatory options are projected to reduce loadings of steam electric pollutants to surface waters relative to the baseline, and thus they may affect the uses of these waters for drinking water supply and agriculture. EPA implemented a treatment cost elasticity approach to quantify avoided drinking water treatment costs from reductions in total nitrogen and total suspended solids. This analysis is summarized in this section and described in more detail in Chapter 9 (see Section 9.1).

2.3.1 Drinking Water Treatment Costs

The regulatory options have the potential to affect drinking water treatment costs. Numerous studies have shown an unequivocal link between higher treatment costs and lower source water quality (see Heberling et al. (2022) for a non-exhaustive list of studies). Using data from 24 U.S. and non-U.S. studies, Price and Heberling (2018) developed elasticities for various water quality parameters, including nitrogen concentrations, phosphorus and sediment loadings, TOC, turbidity, and pH. EPA used these elasticities for turbidity and nitrogen to estimate potential drinking water treatment cost savings. The effects of reductions in other pollutants such as phosphorus, halogens, metals, and toxic chemicals are described qualitatively due to uncertain elasticities between these parameters and drinking water treatment costs, the lack of information on baseline concentrations of these pollutants at source water intakes, and to avoid the possibility of double-counting treatment cost savings.

2.3.1.1 Nutrients

Eutrophication, which is most commonly caused by an overabundance of nitrogen and phosphorus, is one of the main causes of taste and odor impairment in drinking water and can have a major negative impact on public perceptions of drinking water safety. The incremental cost of treating drinking water to address foul tastes and odors due to excess nutrients and the presence of algal blooms can be substantial (Mosheim & Ribaudo, 2017). Treatment may involve filtration, chemical treatment, or other processes (see Khera, Ransom and Speth (2013) for more information on treatment practices that may be employed by small drinking water systems). Recent work has estimated that drinking water systems nationwide incur nutrient pollution treatment costs in excess of $225 million annually (Andarge, 2022). Price and Heberling (2018) combined prior studies of the effect of nutrients on drinking water treatment costs, showing that a 1 percent change in nitrogen (as nitrate) concentration in source water leads to lead to a 0.05 to 0.06 percent change in drinking water treatment costs among all U.S. and non-U.S. studies. The one U.S. study with key controls for possible confounders yielded an elasticity of 0.06, but EPA instead employed a range of elasticity values of 0.05 to 0.06 to incorporate uncertainty. EPA combines the range of elasticities with estimates of baseline drinking water treatment costs to estimate the cost savings that are anticipated to accrue from this regulatory action. Given the uncertainty in the treatment cost elasticity for phosphorus, EPA did not calculate cost changes with respect to phosphorus. From nitrogen pollution reductions alone, EPA estimated annualized drinking water treatment cost savings from $357,000 to $552,000 across all regulatory options assuming a 2 percent discount rate. See details in Section 9.1.

2.3.1.2 Total Suspended Solids

Drinking water treatment costs associated with fluctuations in TSS have been quantified in prior EPA regulatory analyses including the 2004 Meat and Poultry Products Effluent Limitation Guidelines and the 2009 Effluent Limitation Guidelines and Standards for the Construction and Development Industry (U.S. EPA, 2004b, 2009b). Water systems address TSS using chemical treatment with coagulants such as alum or ferrous sulfate. Coagulant application varies in dosage depending on the influent concentrations of TSS, and thus water systems accrue variable costs in the form of coagulant purchases that vary with TSS in source water. Treatment for TSS also produces coagulated sediment in proportion to the influent concentration of TSS and the quantity of coagulant added, and disposal of this coagulated sediment results in additional variable costs for drinking water systems. Elasticity estimates for TSS in Price and Heberling (2018) are based on three studies, two of which date to 1987 and 1988. Only one of these studies included key controls, suggesting that a 1 percent change in sediment loads results in drinking water treatment cost changes of 0.05 percent. The elasticity estimates for turbidity in Price and Heberling (2018) are more precisely estimated across twelve studies, and the five studies controlling for key confounders suggest that a 1 percent increase in turbidity increases drinking water treatment costs by 0.10 to 0.12 percent. EPA therefore converts TSS measurements to turbidity levels and applies the turbidity elasticity from Price and Heberling (2018) to derive treatment cost savings from TSS reductions. The approach of converting TSS to turbidity was also applied for this benefit category in the 2009 Effluent Limitation Guidelines and Standards for the Construction and Development Industry (U.S. EPA, 2009b). EPA estimates that annualized treatment cost savings from TSS loading reductions are between $92,000 and $160,000 at a 2 percent discount rate. See details in Section 9.1.

2.3.1.3 Metals and Toxic Chemicals

EPA conducted a screening-level assessment to evaluate the potential for changes in costs incurred by public drinking water systems from changes in metal and toxic concentrations in source waters and concluded that such changes, while they may exist, are likely to be negligible. The assessment involved identifying the pollutants for which treatment costs may vary depending on source water quality, estimating changes in downstream concentrations of these pollutants at the location of drinking water intakes, and determining whether modeled water quality changes have the potential to affect drinking water treatment costs. Based on this analysis, EPA determined that there are no drinking water systems drawing water at levels that exceed an MCL for metals and other toxics[17] listed in Table 2-2 such as selenium and cyanide under either the baseline or the regulatory options (see Section 4.3.2.3 for details). EPA estimated no changes in MCL exceedances under the regulatory options. Accordingly, EPA did not conduct an analysis of changes in treatment costs incurred by public water systems (PWS) given the relatively small changes in source water quality expected under the final rule and data gaps regarding effects on treatment system operations.

2.3.1.4 Halogens

Halogens found in source water can react during routine drinking water treatment to generate harmful DBPs at levels that vary with site-specific conditions (Good & VanBriesen, 2017, 2019; Regli et al., 2015; U.S. EPA, 2016c). EPA estimated the costs of controlling DBP levels to the MCL in treated water as part of the Stage 2 Disinfectants and Disinfection Byproduct Rule (DBPR). These costs include treatment technology changes as well as non-treatment costs such as routine monitoring and operational evaluations. PWS may adjust their operations to control DBP levels, such as changing disinfectant dosage, moving the chlorination point, or enhancing coagulation and softening. These changes carry “negligible costs” (U.S. EPA, 2005c, pages 7-19). Where low-cost changes are insufficient to meet the MCL, PWS may need to incur irreversible capital costs to upgrade their treatment process to use alternative disinfection technologies such as ozone, ultraviolet light, or chloride dioxide; switch to chloramines for residual disinfection; or add a pre-treatment stage to remove DBP precursors (*e.g.*, microfiltration, ultrafiltration, aeration, or increased chlorine levels and contact time). Some drinking water treatment facilities have already upgraded their treatment systems as a direct result of halogen discharges from steam electric power plants (*United States of America v. Duke Energy*, "United States of America v. Duke Energy," 2015; Rivin, 2015). However, not all treatment technologies remove sufficient organic matter to control DBP formation to required levels (Watson, Farré & Knight, 2012). Thus, increased halogens levels in raw source water could translate into permanently higher drinking water treatment costs at some plants, in addition to posing increased human health risk. Conversely, reducing halogen levels in source waters can reduce the health risk, even where treatment changes have already occurred.[18] In some cases, operation and maintenance (O&M) costs may also be reduced.

EPA quantified halogen treatment cost elasticities using estimated operation and maintenance cost changes presented in Chen et al. (2010). According to the estimates in that study, a one percent change in bromide concentration in source waters leads to 0.14 and 0.86 percent change in drinking water operation and maintenance costs in small and large water systems, respectively, in California. However, EPA did not estimate PWS-level avoided treatment costs from bromide reductions resulting from this regulatory action due to significant uncertainty in these elasticities. To start, existing treatment technologies at the majority of PWS are not designed to remove halogens from raw surface waters, and so the coastal drinking water systems

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[17] Modeled drinking water concentrations reflect discharged pollutant loads from steam electric plants and from other facilities reporting to the Toxics Resources Inventory (TRI).

[18] Regli, S., Chen, J., Messner, M., Elovitz, M. S., Letkiewicz, F. J., Pegram, R. A., Pepping, T. J., . . . Wright, J. M. (2015). Estimating potential increased bladder cancer risk due to increased bromide concentrations in sources of disinfected drinking waters. *Environmental Science & Technology*, *49*(22), 13094-13102. estimated benefits of reducing bromide across various types of water treatment systems.

studied in Chen et al. (2010), which already contend with issues of seawater intrusion, are likely not representative of other drinking water systems. In addition, there are other environmental sources of halogens, and EPA has insufficient data on baseline bromide concentrations at source waters affected by this regulatory action. While significant uncertainty prevented an analysis of avoided treatment costs from bromide, the Agency assessed the changes in levels of halogens downstream from steam electric power plant outfalls and estimated health outcomes (avoided bladder cancer cases) associated with reduced DBP formation at downstream PWS (see Section 2.1.1 for a discussion of this benefit category and Chapter 4 for details of the analysis).[19]

2.3.1.5 Chloride and Dissolved solids

Finally, excess chloride and TDS can corrode distribution system pipes and lead to the buildup of scale (a mineral deposit), reducing water flow (U.S EPA, 2023m). Increased corrosion in water distribution systems can also increase the leaching of lead and copper. Stets et al. (2018) found a strong statistical connection between source water chemistry (*i.e.*, the chloride-sulfate mass ratio) and the probability of lead action level exceedances (ALEs) in drinking water facilities. Because corrosion in water distribution systems is a costly problem, the regulatory options have the potential to reduce costs to drinking water systems by reducing chloride and TDS loadings and, as a result, corrosivity of source water.

2.3.2 Effects on Household Averting Expenditure

Households who perceive their tap water as unsafe frequently buy bottled water or engage in other averting behaviors (*e.g.*, use filtration systems) aimed at reducing potential exposure to harmful pollutants, and these actions have associated costs. For example, Javidi and Pierce (2018) estimate the minimum expenditures on bottled water by all U.S. households who perceive their tap water as unsafe at $7.0 billion (2023$) annually.[20] In particular, frequent algal blooms are generating growing public concern due to their impact on drinking water safety. A study by Liu and Klaiber (2023) found that averting behavior in response to a 3-day water advisory due to a harmful algal bloom outbreak in 2014 in Toledo, Ohio persisted for up to a month with total averting costs for each household averaging approximately $4.60.[21] The regulatory options have the potential to affect source water quality and, as a result, to affect households' perception of tap water safety and reliance on bottled water to meet their consumption standards.

2.3.3 Irrigation and Other Agricultural Uses

Irrigation accounts for 42 percent of the total U.S. freshwater withdrawals and approximately 80 percent of the Nation's consumptive water use. Irrigated agriculture provides important contributions to the U.S. economy accounting for approximately 40 percent of the total farm sales (Hellerstein, Vilorio & Ribaudo, 2019). Pollutants in steam electric power plant discharges can affect the quality of water used for irrigation and livestock watering. Although elevated nutrient concentrations in irrigation water would not adversely

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[19] EPA's separate proposed rulemaking to regulate discharges of per- and polyfluoroalkyl substances in drinking water could result in implementation of drinking water treatment technologies that would reduce DBP levels during the analysis period.

[20] Values adjusted from $5.65 billion per year (in 2017$), using the CPI.

[21] The study relied on household level data for bottled water purchases to estimate household effect models of averting behavior. The average increase in bottled water expenditures was calculated across all households in the affected areas, of which only some households purchased bottled water after the 3-day advisory. Between 12 percent and 20 percent of households purchased bottled water before the drinking water advisory. The share increased to 34 percent in the two weeks following the 3-day drinking water advisory (66 percent did not purchase bottled water after the 3-day advisory). Values adjusted from $3.60 per household per year (in 2014$), using the CPI.

affect its usefulness for plants, other steam electric pollutants, such as arsenic, mercury, lead, cadmium, and selenium have the potential to affect soil fertility and enter the food chain (National Research Council, 1993; Zhang et al., 2018). For example, the same heavy metals found in oilfield produced waters (including barium, lead, and chromium) have been shown to accumulate in soil, plants, and oranges (Zhang et al., 2018). Additionally, nutrients can increase eutrophication, promoting cyanobacteria blooms that can kill livestock and wildlife that drink the contaminated surface water. TDS can impair the utility of water for both irrigation and livestock use. EPA did not quantify or monetize effects of quality changes in agricultural water sources arising from the regulatory options due to data limitations on how costs vary with relatively small estimated changes in water quality.

2.4 Other Economic Effects

The regulatory options may have other economic effects stemming from changes in sediment deposition in reservoirs and navigational waterways; changes in tourism, commercial fish harvests, and property values.[22] EPA estimated the changes in sediment deposition in reservoirs and navigational waterways. Chapter 9 discusses the associated benefits. Other benefit categories (*e.g.*, effects on property values) are discussed qualitatively in the following sections.

2.4.1 Reservoir Capacity

Reservoirs serve many functions, including storage of drinking and irrigation water supplies, flood control, hydropower supply, and recreation. Streams can carry sediment into reservoirs, where it can settle and build up over time, reducing reservoir capacity and the useful life of reservoirs (Graf et al., 2010; Palinkas & Russ, 2019; Rahmani et al., 2018). Reservoir capacity has been diminishing over time. At a national scale, Randle et al. (2021) found that total reservoir storage capacity has dropped from a peak of 850 Gm^3 to 810 Gm^3. At a state scale, Rahmani et al. (2018) found that all 24 federally operated reservoirs in Kansas have collectively lost 17 percent of their original capacity with the highest single-reservoir loss of 45 percent. Dredging and other sediment management strategies can be used to reclaim capacity (Hargrove et al., 2010; Miranda, 2017; Morris, 2020; Randle et al., 2021; Winkelman. M.O., Sens & Marcus, 2019).[23] EPA expects that changes in suspended solids discharges under the regulatory options could affect reservoir maintenance costs by changing the frequency or volume of dredging activity. Changes in sediment loads could result in a modest decrease in dredging costs in reservoirs under all regulatory options. See Section 9.2 for details.

2.4.2 Sedimentation Changes in Navigational Waterways

Navigable waterways, including rivers, lakes, bays, shipping channels and harbors, are an integral part of the United States' transportation network (Clark, Haverkamp & Chapman, 1985). Navigable channels are prone to reduced functionality due to sediment build-up, which can reduce the navigable depth and width of the waterway (Clark, Haverkamp & Chapman, 1985; Ribaudo & Johansson, 2006). For many navigable waters,

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[22] EPA estimated changes in the marketability of coal combustion ash as a benefit of the 2015 rule (U.S. Environmental Protection Agency. (2015a). *Benefit and Cost Analysis for the Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category*. (EPA-821-R-15-005).). However, based on the baseline for this rule which already requires ash to be handled dry, EPA does not expect incremental changes in the amount of ash handled dry vs. wet and benefits from increased marketing of coal combustion ash under any of the regulatory options.

[23] Other sedimentation management strategies may be used instead of, or in combination with, dredging. This includes reducing sediment yield through watershed management practices and routing sediments through or around reservoirs (Morris, G. L. (2020). Classification of Management Alternatives to Combat Reservoir Sedimentation. *Water*, *12*(3). https://doi.org/10.3390/w12030861 ; Randle, T. J., Morris, G. L., Tullos, D. D., Weirich, F. H., Kondolf, G. M., Moriasi, D. N., Annandale, G. W., . . . Wegner, D. L. (2021). Sustaining United States reservoir storage capacity: Need for a new paradigm. *Journal of Hydrology*, *602*, 126686. https://doi.org/https://doi.org/10.1016/j.jhydrol.2021.126686).

periodic dredging is necessary to remove sediment and keep them passable. For example, the U.S. Army Corps of Engineers (USACE) maintains the Southwest Pass[24], the most highly utilized commercial deep-draft waterway in the country, and its rapid-onset shoaling has led to prolonged periods of draft restrictions for transiting vessels (*e.g*., reductions in the amount of cargo that can be transported per voyage). To counteract channel shoaling, the USACE has dredged an annual average 25 million cubic yards of sediment since 2015 (Hartman et al., 2022). Dredging navigable waterways can be costly. Following the previous example, total dredging expenditures in the Southwest Pass for the 2019 fiscal year amounted to $147.8 million (dredging expenditures between the 2015 and 2018 fiscal years ranged from $66.0 million to $65.4 million) (Hartman et al., 2022).

EPA estimated that all regulatory options would reduce sediment loadings to surface waters and reduce dredging of navigational waterways. EPA quantified and monetized these benefits based on the avoided cost for projected changes in future dredging volumes. Section 9.2 describes this analysis.

2.4.3 Commercial Fisheries

Pollutants in steam electric power plant discharges can reduce fish populations by inhibiting reproduction and survival of aquatic species. These changes may negatively affect commercial fishing industries as well as consumers of fish, shellfish, and fish and seafood products. Estuaries are particularly important breeding and nursery areas for commercial fish and shellfish species (Alkire, Silldorff & Wang, 2020; Brame et al., 2019; Beck et al., 2001). In some cases, excessive pollutant loadings can lead to the closure of shellfish beds, thereby reducing shellfish harvests and causing economic losses from reduced harvests (Jin, Thunberg & Hoagland, 2008; Trainer et al., 2007; Islam & Masaru, 2004). Improved water quality due to reduced discharges of steam electric pollutants would enhance aquatic life habitat and, as a result, contribute to reproduction and survival of commercially harvested species and larger fish and shellfish harvests, which in turn could lead to an increase in producer and consumer surplus. Conversely, an increase in pollutant loadings could lead to negative impacts on fish and shellfish harvest.

EPA did not quantify or monetize impacts to commercial fisheries under the regulatory options. EPA estimated that eight steam electric power plants discharge BA transport water, FGD wastewater, CRL or legacy wastewater directly to the Great Lakes or to estuaries. Large distances and stream flows greatly reduce the relative impact of steam electric power plants discharging upstream from these systems. Although estimated decreases in annual average pollutant loads under the regulatory options may benefit local fish populations and commercial harvest, the overall effects to commercial fisheries arising from the regulatory options are difficult to quantify but are likely to be relatively small. Commercial species potentially affected by steam electric discharges account for approximately 1 percent of total landings value in the United States.[25]

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[24] This is the entrance channel for a port system which encompasses waters ranging from the Mississippi River in Baton Rouge, Louisiana to the Gulf of Mexico Project (Hartman, M. A., Mitchell, K. N., Dunkin, L. M., Lewis, J., Emery, B., Lenssen, N. F., & Copeland, R. (2022). Southwest Pass Sedimentation and Dredging Data Analysis. *Journal of Waterway, Port, Coastal, and Ocean Engineering*, *148*(2), 05021017. https://doi.org/doi:10.1061/(ASCE)WW.1943-5460.0000684).

[25] Based on U.S. commercial fisheries landing values in 2019. EPA obtained commercial fisheries landing data for areas that may be affected by steam electric discharges (Mississippi (Big Lake, connected to Biloxi Bay), Tampa, FL area (closest port to Hillsborough Bay), Lake Eerie, and Lake Michigan) and compared the potentially affected commercial fisheries landing value to total U.S. commercial fisheries landing value (marine and Great Lakes). EPA obtained commercial fishery landing value for Mississippi and the U.S. from NOAA Fisheries (National Oceanic and Atmospheric Administration. (2022). *NOAA Fisheries - U.S. Commercial Fish Landings*. https://www.fisheries.noaa.gov/foss/f?p=215:200:1735541630262:Mail:NO:::), for the Tampa area from the Florida Fish and Wildlife Conservation Commission (Florida Fish and Wildlife Conservation Commission. (2022). *Commercial Fisheries Landings Summaries*. https://app.myfwc.com/FWRI/PFDM/ReportCreator.aspx), and for the Great Lakes

Moreover, most species of fish have numerous close substitutes. The economic literature suggests that when there are plentiful substitute fish products (*e.g.*, chicken is substitute for fish) the measure of consumer welfare (consumer surplus) is unlikely to change as a result of small changes in fish landings, such as those EPA expects under the regulatory options.

2.4.4 Tourism

Discharges of pollutants may also affect the tourism and recreation industries (*e.g.*, boat rentals, sales at local restaurants and hotels) and, as a result, local economies in the areas surrounding affected waters due to changes in recreational opportunities (U.S. Bureau of Economic Analysis, 2021; Mojica & Fletcher, 2020; Highfill & Franks, 2019). The effects of water quality on tourism are likely to be highly localized. Moreover, since substitute tourism locations may be available, increased tourism in one location (*e.g.*, the vicinity of steam electric power plants) may lead to a reduction in tourism in other locations or vice versa. Due to the relatively small water quality changes expected from the regulatory options (see Section 3.4 for details) and availability of substitute sites, the overall effects on tourism and, as a result, social welfare is likely to be negligible. Therefore, EPA did not quantify or monetize this benefit category.

2.4.5 Property Values

Discharges of pollutants may affect the aesthetic quality of water resources by altering water clarity, odor, and color in the receiving and downstream reaches. Technologies implemented by steam electric power plants to comply with the regulatory options remove nutrients and sediments to varying degrees and have varying effects on water eutrophication, algae production, water turbidity, and other surface water characteristics. Several studies (*e.g.*, Austin, 2020; Bin & Czajkowski, 2013; Cassidy, Meeks & Moore, 2023; Gibbs et al., 2002; Guignet et al., 2022; Irwin & Wolf, 2022; Kemp, Ng & Mohammad, 2017; Kuwayama, Olmstead & Zheng, 2022; Leggett & Bockstael, 2000; Liu, Opaluch & Uchida, 2017; Mamun et al., 2023; Moore et al., 2020; Netusil, Kincaid & Chang, 2014; Tang, Heintzelman & Holsen, 2018; Tuttle & Heintzelman, 2014; Walsh, Milon & Scrogin, 2011; Walsh et al., 2017; Wolf, Klaiber & Gopalakrishnan, 2022) suggest that both waterfront and non-waterfront properties are more desirable when located near unpolluted water. For example, a meta-analysis of 18 hedonic studies (Guignet et al., 2022) suggests that, on average, a one-percent increase in water clarity leads to a 0.19 percent increase in waterfront home prices and 0.04 percent increase in non-waterfront homes prices within 500 meters of the waterbody.[26] The authors also found that site specific effects on home prices are likely to be influenced by the baseline water clarity and vary by region. A hedonic analysis of property values across six Ohio counties (Wolf & Klaiber, 2017) found a decline in property values from increased frequency of algal blooms in lakes between 11 percent and 17 percent for near lake homes and 22 percent for lake adjacent homes. Public perception of potential health risks associated with toxic pollutant discharges from steam electric plants may also have a negative impact on nearby property values. For example, Austin (2020) finds that, in North Carolina, negative impacts of coal ash discharges on drinking water led to a 12 to 14 percent decline in sale price for homes within one mile of a coal ash pond after potential risks were made more salient by a state regulation. Therefore, the value of properties located in

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from the Great Lakes Fishery Commission (Great Lakes Fishery Commission. (2022). *Commercial fish production in the Great Lakes 1867–2020*. http://www.glfc.org/great-lakes-databases.php). EPA assumed that all fish species in Lake Eerie and Lake Michigan may be affected by steam electric discharges. For commercial fishery landings in Tampa and Mississippi, EPA removed deep sea fish species (*e.g.*, tuna, sharks, jacks, and octopus) from consideration of fish potentially affected by steam electric power plant discharges since they are unlikely to use the estuarine areas where discharges occur.

[26] These elasticities are based on the base meta-regression (see Model 1 in Table 3 on page 204, Guignet, D., Heberling, M. T., Papenfus, M., & Griot, O. (2022). Property values, water quality, and benefit transfer: A nationwide meta-analysis. *Land Economics, 050120-0062R1*.).

proximity to waters affected by steam electric plant discharges may increase due to reductions in discharges of FGD wastewater, BA transport water, CRL, and legacy wastewater.

EPA did not quantify or monetize the potential change in property values associated with the regulatory options because the water quality metrics or pollutants addressed in existing studies do not provide a good match to the list of pollutants covered by the steam electric ELG. As shown in Guignet et al. (2022), water clarity is the most common water quality measure analyzed in the hedonic literature, followed by fecal coliform and *chlorophyll a*.[27] The magnitude of the potential effect on property values from reducing steam electric discharges is uncertain. It depends on many factors, including the number of housing units located in the vicinity of the affected waterbodies,[28] community characteristics (*e.g.*, residential density), housing stock (*e.g.*, single family or multiple family), and the effects of steam electric pollutants on the aesthetic quality of surface water. Because changes in the aesthetic quality of surface waters (*e.g.*, clarity) that may result from the relatively small changes in pollutant concentrations under the regulatory options are difficult to quantify, EPA did not estimate the impacts of the final rule on property values. In addition, there may be an overlap between shifts in property values and the estimated total WTP for surface water quality changes discussed in Section 2.2.1.

2.5 Changes in Air Pollution

The final rule is expected to affect air pollution through three main mechanisms: 1) changes in energy use by steam electric power plants to operate wastewater treatment and other systems needed to comply with the final rule; 2) changes in transportation-related emissions due to changes in trucking of CCR and other waste to on-site or off-site landfills; and 3) the change in the profile of electricity generation due to relatively higher cost to generate electricity at plants incurring ELG compliance costs. The three mechanisms can produce changes in different directions. For example, increased energy use by power plant tend to increase air emissions associated with power generation, but those changes are relatively small when compared to the changes resulting from shifts in the electricity generation mix away from coal-fired generation and toward sources with lower emission factors. These shifts in generation mix result tend to reduce overall emissions at the national level, although the localized changes in air pollutant emissions may be positive or negative depending on which electricity generating units produce more or less electricity as a result of these shifts.

As described in Chapter 5 of the RIA, EPA used the Integrated Planning Model (IPM®), a comprehensive electricity market optimization model that can evaluate impacts within the context of regional and national electricity markets, to analyze impacts of the final rule (*i.e.*, Option B). Electricity market analyses using IPM project that the final rule (Option B) will expand on the baseline trend by shifting away from coal fired electric power generation toward generation from other energy sources, such as natural gas and renewables. Relative to the baseline, IPM projects coal-fired generation to decline as a result of the final rule. These changes are offset in part by an increase in natural gas generation, nuclear generation, and generation by renewables. Differences in emissions factors across energy sources generally results in net reductions in air

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[27] The majority of recently published studies that were not included in ibid. also analyzed impacts on water clarity on home prices (e.g., Irwin, N., & Wolf, D. (2022). Time is money: Water quality's impact on home liquidity and property values. *Ecological economics, 199*, 107482. , Mamun, S., Castillo-Castillo, A., Swedberg, K., Zhang, J., Boyle, K. J., Cardoso, D., Kling, C. L., . . . Phaneuf, D. (2023). Valuing water quality in the United States using a national dataset on property values. *Proceedings of the National Academy of Sciences, 120*(15), e2210417120.).

[28] In a review of 36 hedonic studies that focus on the impact of water quality on housing values, Guignet, D., Heberling, M. T., Papenfus, M., & Griot, O. (2022). Property values, water quality, and benefit transfer: A nationwide meta-analysis. *Land Economics, 050120-0062R1*. note that some studies have detected property value impacts up to a mile away from impacted waterways.

emissions from electricity generating units across all modeled pollutants at the national level (CO_2, SO_2, NO_X, direct $PM_{2.5}$, PM_{10}, Hg, and hydrogen chloride (HCl)). Overall for the three mechanisms (auxiliary services, transportation, and market-level generation), EPA estimates net reductions in CO_2, SO_2, and NO_X emissions as compared to the baseline at the national level. EPA also estimated small increases in methane (CH_4) emissions from transportation, but these increases are much smaller than the net reductions in CO_2 emissions. However, the distribution of the changes may result in localized increases even as the overall changes nationwide are decreases, and air emissions of some pollutants may increase in some years and decrease in others. See the RIA for details (U.S. EPA, 2024e).

CO_2 is the most prevalent of the greenhouse gases, which are air pollutants that EPA has determined endanger public health and welfare through their contribution to climate change. EPA used estimates of the social cost of greenhouse gases (SC-GHG) – specifically, the social cost of carbon (SC-CO_2) and of the social cost of methane (SC-CH_4) – to monetize the benefits of changes in CO_2 and CH_4 emissions as a result of the final rule.. The SC-GHG is the monetary value of the net harm to society associated with emitting a metric ton of the GHG in question into the atmosphere in a given year, or the benefit of avoiding that increase. In principle, the SC-GHG includes the value of all climate change impacts, including (but not limited to) changes in net agricultural productivity, human health effects, property damage from increased flood risk and natural disasters, disruption of energy systems, risk of conflict, environmental migration, and the value of ecosystem services. Chapter 8 details this analysis.

NO_X, and SO_2 are known precursors to $PM_{2.5}$, a criteria air pollutant that has been associated with a variety of adverse health effects, including premature mortality and hospitalization for cardiovascular and respiratory diseases (*e.g.*, asthma, chronic obstructive pulmonary disease [COPD], and shortness of breath). EPA quantified changes in direct $PM_{2.5}$ emissions and in emissions of $PM_{2.5}$ and ozone[29] precursors NO_X and SO_2 and assessed impacts of those emission changes on air quality changes across the country using the Comprehensive Air Quality Model with Extensions (CAMx) (Ramboll Environ International Corporation, 2016). EPA then used spatial fields of baseline and post-compliance air pollutant concentrations as input to Benefits Mapping and Analysis Program—Community Edition (BenMAP-CE) to estimate incremental human health effects (including the potential for premature mortality and morbidity) from changes in ambient air pollutant concentrations (U.S. EPA, 2018a). Chapter 8 details this analysis.

The final rule may also affect air quality through changes in electricity generation units emissions of larger particulate matter (PM_{10}) and hazardous air pollutants (HAP) including mercury and hydrogen chloride. The health effects of mercury are detailed in the EA (U.S. EPA, 2024b). Hydrogen chloride is a corrosive gas that can cause irritation of the mucous membranes of the nose, throat, and respiratory tract. For more information about the impacts of mercury and hydrogen chloride emissions, see the Mercury and Air Toxics Standards (MATS) for Power Plants, [30] including the 2023 proposed *National Emission Standards for Hazardous Air Pollutants: Coal- and Oil-Fired Electric Utility Steam Generating Units Review of the Residual Risk and Technology Review* (88 FR 24854).

The final rule may also affect air quality if steam electric power plants alter their coal storing and handling practices, since Jha and Muller (2018) found that a 10 percent increase in coal stockpiles held by U.S. power

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[29] Emissions of nitrogen oxides (NOx) lead to formation of both ozone and $PM_{2.5}$ while SO_2 emissions lead to formation of $PM_{2.5}$ only.

[30] See https://www.epa.gov/stationary-sources-air-pollution/mercury-and-air-toxics-standards.

plants results in a 0.09 percent increase in average $PM_{2.5}$ concentration levels within 25 miles of these plants. In addition to health effects from air emissions, air pollution can create a haze that affects visibility. Reduced visibility could impact views in national parks by softening the textures, fading colors, and obscuring distant features and therefore reduce the value of recreational activities (*e.g.*, Boyle et al., 2016; Pudoudyal, Paudel & Green, 2013). A number of studies (*e.g.*, Bayer, Keohane & Timmins, 2006; Beron, Murdoch & Thayer, 2001; Chay & Greenstone, 1998) also found that reduced air quality and visibility can negatively affect residential property values.

2.6 Summary of Benefits Categories

Table 2-3 summarizes the potential social welfare effects of the regulatory options analyzed for the final rule and the level of analysis applied to each category. As indicated in the table, only a subset of potential effects can be quantified and monetized. The monetized welfare effects include reductions in some human health risks, use and non-use values from surface water quality improvements, reduced costs for dredging reservoirs and navigational waterways, and changes in air emissions. Other welfare effect categories, including changes in waters exceeding NRWQC, were quantified but not monetized. Although EPA was not able to quantify or monetize other welfare effects, including some other human health risks and impacts to commercial fisheries, those unquantified benefits may be relatively small compared to other monetized benefits.[31] EPA evaluated these effects qualitatively as discussed above in Section 2.1 through Section 2.5.

Table 2-3: Estimated Welfare Effects of Changes in Pollutant Discharges from Steam Electric Power Plants

Category	Effect of Regulatory Options	Benefits Analysis		
		Quantified	Monetized	Methods (Report Chapter where Analysis is Detailed)
Human Health Benefits from Surface Water Quality Improvements				
Changes in human health effects (*e.g.*, bladder cancer) associated with halogenated DBP exposure via drinking water	Changes in exposure to halogenated DBPs in drinking water	✓	✓	VSL and COI (Chapter 4)
IQ losses to children ages 0 to 7	Changes in childhood exposure to lead from consumption of self-caught fish[a]	✓	✓	IQ point valuation (Chapter 5)
Need for specialized education	Changes in childhood exposure to lead from consumption of self-caught fish[a]	✓	✓	Qualitative discussion (Chapter 5)
Incidence of cardiovascular disease in adults	Changes in exposure to lead from consumption of self-caught fish[a]	✓	✓	VSL (Chapter 5)
IQ losses in infants	Changes in in-utero mercury exposure from maternal consumption of self-caught fish[a]	✓	✓	IQ point valuation (Chapter 5)
Incidence of skin cancer	Changes in exposure to arsenic from consumption of self-caught fish[a]	✓	✓	COI (Chapter 5); Qualitative discussion (Chapter 2)

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[31] The 2015 and 2020 rules, which are included in the baseline for this analysis, significantly reduced toxic pollutant and nutrient loadings, making additional reductions estimated for this final rule smaller, particularly when compared to the benefits that can be quantified and monetized.

Table 2-3: Estimated Welfare Effects of Changes in Pollutant Discharges from Steam Electric Power Plants

Category	Effect of Regulatory Options	Benefits Analysis		
		Quantified	**Monetized**	**Methods (Report Chapter where Analysis is Detailed)**
Other adverse health effects (cancer and non-cancer)	Changes in exposure to toxic pollutants (lead, cadmium, thallium, etc.) via fish consumption or drinking water	✓		Human health criteria exceedances (Chapter 5); Exposure above non-cancer health thresholds (Chapter 4, EA; U.S. EPA, 2024b); Qualitative discussion (Chapter 2)
Reduced adverse health effects (*e.g.*, rash and irritation from dermal exposure to toxins in HABs)	Changes in exposure to pollutants from recreational water uses			Qualitative discussion (Chapter 2)
Ecological Condition and Recreational Use Effects from Surface Water Quality Changes				
Aquatic and wildlife habitat[b]	Changes in ambient water quality in receiving reaches	✓	✓	Benefit transfer (Chapter 6); Qualitative discussion (Chapter 2)
Water-based recreation[b]	Changes in swimming, fishing, boating, and near-water activities from water quality changes			
Aesthetics[b]	Changes in aesthetics from shifts in water clarity, color, odor, including nearby site amenities for residing, working, and traveling			
Non-use values[b]	Changes in existence, option, and bequest values from improved ecosystem health			
Protection of T&E species	Changes in T&E species habitat and potential effects on T&E species populations	✓		Habitat range intersecting with reaches with NRWQC exceedances (Chapter 7); Qualitative discussion (Chapter 2)
Sediment contamination	Changes in deposition of toxic pollutants to sediment			Qualitative discussion (Chapter 2)
Water Supply and Use				
Water treatment costs for drinking water	Changes in quality of source water used for drinking	✓	✓	Avoided cost of drinking water treatment (Chapter 9); Qualitative discussion (Chapter 2)
Water treatment costs for irrigation and other agricultural uses	Changes in quality of source water used for irrigation and other agricultural uses			Qualitative discussion (Chapter 2)
Other Economic Effects				
Dredging costs	Changes in sedimentation and costs for maintaining navigational waterways and reservoir capacity	✓	✓	Avoided cost of dredging (Chapter 9); Qualitative discussion (Chapter 2)

Table 2-3: Estimated Welfare Effects of Changes in Pollutant Discharges from Steam Electric Power Plants

Category	Effect of Regulatory Options	Benefits Analysis		
		Quantified	Monetized	Methods (Report Chapter where Analysis is Detailed)
Commercial fisheries	Changes in fisheries yield and harvest quality due to aquatic habitat changes			Qualitative discussion (Chapter 2)
Tourism industries	Changes in participation in water-based recreation			Qualitative discussion (Chapter 2)
Property values	Changes in property values from changes in water quality			Qualitative discussion (Chapter 2)
Air Quality-Related Effects				
Air emissions of $PM_{2.5}$, NO_X and SO_2	Changes in mortality and morbidity from exposure to particulate matter ($PM_{2.5}$) emitted directly or linked to changes in NO_X and SO_2 emissions (precursors to $PM_{2.5}$ and ozone)	✓	✓	VSL and COI (Chapter 8); Qualitative discussion (Chapter 2)
Air quality effects of coal stockpiles	Air quality effects of storing and handling coal at steam electric power plants			Qualitative discussion (Chapter 2)
Air emissions of NO_X and SO_2	Changes in ecosystem effects; visibility impairment; and human health effects from direct exposure to NO_2, SO_2, and hazardous air pollutants.			Qualitative discussion (Chapters 2 and 8)
Air emissions of CO_2 and CH_4	Changes in climate change effects	✓	✓	Social cost of greenhouse gases (SC-GHG) (Chapter 8)

a. Reductions in discharges of lead, mercury, and other toxic pollutants may reduce concentrations of these pollutants in open seas, thus reducing levels of pollutants in high trophic level fish harvested commercially. There are unquantified benefits associated with all of these end points for those who consume commercially harvested fish, but these benefits are very difficult to estimate.

b. These values are implicit in the total WTP for water quality improvements.

Source: U.S. EPA Analysis, 2024

3 Water Quality Effects of Regulatory Options

Changes in the quality of surface waters, aquatic habitats and ecological functions under the regulatory options depend on several factors, including the operational characteristics of steam electric power plants, treatment technologies implemented to control pollutant levels, the timing of treatment technology implementation, and the hydrography of reaches receiving steam electric pollutant discharges, among others. This chapter describes the surface water quality changes projected under the regulatory options. EPA modeled water quality based on loadings estimated for the baseline and for each of the three regulatory options (Option A through Option C). The differences in concentrations between the baseline and option scenarios represent the changes attributable to the regulatory options. These changes inform the analysis of several of the benefits described in Chapter 2 and detailed in later chapters of this report.

The analyses use pollutant loading estimates detailed in the TDD (U.S. EPA, 2024f) and expand upon the analysis of immediate receiving waters described in the EA (U.S. EPA, 2024b) by estimating changes in both receiving and downstream reaches. The EA provides additional information on the effects of steam electric power plant discharges on surface waters and how they may change under the regulatory options.

3.1 Waters Affected by Steam Electric Power Plant Discharges

EPA estimates the regulatory options potentially affect 232 steam electric power plants with coal-fired generating units after December 31, 2028 and/or CRL or legacy wastewater discharges. EPA used the United States Geological Survey (USGS) medium-resolution National Hydrography Dataset (NHD) (USGS, 2018) to represent and identify waters affected by steam electric power plant discharges, and used additional attributes provided in version 2 of the NHDPlus dataset (U.S. EPA, 2019g) to characterize these waters.

Of the plants represented in the analysis, EPA estimated that 110 plants have non-zero pollutant discharges under the baseline or the regulatory options for the wastestreams modeled for the benefits analyses (FGD wastewater, BA transport water, CRL, or legacy wastewater).[32, 33] In the aggregate, the 110 plants discharge to 126 waterbodies (as categorized in NHDPlus), including lakes, rivers, and estuaries.[34] Receiving reaches that lack NHD classification for both waterbody area type and stream order generally correspond to reaches that do not have valid flow paths[35] for analysis of the fate and transport of steam electric power plant discharges (see Section 3.3). Eleven steam electric power plants discharge FGD wastewater, BA transport water, CRL or legacy wastewater to tidal reaches or the Great Lakes directly or through immediate tributaries or to waters not connected to the hydrographic network.[36] EPA did not assess pollutant loadings and water quality changes

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[32] The benefits analyses do not include loadings from unmanaged CRL and therefore omit some plants that are estimated to have only this wastestream. These plants may incur compliance costs to comply with limits for unmanaged CRL for any discharge that a permitting authority deems is the functional equivalent of a direct discharge and require a permit, but changes in unmanaged CRL loads were not modeled explicitly. Costs are included, however, in the social costs presented in Chapters 11 and 12.

[33] Of these 110 plants, 12 plants discharge to more than one waterbody. Also, of the 110 plants, 104 plants have non-zero pollutant discharges under the baseline or the regulatory options for FGD wastewater, BA transport water, or CRL (6 plants have estimated loads for legacy wastewater only).

[34] Some plants discharge waste streams to multiple (two or three) different receiving waters.

[35] In NHDPlus, the flow path represents the distance traveled as one moves downstream from the reach to the terminus of the stream network. An invalid flow path suggests that a reach is disconnected from the stream network.

[36] Four plants (Edgewater, Elm Road, JH Campbell, and Oak Creek) discharge non-zero loads to Lake Michigan, one plant (Monroe) discharges to Lake Erie, one plant (Bay Front) discharges to Lake Superior, and four plants (Big Bend, Jack Watson, Crist, and Winyah) discharge to estuaries or other tidal waters either directly or through immediate tributaries. Because Great

associated with these waterbodies because of the lack of a defined flow path in NHDPlus, and in the case of Great Lakes and esturaries the complexity of flow patterns and the relatively small changes in concentrations expected.[37] Thus, EPA estimated changes in water quality downstream from 101 steam electric plants associated with a total of 114 receiving reaches representing the waterbodies in NHDPlus.[38]

3.2 Changes in Pollutant Loadings

EPA estimated post-technology implementation pollutant loadings for each plant under the baseline and the regulatory options. The TDD details the methodology (U.S. EPA, 2024f). The sections below discuss the approach EPA used to develop a profile of loading changes over time under the baseline and each regulatory option and summarize the results.

3.2.1 Implementation Timing

Benefits analyses account for the temporal profile of environmental changes as the public values changes occurring in the future less than those that are more immediate (OMB, 2023). As discussed in Section 1.3.3, for the purpose of the economic impact and benefit analysis, EPA generally estimates that plants will implement control technologies to meet the applicable rule limitations and standards as their permits are renewed, and no later than December 31, 2029. This schedule recognizes that control technology implementation is likely to be staggered over time across the universe of steam electric power plants. This in turn can translate into variations in pollutant loads to waters over time.

To estimate the benefits of the regulatory options, EPA first developed a time profile of loadings for each scenario (*i.e.*, baseline and each regulatory option), electricity generating unit (EGU), wastestream, and pollutant that reflects the baseline loadings, the estimated loadings under the applicable technology basis, the estimated technology implementation year for the plant, and the timing of any retirements or repowerings. Specifically, EPA used baseline loadings starting in 2025 through the applicable technology implementation year, applicable technology-based loadings corresponding to the analyzed scenario (baseline or regulatory option) for all years following a plant's modeled implementation year, and zero loadings following a unit's retirement or repowering (where applicable).

EPA then used this year-explicit time profile to calculate the annual average loadings discharged by each plant for two distinct periods within the overall period of analysis of 2025 through 2049:[39]

Lakes and estuaries are complex waterbodies accurately modeling water quality impacts to these waters would require the application of more complex models that was not feasible within this rulemaking. Finally, one plant (Gerald Gentleman) discharges to a reservoir not connected to the stream network.

[37] EPA looked at the changes in pollutant loadings and impacts to these systems in selected case studies as part of the analysis of the 2015 rule. See 2015 EA for details; U.S. Environmental Protection Agency. (2015b). *Environmental Assessment for the Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category*. (EPA 821-R-15-006).

[38] EPA analyzed a total of 185 plants with plants with coal-fired generating units after December 31, 2028 and/or that generate the wastestreams within the scope of the final rule. Not all these plants have costs and/or loads under the baseline or regulatory options, so while the modeling scope is all 185 plants, as discussed in this section, some plants have zero loads whereas others discharge to waters that lack a valid flow path (*e.g.*, Great Lakes and estuaries), leaving 104 plants for which EPA analyzed changes in downstream water quality.

[39] EPA had initially analyzed regulatory options for which the technology implementation deadline was set to of 2030 and the average loads calculated for two periods that reflected that deadline (*i.e.*, 2026-2030 and 2031-2050). While EPA later revised the compliance deadline to 2029, the Agency did not recalculate the average loads but instead shifted the periods and the associated loading reductions by one year (*i.e.*, 2025-2029 and 2030-2049). Because of the timing of the retirement of some generating units

- Period 1, which extends from 2025 through 2029, when the universe of plants would transition from current (baseline) treatment practices to practices that achieve the revised limits, and
- Period 2, which extends from 2030 through 2049 and is the post-transition period during which the full universe of plants is projected to employ treatment practices that achieve the revised limits.

The analysis accounts for each plant's technology implementation year(s) and for announced unit retirements or repowerings. Using average annual values for two distinct periods instead of a single average over the entire period of analysis enables EPA to better represent the rule implementation and capture the transitional effects of the regulatory options. While using an annual average does not show the differences between the baseline and regulatory options for individual years within Period 1, EPA considers that the average provides a reasonable measure of the transitional effects of the regulatory options given the categories of benefits that EPA is analyzing, which generally result from changes in multi-year processes.

As discussed in the RIA (U.S. EPA, 2024e), there is uncertainty in the exact timing of when individual steam electric power plants would be implementing technologies to meet the final rule or the other regulatory options. This benefits analysis uses the same plant- and wastestream-specific technology installation years used in the cost and economic impact analyses. To the extent that technologies are implemented earlier or later, the annualized loading values presented in this section may under- or overstate the annual loads during the analysis period.

3.2.2 Results

Differences in the stringency of effluent limits and pretreatment standards and the timing of their applicability to steam electric power plants (and the resulting treatment technology implementation) mean that changes in pollutant loads between the regulatory options and the baseline vary over the period of analysis. Within the period of analysis, the years 2025-2029 represent a period of transition as plants implement treatment technologies to meet the revised limits under the regulatory options, whereas years 2030 through 2049 have steady state loadings that reflect implementation of technologies across all plants.[40]

Table 3-1 summarizes the average annual reductions during Period 1 and Period 2 in FGD wastewater, BA transport water, CRL, legacy wastewater,[41] and total loads for selected pollutants that inform EPA's analysis of the benefits discussed in Chapters 4 through 7 and Chapters 9 and 10. The regulatory options are estimated to result in either no change or in *reductions* in pollutant loadings under an option as compared to the baseline, with the reductions generally increasing as one progresses from Option A to Option C. Further, loading reductions are largest during Period 2 when all steam electric plants have implemented the treatment technologies associated with the limits, as compared to the transition period represented by Period 1.

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relative to technology installation, the loading reductions reflected in analysis for Period 2 are smaller than would have been obtained had EPA recalculated the average loads to reflect the earlier compliance year. The difference ranges between 0 percent and 7 percent, depending on the pollutant and regulatory option, with an average across pollutants of 2 percent for the final rule (Option B).

[40] This steady state reflects unit retirements and repowerings. EPA accounted for unit retirements and repowerings by zeroing out the loadings starting in the year following the change in status.

[41] Loading reductions associated with legacy wastewater limits will occur only as plants close and dewater their existing ponds. There is uncertainty on when plants may do so. For the purpose of this benefits analysis, EPA conservatively assumed that pond closures will occur after 2049 and therefore estimated no loading reductions during the period of analysis for Options B and C. To the extent that facilities close their ponds earlier, then the analysis understates the benefits of these two options.

Legacy wastewater discharges and loading reductions achieved by the legacy wastewater limits in the final rule would occur only as plants close and dewater their existing ponds. Given the uncertainty on when plants may do so, for the purpose of this analysis EPA estimated no loading reductions during the period of analysis. Similarly, certain plants could be required to treat unmanaged CRL discharged from landfills, surface impoundments, or other features to meet the limits in the final rule. These limits would apply only in cases where a permitting authority deems, on a case-by-case basis, that the discharge is functionally equivalent to a direct discharge and requires a permit. Because these discharges are uncertain, EPA did not include changes in pollutant loads from unmanaged CRL in the main analysis. Because the cost analysis detailed in the RIA (U.S. EPA, 2024e) and the social costs presented in Chapters 11 and 12 of this document includes these costs (based on the assumption that plants treat legacy wastewater discharges in 2049 and comply with the unmanaged CRL limits in the same year as limits for other wastestreams), the benefits of the final rule are understated when compared to the social costs.

Table 3-1: Annual Average Reductions in Total Pollutant Loading in Period 1 (2025-2029) and Period 2 (2030-2049) for Selected Pollutants in Steam Electric Power Plant Discharges, Compared to Baseline (lb/year)

Pollutant	Option A[a]					Option B (Final Rule)[a]					Option C[a]				
	BA[b]	CRL[c]	FGD	Legacy	Total[d]	BA[b]	CRL[c]	FGD	Legacy[e]	Total[d]	BA[b]	CRL[c]	FGD	Legacy[e]	Total[d]
Period 1 (2025-2029)															
Antimony	39	0	48	0	88	39	21	48	0	108	41	22	55	0	117
Arsenic	21	143	66	0	230	21	175	66	0	263	22	177	75	0	274
Barium	238	512	1,600	0	2,350	238	805	1,600	0	2,640	251	819	1,810	0	2,880
Beryllium	0	0	15	0	15	0	0	15	0	15	0	0	17	0	17
Boron	11,900	0	2,600,000	0	2,610,000	11,900	121,000	2,600,000	0	2,730,000	12,500	127,000	2,930,000	0	3,070,000
Bromide	2,430,000	11,400	0	0	2,440,000	2,430,000	11,400	0	0	2,440,000	2,670,000	12,000	0	0	2,690,000
Cadmium	2	22	48	0	71	2	45	48	0	94	2	46	54	0	101
Chromium	11	9,180	73	0	9,260	11	9,220	73	0	9,300	12	9,220	83	0	9,310
Copper	9	31	43	0	82	9	52	43	0	103	9	53	48	0	110
Cyanide	0	0	10,800	0	10,800	0	0	10,800	0	10,800	0	0	12,200	0	12,200
Lead	23	0	39	0	62	23	0	39	0	62	25	0	43	0	68
Manganese	342	672	143,000	0	144,000	342	15,600	143,000	0	159,000	361	16,400	161,000	0	178,000
Mercury	0	4	1	0	5	0	5	1	0	6	0	5	1	0	6
Nickel	39	198	72	0	309	39	247	72	0	358	41	250	81	0	372
TN	5,900	0	85,800	0	91,700	5,900	0	85,800	0	91,700	6,220	0	96,800	0	103,000
TP	496	0	3,690	0	4,190	496	0	3,690	0	4,190	523	0	4,160	0	4,680
Selenium	27	0	66	0	93	27	497	66	0	590	29	522	74	0	625
Thallium	3	2	112	0	117	3	9	112	0	123	3	9	126	0	138
TSS	29,900	137,000	99,300	0	267,000	29,900	185,000	99,300	0	314,000	31,500	187,000	112,000	0	330,000
Zinc	76	614	226	0	916	76	724	226	0	1,030	80	729	256	0	1,060
Period 2 (2030-2049)															
Antimony	56	1	59	0	116	56	47	59	0	161	56	50	61	0	167
Arsenic	30	314	81	0	425	30	385	81	0	496	30	390	83	0	503
Barium	343	1,120	1,950	0	3,410	343	1,770	1,950	0	4,060	345	1,810	2,010	0	4,170
Beryllium	0	0	19	0	19	0	0	19	0	19	0	0	19	0	19
Boron	17,100	0	3,170,000	0	3,180,000	17,100	269,000	3,170,000	0	3,450,000	17,200	286,000	3,260,000	0	3,570,000
Bromide	4,600,000	16,400	0	0	4,620,000	4,600,000	16,400	0	0	4,620,000	4,630,000	16,600	0	0	4,650,000
Cadmium	2	47	58	0	107	2	99	58	0	159	2	102	60	0	164
Chromium	16	20,100	89	0	20,200	16	20,200	89	0	20,300	17	20,200	92	0	20,300
Copper	13	67	52	0	132	13	114	52	0	178	13	117	54	0	183
Cyanide	0	0	13,100	0	13,100	0	0	13,100	0	13,100	0	0	13,500	0	13,500
Lead	34	0	47	0	80	34	0	47	0	80	34	0	48	0	82
Manganese	493	1,470	174,000	0	176,000	493	34,700	174,000	0	209,000	496	36,900	180,000	0	217,000
Mercury	0	10	1	0	11	0	11	1	0	12	0	11	1	0	12
Nickel	56	433	88	0	577	56	542	88	0	686	57	549	90	0	696
TN	8,490	0	104,000	0	113,000	8,490	0	104,000	0	113,000	8,550	0	108,000	0	116,000

Table 3-1: Annual Average Reductions in Total Pollutant Loading in Period 1 (2025-2029) and Period 2 (2030-2049) for Selected Pollutants in Steam Electric Power Plant Discharges, Compared to Baseline (lb/year)

Pollutant	Option A[a]					Option B (Final Rule)[a]					Option C[a]				
	BA[b]	CRL[c]	FGD	Legacy	Total[d]	BA[b]	CRL[c]	FGD	Legacy[e]	Total[d]	BA[b]	CRL[c]	FGD	Legacy[e]	Total[d]
TP	714	0	4,500	0	5,210	714	0	4,500	0	5,210	719	0	4,630	0	5,350
Selenium	40	0	80	0	119	40	1,060	80	0	1,180	40	1,140	82	0	1,260
Thallium	4	5	136	0	144	4	19	136	0	159	4	20	140	0	164
TSS	43,000	301,000	121,000	0	465,000	43,000	406,000	121,000	0	570,000	43,300	413,000	125,000	0	581,000
Zinc	109	1,340	276	0	1,730	109	1,590	276	0	1,970	110	1,600	284	0	2,000

TN = Nitrogen, total (as N); TP = Phosphorus, total (as P); TSS = Total suspended solids

a. All numbers presented with three significant figures.

b. EPA did not estimate changes in ammonia, beryllium, and cyanide loadings associated with BA transport water.

c. EPA did not estimate changes in ammonia, beryllium, bromide, cyanide, lead, nitrogen, and phosphorus associated with CRL. Additionally, the unmanaged CRL loadings presented in this table do not include unmanaged CRL discharged from landfills, surface impoundments, or other features which a permitting authority could deem, on a case-by-case basis, to be functionally equivalent to a direct discharge. These loadings are not included in the benefits analyses, but costs for treating the unmanaged CRL discharges are included in the social costs presented in Chapters 11 and 12.

d. FGD, BA, CRL and legacy wastewater loadings may not add up to the total due to independent rounding.

e. The loading reductions from legacy wastewater under Options B and C are estimated to occur only as plants close and dewater their ponds. For the purpose of this analysis, pond closures are estimated to occur after 2049 (*i.e.,* outside of the period of analysis) and therefore the loading reductions are zero across all pollutants for both options. Note that no legacy wastewater loading reductions are anticipated under Option A irrespective of the assumed pond closure year.

Source: U.S. EPA Analysis, 2024.

3.3 Water Quality Downstream from Steam Electric Power Plants

EPA used the estimated annual average changes in total pollutant loadings for Periods 1 and 2 to estimate concentrations downstream from each plant. Using the same approach as for the analysis of the 2020 rule and 2023 proposal, EPA applied two models to estimate downstream concentrations from each plant for each period:

- The D-FATE dilution model to estimate pollutant concentrations downstream from the plants. D-FATE (Downstream Fate And Transport Equations) calculates concentrations in each downstream medium-resolution NHD reach using annual average Enhanced Runoff Method (EROM) flows from NHDPlus v2 and mass conservation principles.

- USGS's SPAtially Referenced Regressions On Watershed attributes (SPARROW) to estimate flow-weighted nutrient (TN and TP) and suspended sediment concentrations. The SPARROW models provide baseline and regulatory option concentrations of TN, TP, and suspended solids concentration (SSC). EPA used the calibrated regional models published by the USGS (Ator, 2019; Hoos & Roland Ii, 2019; Robertson & Saad, 2019; Wise, 2019; Wise, Anning & Miller, 2019). These models define the stream network using the same medium-resolution NHD reaches used in D-FATE.

The models represent discharges to reaches represented in the NHD. As discussed in Section 3.1, EPA omitted wastestreams discharged by 11 steam electric power plants to the Great Lakes, estuaries or other waters that lack a valid flowpath.

In the D-FATE model, EPA used stream routing and flow attribute information from the medium-resolution NHDPlus v2 to track masses of pollutants from steam electric power plant discharges and other pollutant sources as they travel through the hydrographic network. For each point source discharger, the D-FATE model estimates pollutant concentrations for the receiving reach and all downstream reaches based on NHD mean annual flows. In-stream flows are kept constant (*i.e.*, discharges have no effect on flows). EPA notes that steam electric power plant discharges frequently constitute a return of flow withdrawn for plant use from the same surface water. In addition, FGD and BA wastewater discharges generally comprise a very small fraction of annual mean flows in the NHDPlus v2 dataset.[42]

Following the approach used in the analysis of the 2015 and 2020 rules and the 2023 proposal (U.S. EPA, 2015a, 2020b, 2023c) to estimate pollutant concentrations, EPA also included loadings from major dischargers (in addition to the steam electric power plants) that reported to the Toxics Release Inventory (TRI). EPA used loadings reported to the TRI in 2021.[43] TRI data were available for a subset of toxics: arsenic, barium, chromium, copper, lead, manganese, mercury, nickel, selenium, thallium, and zinc. EPA summed reach-specific concentrations from TRI dischargers and concentration estimates resulting from steam electric power plant loadings to represent water quality impacts from multiple sources. The pollutant concentrations calculated in the D-FATE model are used to derive fish tissue concentrations used to analyze human health effects from consuming self-caught fish (see Chapter 5), analyze nonmarket benefits of water

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[42] Steam electric power plant FGD discharge rates are typically approximately 1 million gallons per day (MGD), whereas the annual mean stream flows in receiving waters average approximately 15,000 MGD.

[43] EPA had used 2019 TRI loadings for the analysis of the 2023 proposed rule. According to EPA TRI National Analysis, TRI releases to water reported in 2021 were approximately 2 percent lower, in the aggregate, than releases reported in 2019 (196.4 million pounds versus 200.9 million pounds) (U.S. Environmental Protection Agency. (2023r, March 15, 2023). *TRI National Analysis: Water Releases*. Retrieved November 28, 2023 from https://www.epa.gov/trinationalanalysis/water-releases).

quality improvements (see Chapter 6), and assess potential impacts to T&E species whose habitat ranges intersect with waters affected by steam electric plant discharges (see Chapter 7).

3.4 Overall Water Quality Changes

Following the approach used in the analysis of the 2015 and 2020 rules and 2023 proposal (U.S. EPA, 2015a; 2020b, 2023c), EPA used a WQI to link water quality changes from reduced toxics, nutrient and sediment discharges to effects on human uses and support for aquatic and terrestrial species habitat. The WQI translates water quality measurements, gathered for multiple parameters (*e.g.*, dissolved oxygen [DO], nutrients) that are indicative of various aspects of water quality, into a single numerical indicator. The WQI ranges from 10 to 100 with low values indicating poor quality and high values indicating good water quality.

As detailed in U.S. EPA (2015a), the WQI includes seven parameters: DO, BOD, fecal coliform (FC), TN, TP, suspended solids, and one aggregate subindex for toxics. The pollutants considered in the aggregate subindex for toxics are those that are discharged by modeled steam electric power plants or 2021 TRI dischargers and that have chronic aquatic life-based NRWQC. Pollutants that meet these qualifications include arsenic, cadmium, hexavalent chromium, copper, lead, mercury, nickel, selenium, and zinc. See the EA for details on NRWQC (U.S. EPA, 2024b). The subindex curve for toxics assigns the lowest WQI value of 0 to waters where exceedances are observed for the *nine* toxics analyzed, and a maximum WQI value of 100 to waters where there are no exceedances. Intermediate values are distributed between 100 and 0 in proportion to the number of exceedances.

3.4.1 WQI Data Sources

To calculate the WQI, EPA used modeled NRWQC exceedances for toxics (using concentrations from D-FATE) and modeled concentrations for TN, TP, and total suspended solids (TSS) from the respective SPARROW regional models. Following the approach used for the 2020 rule and 2023 proposal analyses, the USGS National Water Information System (NWIS) provided concentration data for three parameters that are held constant between the baseline and regulatory options: 1) fecal coliform, 2) dissolved oxygen, and 3) biochemical oxygen demand (see Section 3.4.1.2).[44, 45]

3.4.1.1 Exceedances of Water Quality Standards and Criteria

For each regulatory option, EPA identified reaches that do not meet NRWQC for aquatic life in Periods 1 and 2.[46] Table 3-2 summarizes the number of reaches with estimated exceedances of NRWQC in the baseline and

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[44] USGS's NWIS provides information on the occurrence, quantity, quality, distribution, and movement of surface and underground waters based on data collected at approximately 1.5 million sites in all 50 States, the District of Columbia, and U.S. territories. More information on NWIS can be found at http://waterdata.usgs.gov/nwis/.

[45] The 2020 rule and 2023 proposal analysis used data ranging from 2007-2017. This dataset was updated for this analysis to include data ranging from 2007-2022.

[46] Aquatic life criteria are the highest concentration of pollutants in water that are not expected to pose a significant risk to the majority of species in a given environment. For most pollutants, aquatic NRWQC are more stringent than human health NRWQC and thus provide a more conservative estimate of potential water quality impairment. Chronic criteria are derived using longer term (7-day to greater than 28-day) toxicity tests if available, or an acute-to-chronic ratio procedure where the acute criteria is derived using short term (48-hour to 96-hour) toxicity tests (U.S. Environmental Protection Agency. (2017a). *Chapter 3: Water Quality Criteria. Water Quality Standards Handbook*. (EPA 823-B-17-001). Retrieved from https://www.epa.gov/sites/production/files/2014-10/documents/handbook-chapter3.pdf). More information on aquatic NRWQC can be found at https://www.epa.gov/wqc/national-recommended-water-quality-criteria-aquatic-life-criteria-table and in the *EA* (U.S. Environmental Protection Agency. (2023g). *Environmental Assessment for Proposed Supplemental Revisions to the Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category*.).

under the regulatory options. In Period 2, the final rule (Option B) is estimated to eliminate all exceedances of chronic criteria for 5 reaches (of 40 reaches with at least one exceedance), and eliminate all exceedances of acute criteria for all four reaches with baseline exceedances.

Table 3-2: Estimated Exceedances of National Recommended Water Quality Criteria under the Baseline and Regulatory Options

Regulatory Option	Number of Reaches with at Least One NRWQC Exceedance	
	Chronic	Acute
Period 1 (2025-2029)		
Baseline	42	4
Option A	42	2
Option B (Final Rule)	40	2
Option C	40	2
Period 2 (2030-2049)		
Baseline	40	4
Option A	40	2
Option B (Final Rule)	35	0
Option C	35	0

Source: U.S. EPA Analysis, 2024

Refer to the EA for additional discussion of comparisons of receiving and downstream water pollutant concentrations to acute and chronic aquatic NRWQC (U.S. EPA, 2024b).

3.4.1.2 Sources for Ambient Water Quality Data

Following the approach used for the analysis of the 2020 rule and 2023 proposal, EPA used average monitoring values for fecal coliform, dissolved oxygen, and biochemical oxygen demand for 2007-2022 where available. EPA used a successive average approach to assign average values for the three WQI parameters not explicitly modeled (*i.e.*, DO, BOD, fecal coliform). The approach, which adapts a common sequential averaging imputation technique, involves assigning the average of ambient concentrations for a given parameter within a hydrologic unit to reaches within the same hydrologic unit with missing data, and progressively expanding the geographical scope of the hydrologic unit (Hydrologic unit code (HUC8, HUC6, HUC4, and HUC2) to fill in all missing data.[47] This approach is based on the assumption that reaches located in the same watershed generally share similar characteristics. Using this estimation approach, EPA compiled ambient water quality data and/or estimates for all analyzed NHD reaches. As discussed below, the values of the three WQI parameters not explicitly modeled are kept constant for the baseline and regulatory policy scenarios. This approach has not been peer reviewed, but it has been used by EPA for several prior rules and reviewed by the public during the associated comment periods.

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[47] Hydrologic Unit Codes (HUCs) are cataloguing numbers that uniquely identify hydrologic features such as surface drainage basins. The HUCs consist of 8 to 14 digits, with each set of 2 digits giving more specific information about the hydrologic feature. The first pair of values designate the region (of which there are 22), the next pair the subregion (approximately 245), the third pair the basin or accounting unit (approximately 405), and the fourth pair the subbasin, or cataloguing unit (approximately 2,400) (U.S. Geological Survey. (2007). *National Hydrography Dataset (NHD)*. Retrieved from http://nhd.usgs.gov/data.html, U.S. Geological Survey. (2022). *Federal Standards and Procedures for the National Watershed Boundary Dataset (WBD)*. Retrieved from https://pubs.usgs.gov/tm/11/a3/pdf/tm11-a3_5ed.pdf). Digits after the first eight offer more detailed information at the watershed and subwatershed levels. In this discussion, a HUC level refers to a set of waters that have that number of HUC digits in common. For example, the HUC6 level includes all reaches for which the first six digits of their HUC are the same.

The water quality analysis included a total of 11,607 medium-resolution NHD reaches that are potentially affected by steam electric power plants under the baseline. Of these 11,607 NHD reaches, EPA estimated concentrations for 11,080 reaches from steam electric power plants. Table 3-3 summarizes the data sources used to estimate baseline and regulatory option values by water quality parameter.

Table 3-3: Water Quality Data used in Calculating WQI for the Baseline and Regulatory Options

Parameter	Baseline	Regulatory Option
TN	Concentrations calculated using SPARROW (baseline run)	Concentrations calculated using SPARROW (regulatory option run)
TP	Concentrations calculated using SPARROW (baseline run)	Concentrations calculated using SPARROW (regulatory option run)
TSS	Concentrations calculated using SPARROW (baseline run)	Concentrations calculated using SPARROW (regulatory option run)
DO	Observed values averaged at the WBD watershed level	No change. Regulatory option value set equal to baseline value
BOD	Observed values averaged at the WBD watershed level	No change. Regulatory option value set equal to baseline value
Fecal Coliform	Observed values averaged at the WBD watershed level	No change. Regulatory option value set equal to baseline value
Toxics	Baseline exceedances calculated using D-FATE model	Regulatory option exceedances calculated using D-FATE model

WBD = Watershed Boundary Dataset. The WBD is a companion dataset to the NHD

Source: U.S. EPA Analysis, 2022.

3.4.2 WQI Calculation

EPA used the approach described in the BCA for the 2015 and 2020 rules and 2023 proposal (U.S. EPA, 2015a, 2020b, 2023c) to estimate WQI values for each reach under the baseline and each option. EPA used updated subindex curves for TN, TP, and TSS previously used for the 2023 proposed revisions to the ELGs for the Meat and Poultry Products Point Source Category (U.S. EPA, 2023d) and reflect data from the 2013-2014 and 2018-2019 National Rivers and Streams Assessments (NRSA) (U.S. EPA, 2020e, 2023j).[48]

Implementing the WQI methodology involves three key steps: 1) obtaining water quality levels for each of seven parameters included in the WQI; 2) transforming parameter levels to subindex values expressed on a common scale; and 3) aggregating the individual parameter subindices to obtain an overall WQI value that reflects waterbody conditions across the seven parameters. These steps are repeated for each reach to calculate the WQI value for the baseline, and for each analyzed regulatory option. See details of the calculations in Appendix C, including the subindex curves used to transform levels of individual parameters. The scope of this analysis is the same as that for the analysis of nonmarket benefits of water quality

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[48] The NRSA is a component of EPA's National Aquatic Resources Survey (NARS). The NRSA provides information on the conditions of the nation's rivers and streams and is conducted at regular intervals (2008-2009, 2013-2014, and 2018-2019) using a consistent approach. This enables comparison of stream conditions over time. The NRSA has several interesting features to support the development of a water quality index: it is based on a statistical representation of rivers and streams, it provides data for key indicators of biological, chemical and physical conditions, and includes both measured data and a categorical assessment of the conditions (poor, fair, good) for selected indicators. In particular, the 2013-2014 and 2018-2019 surveys provide categorical assessments of chemical conditions related to TN and TP.

improvements discussed in Chapter 6, which focuses on reaches within 300 km of a steam electric plant outfall.[49]

3.4.3 Baseline WQI

The WQI value can be related to suitability for potential uses. Vaughan (1986) developed a water quality ladder (WQL) that can be used to indicate whether water quality is suitable for various human uses (*i.e.*, boating, rough fishing, game fishing, swimming, and drinking without treatment). Vaughan identified "minimally acceptable parameter concentration levels" for each of the five potential uses. Vaughan used a scale with a top value of 10 instead of the WQI scale with a top value of 100 to classify water quality based on its suitability for potential uses. Therefore, the WQI value corresponding to a given water quality use classification equals the WQL value multiplied by 10.

Based on the estimated WQI value under the baseline scenario (WQI-BL), EPA categorized each of the 11,080 NHD reaches using five WQI ranges (WQI < 25, 25≤WQI<45, 45≤WQI<50, 50≤WQI<70, and 70≤WQI) (Table 3-4). WQI values of less than 25 indicate that water is not suitable for boating (the recreational use with the lowest associated WQI on the WQL), whereas WQI values greater than 70 indicate that waters are swimmable (the recreational use with the highest associated WQI on the WQL).[50]

Table 3-4: Estimated Percentage of Potentially Affected Reach Miles by WQI Classification: Baseline Scenario

Water Quality Classification	Baseline WQ	Number of Reaches	Percent of Affected Reaches	Number of Reach Miles	Percent of Affected Reach Miles
Period 1 (2025-2029)					
Unusable	WQI<25	4	0.0%	10	0.1%
Suitable for Boating	25≤WQI<45	199	1.8%	352	3.0%
Suitable for Rough Fishing	45≤WQI<50	212	1.9%	214	1.8%
Suitable for Game Fishing	50≤WQI<70	4,231	38.2%	4,304	37.1%
Suitable for Swimming	70≤WQI	6,434	58.1%	6,734	58.0%
Total		**11,080**	**100.0%**	**11,613**	**100.0%**
Period 2 (2030-2049)					
Unusable	WQI<25	4	0.0%	10	0.1%
Suitable for Boating	25≤WQI<45	197	1.8%	349	3.0%
Suitable for Rough Fishing	45≤WQI<50	209	1.9%	211	1.8%
Suitable for Game Fishing	50≤WQI<70	4,236	38.2%	4,309	37.1%
Suitable for Swimming	70≤WQI	6,434	58.1%	6,734	58.0%
Total		**11,080**	**100.0%**	**11,613**	**100.0%**

Source: U.S. EPA Analysis, 2024

3.4.4 Estimated Changes in Water Quality (ΔWQI) from the Regulatory Options

To estimate the benefits of water quality improvements resulting from the regulatory options, EPA calculated the change in WQI for each analyzed regulatory option as compared to the baseline. This analysis was done

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[49] There are an estimated 16,832 NHD reaches on the downstream flow path of steam electric plant outfalls, of which 11,607 NHD reaches are within 300 km of any outfall. A subset of these reaches lack valid annual average flow data to estimate pollutant concentrations, leaving a total of 11,080 NHD reaches with the data needed to estimate WQI values.

[50] EPA did not separately categorize waters where the WQI was greater than or equal to 90 (drinkable water) because surface waters are generally treated before distribution for potable use. Pollutant specific impacts on drinking water are addressed separately in Chapter 4.

for each reach and for each of the two periods. As discussed in Section 1.1, EPA estimated changes in ambient concentrations of TN, TP and TSS using the USGS's SPARROW models and toxics concentrations using the D-FATE model. Although the regulatory options would also indirectly affect levels of other WQI parameters, such as BOD and DO, these other parameters were held constant in this analysis for all regulatory options, due to methodological and data limitations.

The difference in the WQI between baseline conditions and a given regulatory option (hereafter denoted as ΔWQI) is a measure of the change in water quality attributable to the regulatory option. Table 3-5 presents water quality change ranges for the analyzed regulatory options under each analysis period.

Table 3-5: Ranges of Estimated Water Quality Changes for Regulatory Options, Compared to Baseline

Regulatory Option	Minimum ΔWQI	Maximum ΔWQI	25th Percentile ΔWQI	Median ΔWQI	75th Percentile ΔWQI	ΔWQI Interquartile Range
Period 1 (2025-2029)						
Option A	0	1.70	0	7.90×10^{-6}	3.39×10^{-4}	3.39×10^{-4}
Option B (Final Rule)	0	1.70	0	7.91×10^{-6}	3.39×10^{-4}	3.39×10^{-4}
Option C	0	1.70	0	7.91×10^{-6}	4.69×10^{-4}	4.69×10^{-4}
Period 2 (2030-2049)						
Option A	0	10.17	0	1.83×10^{-5}	4.02×10^{-4}	4.02×10^{-4}
Option B (Final Rule)	0	10.17	0	1.89×10^{-5}	4.54×10^{-4}	4.54×10^{-4}
Option C	0	10.17	0	2.67×10^{-5}	4.97×10^{-4}	4.97×10^{-4}

Source: U.S. EPA Analysis, 2024

3.5 Limitations and Uncertainty

The methodologies and data used in the estimation of the environmental effects of the regulatory options involve limitations and uncertainties. Table 3-6 summarizes the limitations and uncertainties and indicates the direction of the potential bias. Uncertainties associated with some of the input data are covered in greater detail in other documents. Regarding the uncertainties associated with use of the NHDPlus attribute data, see the NHDPlus v2 documentation (U.S. EPA, 2019g). Regarding the uncertainties associated with estimated loads, see the TDD (U.S. EPA, 2024f).

Table 3-6: Limitations and Uncertainties in Estimating Water Quality Effects of Regulatory Options

Uncertainty/Limitation	Effect on Water Quality Effects Estimation	Notes
Limited data are available to validate water quality concentrations estimated in D-FATE	Uncertain	The modeled concentrations reflect only a subset of pollutant sources (*e.g.*, steam electric power plant discharges and TRI releases) whereas monitoring data also reflect other sources such as bottom sediments, air deposition, and other point and non-point sources of pollution. TRI releases are also reported by the facilities and could potentially suffer from misreporting or faulty estimation techniques. EPA comparisons of D-FATE estimates to monitoring data available for selected locations and parameters (*e.g.*, bromide concentrations downstream of steam electric power plant discharges) confirmed that D-FATE provides reasonable values. Also refer to the 2015 EA for discussion of model validation for selected case studies (U.S. EPA, 2015b)
Steam electric power plant discharges have no effects on reach annual average or seasonal flows	Overestimate	The degree of overestimation in the estimation of pollutant concentrations, if any, would be small given that steam electric power plant discharge flows tend to be very small as compared to flows in modeled receiving and downstream reaches. Further, EPA acknowledges that the effect of steam electric power plant discharges on reach flows may vary seasonally due to low- and high-flow periods.
Ambient water toxics concentrations are based only on loadings from steam electric power plants and other TRI discharges.	Uncertain	Concentration estimates do not account for background concentrations of these pollutants from other sources, such as legacy pollution in sediments, non-point sources, point sources that are not required to report to TRI, air deposition, etc. Not including other contributors to background toxics concentrations in the analysis is likely to result in understatement of baseline concentrations of these pollutants and therefore of NRWQC exceedances. The effect on WQI calculations is uncertain.
Annual loadings are estimated based on EPA's estimated plant-specific technology implementation years	Uncertain	To the extent that technologies are implemented earlier or later, the Period 1 annualized loading values presented in this section may under- or overstate the annual loads during the analysis period. The effect of this uncertainty is limited to Period 1 since loads reach a steady-state level by the technology implementation deadlines applicable to the regulatory options (*e.g.*, by the end of 2029)

Table 3-6: Limitations and Uncertainties in Estimating Water Quality Effects of Regulatory Options

Uncertainty/Limitation	Effect on Water Quality Effects Estimation	Notes
Changes in WQI reflect only reductions in toxics, nutrient, and sediment concentrations.	Underestimate	The estimated changes in WQI reflect only water quality changes resulting directly from changes in toxics, nutrient and sediment concentrations. They do not include changes in other water quality parameters (*e.g.*, BOD, dissolved oxygen) that are part of the WQI and for which EPA used constant values. Because the omitted water quality parameters are also likely to respond to changes in pollutant loads (*e.g.*, dissolved oxygen levels respond to changes in nutrient levels), the analysis underestimates the water quality changes.
EPA used regional averages of monitoring data from 2007-2022 for fecal coliform, dissolved oxygen, and biochemical oxygen demand, when location-specific data were not available.	Uncertain	The monitoring values were averaged over progressively larger hydrologic units to fill in any missing data. As a result, WQI values may not reflect certain constituent fluctuations resulting from the various regulatory options and/or may be limited in their temporal and spatial relevance. Note that the analysis keeps these parameters constant under both the baseline and regulatory options. Modeled changes due to the regulatory options are not affected by this uncertainty.
Use of nonlinear subindex curves	Uncertain	The methodology used to translate sediment and nutrient concentrations into subindex scores (see Section 3.4.2 and Appendix C) employs nonlinear transformation curves. Water quality changes that fall outside of the sensitive part of the transformation curve (*i.e.*, above/below the upper/lower bounds, respectively) yield no change in the analysis and no benefits in the analysis described in Chapter 6.

4 Human Health Benefits from Changes in Pollutant Exposure via the Drinking Water Pathway

EPA expects that the changes in pollutant loadings from the regulatory options relative to the 2020 rule could affect several aspects of human health by changing bromide and other pollutant discharges to surface waters and, as a result, pollutant concentrations in the reaches that serve as sources of drinking water. The EA provides details on the health effects of steam electric pollutants (U.S. EPA, 2024b).

As described in Section 2.1, human health benefits deriving from changes in pollutant loadings to receiving waters include those associated with changes in exposure to pollutants via treated drinking water use and fish consumption. This chapter addresses the first exposure pathway: drinking water. Chapter 5 addresses the fish consumption pathway.

The changes in pollutant loadings from the regulatory options relative to the 2020 rule could affect human health by changing halogen and other pollutant discharges to surface waters and, as a result, pollutant concentrations in the reaches that serve as sources of drinking water. The EA presents background information regarding the potential impacts of halogen discharges on drinking water quality and human health (U.S. EPA, 2024b). Section 4.1 provides background information on trihalomethane precursor development. Sections 4.2 through 4.4 present EPA's analysis of human health effects from changes in bromide discharges. Section 4.5 summarizes potential impacts on source waters from changes in other pollutant discharges. Section 4.6 discusses uncertainty and limitations associated with the analysis presented in this chapter.

4.1 Background

FGD wastewater and BA transport water discharges contain variable quantities of bromide due to the natural presence of bromide in coal feedstock and from additions of halogens, including bromide-containing salts, and use of brominated activated carbon products to enhance air emissions control (Kolker et al., 2012). Wastewater treatment technologies employed at steam electric power plants vary widely in their ability to remove bromide. A number of studies have documented elevated bromide levels in surface water due to steam electric power plant discharges (*e.g.*, Cornwell et al., 2018; Good & VanBriesen, 2016, 2017; McTigue et al., 2014; Ruhl et al., 2012; States et al., 2013; U.S. EPA, 2017c; 2019c) and have attributed measured increases in bromide levels to the increasing number of installed wet FGD devices at steam electric power plants. FGD wastewaters have been shown to contain relatively high levels of bromide relative to other industrial wastewaters. Modeling studies have sought to quantify the potential for drinking water sources to be affected by FGD wastewater discharges (Good & VanBriesen, 2019).

Bromide does not undergo significant physical (*e.g.*, sorption, volatilization), chemical or biological transformation in freshwater environments and is commonly used as a tracer in solute transport and mixing field studies. Surface waters transport bromide discharges to downstream drinking water treatment facility intakes where they are drawn into the treatment systems.

Although the bromide ion has a low degree of toxicity (World Health Organization, 2009), it can contribute to the formation of brominated DBPs during drinking water disinfection processes, including chlorination, chloramination, and ozonation. Bromate, a regulated DBP under the Safe Drinking Water Act (SDWA), forms when bromine reacts directly with ozone. Chlorine reacts with bromide to produce hypobromite (BrO^-), which reacts with organic matter to form brominated and mixed chloro-bromo DBPs, including three of the four regulated trihalomethanes[51] (THM4, also referred to as total trihalomethanes (TTHM) in this discussion) and two of the five regulated haloacetic acids[52] (HAA5). Additional unregulated brominated DBPs have been cited as an emerging class of water supply contaminants that can potentially pose health risks to humans (Richardson et al., 2007; NTP, 2018; U.S. EPA, 2016c).

There is a substantial body of literature on trihalomethane precursor occurrence, trihalomethane formation mechanisms in drinking water treatment plants, and relationships between source water bromide levels and TTHM levels in treated drinking water. The formation of TTHM in a particular drinking water treatment plant is a function of several factors including chlorine, bromide, organic material, temperature, and pH levels as well as system residence times. There is also substantial evidence linking TTHM exposure to bladder cancer incidence (U.S. EPA, 2016c). Bromodichloromethane and bromoform are likely to be carcinogenic to humans by all exposure routes and there is evidence suggestive of dibromochloromethane's carcinogenicity (NTP, 2018; U.S. EPA, 2016c). The relationships between exposure to DBPs, specifically TTHMs and other halogenated compounds resulting from water chlorination, and bladder cancer are further discussed in Section 4.3.3.2 and U.S. EPA (2019b).

4.2 Overview of the Analysis

Figure 4-1 illustrates EPA's approach for quantifying and valuing the human health effects of altering bromide discharges from steam electric power plants. The analysis entails estimating in-stream changes in bromide levels between conditions under the baseline and each of the three regulatory options (Step 1); estimating the change in source water bromide levels and corresponding changes in TTHM concentrations in treated water supplies (Step 2); relating these estimated changes to changes in exposure and the subsequent changes in the incidence of bladder cancers[53] in the exposed population (Step 3); and estimating the associated monetary value of benefits (Step 4). This approach was implemented in EPA's 2019 proposed rule and the 2023 proposal (U.S. EPA, 2019b, 2023c) and relies on findings from a peer-reviewed paper by Regli et al. (2015) that built on the approach taken in the Stage 2 Disinfectants and Disinfection Byproduct Rule (DBPR) (U.S. EPA, 2005c) to derive a slope factor to relate changes in lifetime bladder cancer risk to changes in TTHM exposure. This analysis also incorporates National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) program data to model incidence of bladder cancers by age and sex, cancer stage, changes in lifetime cancer risk attributable to the regulatory options, and survival outcomes. The life-table modeling approach used by EPA to estimate changes in health outcomes is a widely used method in public health, insurance, medical research, and other studies and was used for analysis of lead-associated health effects in the 2015 rule. The main advantage of this approach is that it allows for explicitly accounting for age and cancer stage-specific patterns in cancer outcomes, as well as for other causes of mortality in the affected population.

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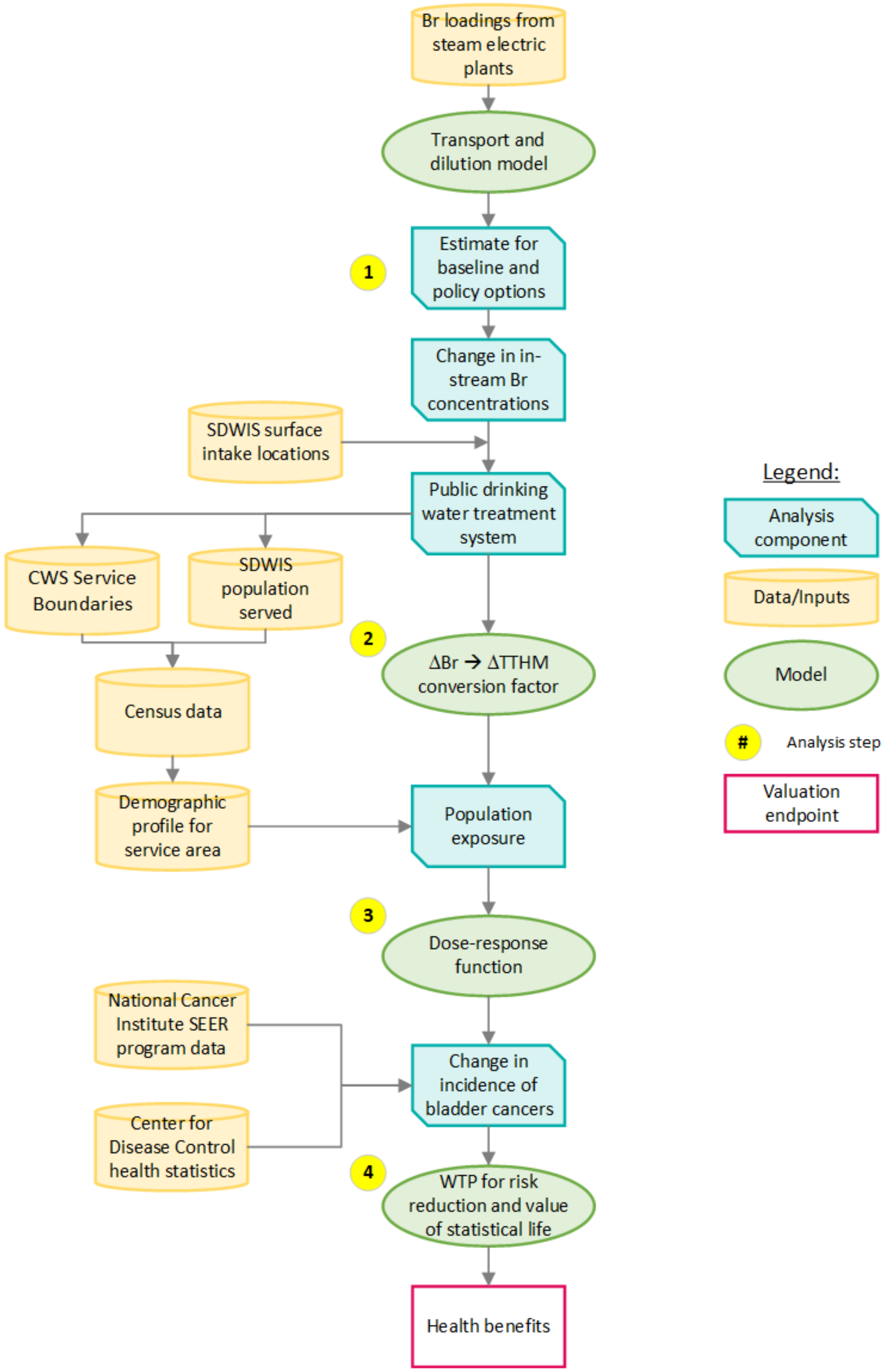
[51] The four regulated trihalomethanes are bromodichloromethane, bromoform, chloroform, and dibromochloromethane.

[52] The five regulated haloacetic acids are dibromoacetic acid, dichloroacetic acid, monobromoacetic acid, monochloroacetic acid, and trichloroacetic acid.

[53] Regli, S., Chen, J., Messner, M., Elovitz, M. S., Letkiewicz, F. J., Pegram, R. A., Pepping, T. J., . . . Wright, J. M. (2015). Estimating potential increased bladder cancer risk due to increased bromide concentrations in sources of disinfected drinking waters. *Environmental Science & Technology*, *49*(22), 13094-13102. estimated the additional lifetime risk from a 1 µg/L increase in TTHM. This relationship holds over the TTHM range expected for systems in compliance with the Stage 2 Disinfectants and Disinfection Byproduct Rule.

Figure 4-1: Overview of Analysis of Estimated Human Health Benefits of Reducing Bromide Discharges.



Source: U.S. EPA Analysis, 2024.

4.3 Estimates of Changes in Halogen Concentrations in Source Water

EPA estimated the change in halogen levels in the source water for PWS that have intakes downstream from steam electric power plants. Halogens such as bromide are precursors for halogenated disinfection byproduct formation in treated drinking water, including certain trihalomethanes addressed by the TTHM MCL. Higher halogen levels in PWS source waters have been associated with higher levels of halogenated DBPs in treated drinking water. The formation of DBPs varies with site-specific factors. *In vitro* toxicology studies with bacteria and mammalian cells have documented evidence of genotoxic (including mutagenic), cytotoxic, tumorigenic, and developmental toxicity properties of iodinated DBPs, but the available data are insufficient at this time to determine the extent of iodinated DBP's contribution to adverse human health effects from exposure to treated drinking water (Richardson et al., 2007; U.S. EPA, 2016c; National Toxicology Program, 2018). Populations exposed to changes in halogenated disinfection byproduct levels in their drinking water under the regulatory options could experience changes in the incidence of adverse health effects, and in turn the total counts of these health effects.

In this section, the Agency presents the number of PWS with modeled changes in bromide concentration in their source water, the magnitude and direction of these changes, and the PWS service population estimated to experience a change in DBP exposure levels due to changes in source water bromide levels.

4.3.1 Step 1: Modeling Bromide Concentrations in Surface Water

EPA estimated steam electric power plant-level bromide loadings associated with FGD wastewater and BA transport water for the baseline and the regulatory options.[54] This chapter presents EPA's best estimate of changes in bromide loadings under each of the regulatory options.

EPA used the D-FATE model described in Section 3.3 to estimate in-stream bromide concentrations downstream from 38 steam electric power plants that EPA estimated have non-zero bromide loads (*i.e.*, discharge FGD wastewater and/or BA transport water) under the baseline or regulatory options. EPA first estimated the annual average bromide loads in Period 1 and Period 2 (see Section 3.2.1). EPA then estimated concentrations in the receiving reach and each downstream reach in Period 1 and Period 2, using conservation of mass principles, until the load reaches the hydrographic network terminus (*e.g.*, Great Lake, estuary).[55] EPA summed individual contributions from all plants to estimate total in-stream concentrations under the baseline and the regulatory options in Period 1 and Period 2. Finally, EPA estimated the change in bromide concentrations in each reach as the difference between each regulatory option and the baseline. The modeled change is not dependent on bromide contributions from other sources (*e.g.*, waterbody background levels).

As summarized in Table 4-1, regulatory options A and B are estimated to result in the same bromide loading reductions, whereas bromide loading reductions are slightly higher under Option C. The reductions are higher in Period 2 than in Period 1 under all regulatory options.

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[54] EPA did not estimate bromide loadings associated with CRL discharges.

[55] As discussed in Section 3.1, EPA did not estimate concentration changes in the Great Lakes or estuaries.

Table 4-1: Estimated Bromide Loading Reductions by Analysis Period and Regulatory Option

Regulatory Option	Number of Steam Electric Plants with non-Zero Changes	Total Bromide Load Reduction (lbs/year)
Period 1 (2025-2029)		
Option A	32	2,444,904
Option B (Final Rule)	32	2,444,904
Option C	32	2,686,485
Period 2 (2030-2049)		
Option A	37	4,615,175
Option B (Final Rule)	37	4,615,175
Option C	38	4,647,249

Source: U.S. EPA Analysis, 2024

4.3.2 Step 2: Modeling Changes in Trihalomethanes in Treated Water Supplies

4.3.2.1 Affected Public Water Systems

For the final rule, EPA updated the universe of PWS potentially affected by steam electric plant discharges to reflect adjustments to the universe of plants projected to be subject to the rule and their associated receiving and downstream reaches. EPA also collected more recent information about the operating characteristics of the water systems (*e.g.*, population served, facility status, wholesale water purchases). EPA used Safe Drinking Water Information System (SDWIS) fourth quarter data for 2022.

EPA's SDWIS database[56] provides the latitude and longitude of surface water facilities[57], including source water intakes for public drinking water treatment systems. To identify potentially affected PWS, the Agency georeferenced each permanent surface water facility associated with non-transient community water systems to the NHD medium-resolution stream network used in D-FATE.[58] Appendix F describes the methodology EPA used to identify the NHD water feature for each facility. The SDWIS database also includes information on PWS primary sources (*e.g.*, whether a PWS relies primarily on groundwater or surface water for their source water), operational status, and population served, among other attributes. For this analysis, EPA used the subset of facilities that identify surface water as their primary water source (specifically surface water intakes and reservoirs) and are categorized as "active" and "permanent" in SDWIS. This subset of facilities corresponds to PWS that are more likely to be affected by upstream bromide releases on an ongoing basis, as compared to other systems that may use surface water sources only sporadically. This approach identifies populations most likely to experience changes in long-term halogenated DBP exposures and associated health effects due to the regulatory options.

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[56] EPA used intake locations and PWS data from the fourth quarter report for 2022. Intake location data are protected from disclosure due to security concerns. SDWIS public data records are available from the Federal Reporting Services system at https://ofmpub.epa.gov/apex/sfdw/.

[57] Surface water facilities include any part of a PWS that aids in obtaining, treating, and distributing drinking water. Facilities in the SDWIS database may include groundwater wells, consecutive connections between buyer and seller PWS, pump stations, reservoirs, and intakes, among others.

[58] This analysis does not include intakes that draw from the Great Lakes or other water bodies not analyzed in the D-FATE model.

PWS can be either directly or indirectly affected by steam electric power plant discharges. Directly affected PWS are systems with surface water intakes drawing directly from reaches downstream from steam electric power plants discharging bromide.[59] Other PWS are indirectly affected because they purchase their source water from another PWS via a "consecutive connection" instead of withdrawing directly from a surface water or groundwater source. For these systems, SDWIS provides information on the PWS that supplies the purchased water. EPA used SDWIS data to identify PWS that may be indirectly affected by steam electric power plant discharges because they purchase water from a directly affected PWS. The total potentially exposed population consists of the people served by either directly or indirectly affected systems.

Table 4-2 summarizes the number of intakes, PWS, and total populations potentially affected by steam electric power plant discharges via the drinking water pathway, and the subset of those intakes and PWS affected by bromide discharges. In this analysis, the average distance from the steam electric power plant discharge point to the drinking water treatment plant intake is 71 miles and approximately 19 percent of the intakes are located within 30 miles of a steam electric power plant outfall. A subset of these PWS is downstream of FGD wastewater and BA transport water discharges containing bromide,[60] specifically 118 affected reaches have intakes used by 151 PWS serving a total of 15.7 million people, directly or indirectly.

Table 4-2: Estimated Reaches, Surface Water Intakes, Public Water Systems, and Populations Potentially Affected by Steam Electric Power Plant Discharges

PWS Impact Category	Number of Reaches with Drinking Water Intakes	Number of Intakes Downstream of Steam Electric Power Plants	Number of PWS	Total Population Served (Million People)
Reaches downstream from steam electric plant discharges				
Direct[a]	223	283	234	18.4
Indirect	Not applicable	Not applicable	682	10.8
Total	**223**	**283**	**916**	**29.2**
Reaches downstream from steam electric plant with non-zero bromide loads				
Direct[b]	118	151	131	11.5
Indirect	Not applicable	Not applicable	366	4.1
Total	**118**	**151**	**497**	**15.7**

a. Includes 16 systems with both intakes downstream of steam electric power plant discharges and that purchase water from other systems with intakes downstream of steam electric power plant discharges.

b. Includes 7 systems with both intakes downstream of steam electric power plant discharges and that purchase water from other systems with intakes downstream of steam electric power plant discharges.

Source: U.S. EPA Analysis, 2024

4.3.2.2 System-Level Changes in Bromide Concentrations in Source Water

EPA estimated the change in bromide concentrations in the source water for each PWS that could result from the regulatory options. In this discussion, the term "system" refers to PWS and their associated drinking water

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[59] To identify potentially affected PWS, EPA looked at all downstream reaches starting from the immediate reach receiving the steam electric power plant discharge to the reach identified as the terminus of the stream network.

[60] Note that when plants retire, bromide may still be present in CRL. The present analysis considers bromide discharges from FGD wastewater and BA transport water only.

treatment operations, whereas the term "facility" refers to the intake that is drawing untreated water from a source reach for treatment at the PWS level.

To estimate changes in bromide concentrations at the PWS level, EPA obtained the number of active permanent surface water sources used by each PWS based on SDWIS data. SDWIS does not provide information on respective source flow contributions from surface water and groundwater facilities for a given PWS. For drinking water treatment systems that have both surface water and groundwater facilities, EPA assessed changes from surface water sources only. This approach is reasonable given that the analysis is limited to the PWS for which SDWIS identifies surface water as primary source.

For intakes located on reaches modeled in D-FATE, EPA calculated the reach-level change in bromide concentration as the difference between the regulatory option and the baseline conditions. Some PWS rely on a single intake facility for their source water supply. If the source water reach associated with this single intake is affected by steam electric power plant bromide discharges, the system-level changes in bromide concentration at the PWS would equal the estimated change in bromide concentration of the source water reach. Other PWS rely on multiple intake facilities that may be located along different source water reaches. System-level changes in bromide concentrations at these PWS are an average of the estimated changes in bromide concentrations associated with each source water reach. For any additional intakes not located on the modeled reaches and for intakes relying on groundwater sources, EPA estimated zero change in bromide concentration. Because SDWIS does not provide information on source flows contributed by intake facilities used by a given PWS, EPA calculated the system-level change in bromide concentration assuming each active permanent source facility contributes equally to the total volume of water treated by the PWS. For example, the PWS-level change in bromide concentration for a PWS with three intakes, of which one intake is directly affected by steam electric power plant discharges, is estimated as one third of the modeled reach concentration change ([ΔBr + 0 + 0]/3).

EPA addressed water purchases similarly, but with the change in bromide concentration associated with the consecutive connection set equal to the PWS-level change estimated for the seller PWS instead of a reach-level change. For facilities affected only indirectly by steam electric power plant discharges, EPA assumed zero change in bromide concentrations for any other unaffected source facility associated with the buyer. EPA also assumed that each permanent source facility contributes an equal share of the total volume of water distributed by the buyer. For the seven PWS classified as both directly and indirectly affected by steam electric power plant bromide discharges, EPA assessed the total change in bromide concentration as the average of the change in concentration from both directly-drawn and purchased water.

Table 4-3 summarizes the distribution of changes in bromide concentrations under the regulatory options for the two analysis periods. The changes depends on the Period, option, source water reach, and PWS but are generally consistent with the changes in bromide loadings associated with FGD and bottom ash transport wastewaters under each regulatory option (see Table 3-1). During Periods 1 and 2, all options show either reductions or no changes in bromide concentrations for all source waters and PWS. For all options, the magnitude and scope (the number of reaches, PWS, and population served) of the bromide reductions are larger during Period 2 than during Period 1.

Table 4-3: Estimated Distribution of Changes in Source Water and PWS-Level Bromide Concentrations by Period and Regulatory Option, Compared to Baseline

ΔBr Range (µg/L)	Number of Source Water Reaches		Number of PWS[a]		Population Served by PWS	
	Reduction ΔBr	No ΔBr (ΔBr = 0)	Reduction ΔBr	No ΔBr (ΔBr = 0)	Reduction ΔBr	No ΔBr (ΔBr = 0)
Period 1 (2025-2029)						
Option A						
0 to 10	109	13	451	65	13,539,103	3,380,007
10 to 30	1	0	2	0	2,521	0
50 to 75	1	0	3	0	123,386	0
Option B (Final Rule)						
0 to 10	109	13	451	65	13,539,103	3,380,007
10 to 30	1	0	2	0	2,521	0
50 to 75	1	0	3	0	123,386	0
Option C						
0 to 10	109	13	451	65	13,539,103	3,380,007
10 to 30	1	0	2	0	2,521	0
50 to 75	1	0	3	0	123,386	0
Period 2 (2030-2049)						
Option A						
0 to 10	117	1	473	36	15,095,692	1,669,547
10 to 30	5	0	9	0	156,392	0
>75	1	0	3	0	123,386	0
Option B (Final Rule)						
0 to 10	117	1	473	36	15,095,692	1,669,547
10 to 30	5	0	9	0	156,392	0
>75	1	0	3	0	123,386	0
Option C						
0 to 10	118	0	485	24	15,598,789	1,166,450
10 to 30	5	0	9	0	156,392	0
>75	1	0	3	0	123,386	0

a. Includes systems potentially directly and/or indirectly affected by steam electric power plant discharges.

Source: U.S. EPA Analysis, 2024.

4.3.2.3 Changes in TTHM Concentration in Treated Water Supplies

The prior step provides the estimated PWS-level change in bromide concentration in the blend of source waters used by a given system. The step described in this section provides the estimated PWS-level change in TTHM concentration associated with this change in bromide concentration.

Regli et al. (2015) applied the Surface Water Analytical Tool (SWAT) version 1.1, which models TTHM concentrations in drinking water treatment plants as a function of precursor levels, source water quality (*e.g.*, bromide and organic material levels), water temperature, treatment processes (*e.g.*, pH, residence time), and disinfectant dose (*e.g.*, chlorine levels) to predict the distribution of changes in TTHM concentrations in finished water associated with defined increments of changes in bromide concentration in source waters. That study estimated the distribution of increments of change in TTHM concentration for a subset of the population of PWS characterized in the 1997-1998 Information Collection Rule (ICR) dataset. Table 4-4 summarizes the results from the Regli et al. (2015) analysis.

Table 4-4: Estimated Increments of Change in TTHM Levels (µg/L) as a Function of Change in Bromide Levels (µg/L)

Change in bromide concentration (µg/L)	Change in TTHM concentration (µg/L)					
	Minimum	5th Percentile	Median	Mean	95th Percentile	Maximum
10	0.0	0.1	1.1	1.3	3.4	10.1
30	0.0	0.3	2.6	3.2	8.3	23.7
50	0.0	0.5	3.7	4.6	11.6	33.2
75	0.0	0.6	4.9	6.0	14.8	42.1
100	0.0	0.8	5.8	7.1	17.5	49.3

Source: Regli et al. (2015), Table 2.

For this analysis, EPA used the results from Regli et al. (2015) to predict TTHM concentration changes for each water treatment plant with changes in bromide concentrations in their source water due to the regulatory options. Figure 4-2 shows the relationship (dashed line) between the change in bromide concentration and the change in TTHM concentration based on fitting a polynomial curve through the median estimates from Table 4-4 (circular markers). EPA used the equation of the best-fit curve[61] to estimate changes in TTHM concentration as a function of changes in bromide concentration within the bromide concentration range presented in Regli et al. (2015) (0 to 100 µg/L). Estimates of TTHM concentration changes presented in the remainder of this section reflect median changes from Regli et al. (2015).[62] EPA evaluated the sensitivity of benefits estimates to the relationship between changes in bromide and changes in TTHM using the 5th and 95th percentile estimates in Table 4-4 in the 2019 and 2023 proposed rules (U.S. EPA, 2019b, 2023b).

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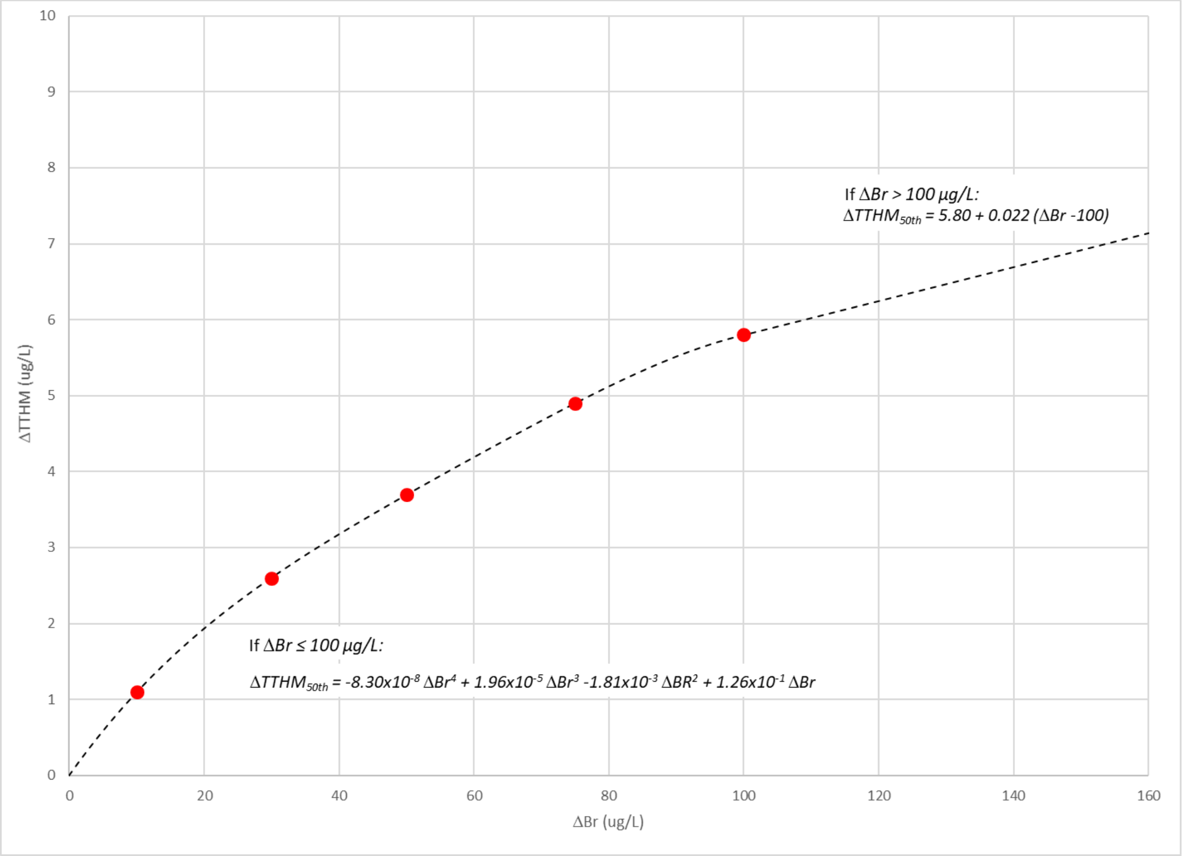
[61] The polynomial curve fits observations in Table 4-4 with residuals of zero over the range of observations.

[62] While Regli, S., Chen, J., Messner, M., Elovitz, M. S., Letkiewicz, F. J., Pegram, R. A., Pepping, T. J., . . . Wright, J. M. (2015). Estimating potential increased bladder cancer risk due to increased bromide concentrations in sources of disinfected drinking waters. *Environmental Science & Technology*, *49*(22), 13094-13102. show similar mean and median changes in TTHM concentrations across the range of changes in bromide concentrations, EPA used the median to minimize potential influence of outlier values or skew in the distribution. Mean changes in TTHM for changes in bromide levels of 10, 30, 50, 75, and 100 µg/L were 1.3, 3.2, 4.6, 6.0 and 7.1 µg/L, respectively. Median changes in TTHM for changes in bromide levels of 10, 30, 50, 75, and 100 µg/L were 1.1, 2.6, 3.7, 4.9, and 5.8 µg/L, respectively.

Figure 4-2: Modeled Relationship between Changes in Bromide Concentration and Changes in TTHM Concentrations based on Median Values in Regli et al. (2015).



Source: U.S. EPA Analysis, 2024, based on Regli et al. (2015).

Table 4-5 shows the distribution of modeled absolute changes in TTHM concentrations and the potentially exposed populations under each of the regulatory options. As shown in the table, the magnitude of estimated bromide concentration changes is generally less than 10 µg/L, corresponding to estimated changes in TTHM concentrations of less than 1.1 µg/L. Compared to the baseline, all options are estimated to reduce TTHM concentrations in treated water.

Table 4-5: Distribution of Estimated Changes in TTHM Concentration by the Number of PWS and Population Served

Absolute ΔBr range[a] (µg/L)	Absolute ΔTTHM range[a] (µg/L)	Number of PWS[b]	Total population served (million people)[c]
Period 1 (2025-2029)			
Option A			
>0 to 10	0.00 to 1.09	451	13.54
10 to 30	1.81 to 1.81	2	0.00
30 to 50	3.82 to 3.82	3	0.12
Option B (Final Rule)			
>0 to 10	0.00 to 1.09	451	13.54
10 to 30	1.81 to 1.81	2	0.00
30 to 50	3.82 to 3.82	3	0.12

Table 4-5: Distribution of Estimated Changes in TTHM Concentration by the Number of PWS and Population Served

Absolute ΔBr range[a] (µg/L)	Absolute ΔTTHM range[a] (µg/L)	Number of PWS[b]	Total population served (million people)[c]
Option C			
>0 to 10	0.00 to 1.09	451	13.54
10 to 30	1.81 to 1.81	2	0.00
30 to 50	3.82 to 3.82	3	0.12
Period 2 (2030-2049)			
Option A			
>0 to 10	0.00 to 0.95	473	15.10
10 to 30	1.23 to 1.82	9	0.16
30 to 50	N/A	0	0.00
50 to 75	N/A	0	0.00
>75	6.48 to 6.48	3	0.12
Option B (Final Rule)			
>0 to 10	0.00 to 0.95	473	15.10
10 to 30	1.23 to 1.82	9	0.16
30 to 50	N/A	0	0.00
50 to 75	N/A	0	0.00
>75	6.48 to 6.48	3	0.12
Option C			
>0 to 10	0.00 to 0.95	485	15.60
10 to 30	1.23 to 1.82	9	0.16
30 to 50	N/A	0	0.00
50 to 75	N/A	0	0.00
>75	6.48 to 6.48	3	0.12

N/A: Not applicable (*i.e.*, there are no observations within the specified ΔBr range)

Source: U.S. EPA Analysis, 2024.

4.3.3 Step 3: Quantifying Population Exposure and Health Effects

EPA used the following steps to quantify changes in human health resulting from changes in TTHM levels in drinking water supplies:

- Characterize the exposed populations;
- Estimate changes in individual health risk; and
- Quantify the changes in adverse health outcomes.

4.3.3.1 Exposed Populations

The exposed populations consist of people served by each affected PWS. SDWIS provides the total population served by each PWS but does not provide detailed information about the geographic extent of the service area. For the final rule, EPA determined the service area of each PWS using a multi-tiered approach based on data availability. EPA first used service areas (SA) identified in the Hydroshare Community Water

Systems Service Boundaries (CWSSB) dataset (SimpleLab EPIC, 2022),[63] then 2022 TIGER ZIP code tabulated areas (ZCTAs), and finally county boundaries when no other data were available.[64] Over 95 percent of PWS with facilities downstream from steam electric plants had boundaries defined in the CWSBB dataset. Three percent of the PWS service areas were matched based on the ZIP code, and approximately one percent were matched based on the county.

EPA overlaid the service area boundaries to the Census block group (CBG) data in the 2021 American Community Survey (U.S. Census Bureau, 2021) to distribute the total population served by each PWS by age group to model health effects as described in Section 4.3.3.3.

EPA assumed that all individuals served by a given PWS are exposed to the same modeled changes in TTHM levels for the PWS, *i.e.*, there are no differences in TTHM concentrations in different parts of the water distribution system.

4.3.3.2 Health Impact Function

The relationship between exposure to DBPs, specifically trihalomethanes and other halogenated compounds resulting from water chlorination, and bladder cancer has been the subject of multiple epidemiological studies (Cantor et al., 2010; U.S. EPA, 2005c; NTP, 2018), a meta-analysis (Villanueva et al., 2003; Costet et al., 2011), and pooled analysis (Villanueva et al., 2004). The relationship between trihalomethane levels and bladder cancer in the Villanueva et al. (2004) study was used to support the benefits analysis for EPA's Stage 2 DBP Rule[65] which specifically aimed to reduce the potential health risks from DBPs (U.S. EPA, 2005c).

Regli et al. (2015) conducted an analysis of potential bladder cancer risks associated with increased bromide levels in surface source water. To estimate risks associated with modeled TTHM levels, they built on the approach taken in EPA's Stage 2 DBP Rule, *i.e.*, deriving a slope factor from the pooled analysis of Villanueva et al. (2004). They showed that the overall pooled exposure-response relationship for TTHM is linear over a range of relevant doses. The linear relationship predicted an incremental lifetime cancer risk of 1 in ten thousand exposed individuals (10^{-4}) per 1 µg/L increase in TTHM. The linear model proposed by Regli et al. (2015) provides a basis for estimating the dose-response relationship associated with changes in TTHM levels estimated for the regulatory options. The linear slope factor enables estimates of the total number of cancer cases associated with lifetime exposures to different TTHM levels.

EPA used the relationship estimated by Regli et al. (2015) to model the impact of changes in TTHM concentration in treated water on the lifetime bladder cancer risk:

Equation 4-1. $$O(x) = O(0) \cdot \exp\,(0.00427 \cdot x),$$

where $O(x)$ are the odds of lifetime bladder cancer incidence for an individual exposed to a lifetime average TTHM concentration in residential water supply of x µg/L and $O(0)$ are the odds of lifetime bladder cancer in

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[63] The CWSSB dataset uses a 3-tiered approach to assign more specific boundaries to PWS service areas. Tier 1 includes all PWS with explicit water service boundaries provided by states. Tier 2 assigns a boundary based on a match with a TIGER place name. Any PWS not in tier 1 or 2 is assigned a circular boundary around provided water system centroids based on a statistical model trained on explicit water service boundary data.

[64] This is compared to the 2019 and 2023 analyses which used counties and ZIP codes, respectively, to determine the demographic and socioeconomic characteristics of the population served.

[65] See DBP Rule documentation at https://www.epa.gov/dwreginfo/stage-1-and-stage-2-disinfectants-and-disinfection-byproducts-rules

the absence of exposure to TTHM in residential water supply. The log-linear relationship (Equation 4-1) has the advantage of being independent from the baseline TTHM exposure level, which is highly uncertain for most affected individuals due to lack of historical data.

4.3.3.3 Health Risk Model and Data Sources

EPA estimated changes in lifetime bladder cancer cases due to estimated changes in lifetime TTHM exposure using a dynamic microsimulation model that estimates affected population life tables under different exposure conditions. Life table approaches are standard among practitioners in demography and risk sciences and provide a flexible method for estimating the probability and timing of health impacts during a defined period (Miller & Hurley, 2003; Rockett, 2010).[66] In this application, the life table approach estimates age-specific changes in bladder cancer probability and models subsequent bladder cancer mortality, which is highly dependent on the age at the time of diagnosis. This age-specific cancer probability addresses variability in age-specific life expectancy across the population alive at the time the change occurs. This model allows for quantification of relatively complex policy scenarios, including those that involve variable contaminant level changes over time.

For this analysis, EPA assumed that the population affected by estimated changes in bromide discharges from steam electric power plants is exposed to baseline TTHM levels prior to implementation of the regulatory options – *i.e.*, prior to 2025 – and to alternative TTHM levels from 2025 through 2049. As described in Section 1.3.3, the period of analysis is based on the approximate life span of the longest-lived compliance technology for any steam electric power plant (20 or more years) and the final year of implementation (2029). The change in TTHM exposure affects the risk of developing bladder cancer beyond this period, however, because the majority of cancer cases manifest during the latter half of the average individual life span (Hrudey *et al.*, 2015). To capture these effects while being consistent with the framework of evaluating costs and benefits incurred from 2025-2049, EPA modeled changes in health outcomes resulting from changes in exposure in 2025-2049. Since changes in cancer incidence occur long after exposure, EPA modeled associated changes in cancer incidence through 2125, though only for the changes attributable to changed exposures in the 2025-2049 timeframe.

Lifetime health risk model data sources, detailed in Table 4-6 (next page), include EPA SDWIS and UCMR 4, ACS 2021 (U.S. Census Bureau, 2019, 2021), the Surveillance, Epidemiology, and End Results (SEER) program database (National Cancer Institute), and the Center for Disease Control (CDC) National Center for Health Statistics.

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[66] EPA has used life table approaches to estimate health risks associated with radon in homes, formaldehyde exposure, and Superfund and RCRA site chemicals exposure, among others (Pawel, D. J., & Puskin, J. S. (2004). The US Environmental Protection Agency’s assessment of risks from indoor radon. *Health physics*, *87*(1), 68-74. ; Munns, W. R., & Mitro, M. G. (2006). *Assessing risks to populations at Superfund and RCRA sites: Characterizing effects on populations*. Ecological Risk Assessment Support Center, Office of Research and …. ; National Research Council. (2011). *Review of the Environmental Protection Agency's Draft IRIS Assessment of Formaldehyde* (978-0-309-21193-2). https://www.nap.edu/catalog/13142/review-of-the-environmental-protection-agencys-draft-iris-assessment-of-formaldehyde).

Table 4-6: Summary of Data Sources Used in Lifetime Health Risk Model

Data element	Modeled variability	Data source	Notes
Number of persons in the affected population in 2025	Age: 1-year groups (ages 0 to 100) Sex: males, females Location: PWS service areas identified based on available Hydroshare CWSSB data, zip codes for PWS from SDWIS[a] and the fourth Unregulated Contaminant Monitoring Rule (UCMR 4) database[b], or the county.	2021 American Community Survey (ACS) (data on age- and sex-specific zip code-level population [U.S. Census Bureau, 2019, 2021] and age- and sex-specific population projections from Woods & Poole Economics Inc. (2021).	ACS data were in 5-year age groups. EPA assumed uniform distribution within each age interval to represent data as 1-year age groups. EPA then grew the age- and sex-specific CBG population data to the beginning of the analysis period (2025) using corresponding county-specific growth rates calculated using the Woods & Poole Economics Inc. (2021) complete demographic database. EPA then computed relevant age- and sex- population shares and used them to distribute location-specific affected population.
Bladder cancer incidence rate (IR) per 100,000 persons	Age at diagnosis: 1-year groups (ages 0 to 100) Sex: males, females	SEER 21 (Surveillance Research Program - National Cancer Institute, 2020b)[c]	Distinct SEER 21 IR data were available for ages 0, 1-4, 5-9, 10-14, 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80-84, 85+ years. EPA assumed that the same IR applies to all ages within each age group.
General population mortality rate	Age: 1-year groups (ages 0 to 100) Sex: males, females	Center for Disease Control (CDC)/National Center for Health Statistics (NCHS) United States Life Tables, 2017	EPA used age- and sex-specific probabilities of dying within the integer age intervals.
Share of bladder cancer incidence at specific cancer stage	Age at diagnosis: 1-year groups (ages 0 to 100) Sex: males, females Cancer stage: localized, regional, distant, unstaged	SEER 21 distribution of bladder cancer incidence over stages by age and sex at diagnosis	Distinct SEER 21 data were available for ages 0-14, 15-39, 40-64, 65-74, 75+. EPA assumed that the same cancer incidence shares by stage apply to all ages within each age group.
Share of cancer deaths among all-cause deaths	Age at diagnosis: 1-year groups (ages 0 to 100) Sex: males, females Cancer type: Malignant neoplasm of bladder	Underlying Cause of Death, 1999-2019 on CDC WONDER Online Database (Centers for Disease Control and Prevention, 2020)	EPA calculated share of cancer deaths among all-cause deaths by age and sex by dividing the number of cancer deaths during 1999-2019 with the number of all-cause deaths during 1999-2019.
Relative bladder cancer survival by cancer stage	Age at diagnosis: 1-year groups (ages 0 to 100) Sex: males, females Duration: 1-year groups (durations 0 to 100 years) Cancer stage: localized, regional,	SEER 18 relative bladder cancer survival by age at diagnosis, sex, cancer stage and duration with diagnosis for 2000-2017 (Surveillance Research Program - National Cancer Institute, 2020a)	Distinct SEER 18 data were available for ages at diagnosis 0-14, 15-39, 40-64, 65-74, 75+. EPA assumed that the same cancer relative survival patterns apply to all ages within each age group. SEER 18 contained data on relative survival among persons that had bladder cancer for 0, 1, 2, 3, 4, 5, 6,

Table 4-6: Summary of Data Sources Used in Lifetime Health Risk Model

Data element	Modeled variability	Data source	Notes
	distant, unstaged Cancer type: Urinary Bladder (Invasive & In Situ) Cancer		7, 8, 9, and 10 years. For disease durations longer than 10 years EPA applied 10-year relative survival rates.

[a] EPA's Safe Drinking Water Information System SDWIS: https://www3.epa.gov/enviro/facts/sdwis/search.html

[b] Where Hydroshare CWSSB data were not available, ICF matched zip-code level populations from the 2021 ACS data (U.S. Census Bureau, 2019, 2021) to zip codes associated with PWS in the SDWIS 2022 Q4 dataset (U.S. EPA, 2022) or the UCMR 4 dataset (U.S. EPA, 2016a). The SDWIS dataset often contains a one-to-many relationship between PWS and zip codes served, whereas the UCMR 4 dataset provides a one-to-one relationship between PWS and zip codes.

[c] SEER program, National Cancer Institute, National Institute of Health

Source: U.S. EPA Analysis, 2024.

Table 4-7 summarizes sex- and age group-specific general population mortality rates and bladder cancer incidence rates used in the model simulations, as well as the sex-specific share of the affected population for each age group. Appendix D summarize sex- and age group-specific distribution of bladder cancer cases over four analyzed stages as well as the age of onset-specific relative survival probability for each stage.

Using available data on cancer incidence and mortality, EPA calculated changes in bladder cancer cases resulting from the regulatory options using the relationship between the change in TTHM concentrations and the change in lifetime bladder cancer risk estimated by Regli et al. (2015) (see Section 4.3.3.2). The analysis accounts for the gradual changes in lifetime exposures to TTHM following estimated changes in annual average bromide discharges and associated TTHM exposure under the regulatory options compared to the baseline.

Table 4-7: Summary of Sex- and Age-specific Mortality and Bladder Cancer Incidence Rates

Sex	Age group	Sex-specific share of the affected population[a]	General population mortality rate (per 100,000)[b]	General population bladder cancer incidence rate (per 100,000)[b,c]
Female	<1	0.006	579	0.000
Female	1-4	0.024	25	0.000
Female	5-9	0.029	12	0.000
Female	10-14	0.030	13	0.000
Female	15-19	0.031	33	0.000
Female	20-24	0.035	47	0.174
Female	25-29	0.040	60	0.264
Female	30-34	0.039	80	0.498
Female	35-39	0.035	113	0.891
Female	40-44	0.032	168	1.540
Female	45-49	0.030	254	2.856
Female	50-54	0.031	378	6.551
Female	55-59	0.032	558	11.381
Female	60-64	0.032	833	18.160
Female	65-69	0.027	1,256	29.084
Female	70-74	0.021	1,997	42.848
Female	75-79	0.015	3,271	57.612
Female	80-84	0.010	5,550	71.083
Female	85+	0.010	13,559	76.378
Male	<1	0.006	702	0.000
Male	1-4	0.025	31	0.000
Male	5-9	0.031	14	0.000
Male	10-14	0.030	19	0.000
Male	15-19	0.031	78	0.112
Male	20-24	0.032	136	0.298
Male	25-29	0.035	148	0.508
Male	30-34	0.040	165	1.103
Male	35-39	0.039	204	2.078
Male	40-44	0.035	281	4.153
Male	45-49	0.032	419	8.823
Male	50-54	0.030	631	18.898
Male	55-59	0.030	933	37.562
Male	60-64	0.030	1,361	67.458
Male	65-69	0.030	1,963	114.313
Male	70-74	0.023	2,977	175.990

Table 4-7: Summary of Sex- and Age-specific Mortality and Bladder Cancer Incidence Rates

Sex	Age group	Sex-specific share of the affected population[a]	General population mortality rate (per 100,000)[b]	General population bladder cancer incidence rate (per 100,000)[b,c]
Male	75-79	0.018	4,704	244.517
Male	80-84	0.011	7,623	315.335
Male	85+	0.006	15,543	357.071

[a] Shares calculated for the total population served by potentially affected PWS, based on Hydroshare service areas data.

[b] Based on the general population of the United States.

[c] Single age-specific rates were aggregated up to the age groups reported in the table using the individual age-specific number of affected persons as weights.

Source: U.S. EPA analysis (2024) of 2021 ACS data (U.S. Census Bureau, 2019, 2021).

4.3.3.4 Model Implementation

EPA analyzed effects of the regulatory options using the dynamic microsimulation model and data sources described in Section 4.3.3.3. As described above, EPA models TTHM changes (ΔTTHM) due to the regulatory options as being in effect for the years 2025 through 2049. After 2049, EPA does not attribute costs or changes in bromide loadings to the rule, and therefore does not model incremental changes in exposures to TTHM.[67]

To estimate changes in bladder cancer incidence, EPA defined and quantified a set of 31,108 unique combinations[68] of the following parameters:

- *Location and TTHM changes*: 154 PWS groups;[69]
- *Age*: age of the population at the start of the evaluation period (2025), ranging from 0 to 100;
- *Sex*: population sex (male or female).

4.3.4 Step 4: Quantifying the Monetary Value of Benefits

EPA estimated total monetized benefits from avoided morbidity and mortality (also referred to as avoided cancer cases and avoided cancer deaths, respectively, in this discussion) from estimated changes in bromide discharges, and estimated changes in TTHM exposure and the resulting estimated bladder cancer incidence rate using a 2 percent discount rate for each of the three regulatory options.[70]

- *Morbidity*: To value changes in the economic burden associated with cancer morbidity EPA relied on base willingness-to-pay (WTP) estimates from Bosworth, Cameron and DeShazo (2009) for colon/bladder cancer in monetizing bladder cancer benefits. The base estimate of WTP per illness avoided based on an affected population of 50,000 for a duration of ten years is $400,000 for

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[67] In other words, costs after 2049 = $0 and Δbromide after 2049 is zero (hence ΔTTHM after 2049 is zero).

[68] The set of 31,108 combinations was determined by multiplying the number of PWS groups by the number of ages and sexes considered (154 x 101 x 2).

[69] The PWS groups represent unique combinations of ΔTTHM values and typically consist of a directly affected PWS and other PWSs serving populations located in the same county and purchasing water from the directly affected PWS. The number of PWS in each PWS group ranges from 1 to 41.

[70] In some cases, benefits are derived from a delay in cancer morbidity and mortality.

colon/bladder cancer (2009 dollars). The value was adjusted for income growth using an assumed elasticity of 0.45, the central elasticity estimate for severe and chronic health effects (U.S. EPA, 2023h); it ranged from $635,947 per case in 2025 to $786,916 per case in 2049. The product of this value and the estimated aggregate reduction in risk of bladder cancer in a given year represents the affected population's aggregate WTP to reduce its probability of bladder cancer in one year.

- *Mortality*: To value changes in excess mortality from bladder cancer EPA extrapolated the default central tendency of the VSL distribution recommended for use in EPA's regulatory impact analyses, $4.8 million (1990 dollars, 1990 income year), to future years, ranging from $13.54 million per death in 2025 to $16.36 million per death in 2049 (U.S. EPA, 2010). The product of VSL and the estimated aggregate reduction in risk of death in a given year represents the affected population's aggregate WTP to reduce its probability of death in one year.

4.4 Results of Analysis of Human Health Benefits from Estimated Changes in Bromide Discharges Analysis

Using the data EPA assembled on cancer incidence and mortality, the Agency estimated changes in bladder cancer cases for the regulatory options using the relationship between TTHM concentrations and the lifetime bladder cancer risk estimated by Regli et al. (2015). Figure 4-3 and Figure 4-4 show the estimated number of bladder cancer cases and premature deaths avoided, respectively, under the three regulatory options by decade. In each decade, the estimated number of bladder cancer cases is never in excess of 26 cases and the estimated number of premature deaths avoided is never in excess of seven deaths avoided.

Options A and B provide the same reductions in bromide loadings and the same benefits, whereas Option C provides additional loading reductions and consequently larger benefits. More than 50 percent of the modeled avoided bladder cancer incidence associated with the regulatory options occurs between 2025 and 2059. This pattern is consistent with existing cancer cessation lag models (*e.g.*, Hrubec & McLaughlin, 1997, Hartge et al., 1987, and Chen & Gibb, 2003) that show between 61 and 94 percent reduction in cancer risk in the first 25 years after exposure cessation (see Appendix D for detail). After 2059, the benefits attributable to exposures incurred under the regulatory options in 2025-2049 decline due to comparably fewer people surviving to mature ages.[71] In the years after 2099, the avoided cases decline considerably and in the last two decades considered in the analysis, the cancer incidences increase relative to baseline incidences.[72]

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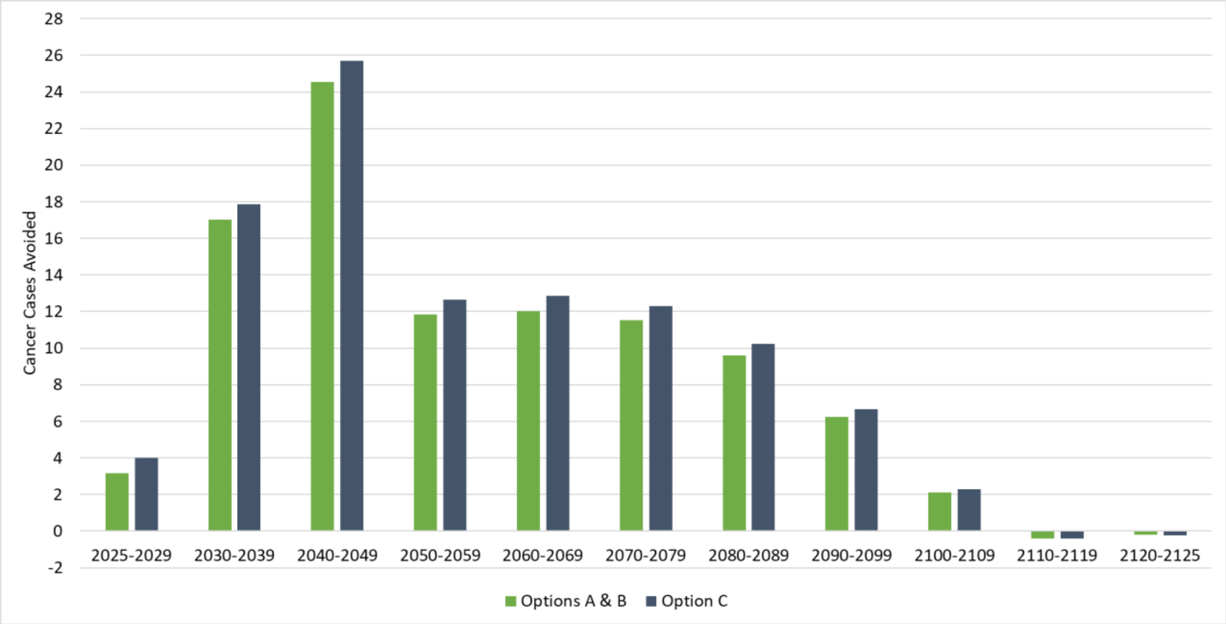
[71] In the period between 2060 and 2099, the estimated avoided cases decline slowly as the living people exposed to the estimated changes in TTHM levels reach 70 years (the age at which the highest annual incidence of bladder cancer is observed). According to American Cancer Society, about 9 out of 10 people diagnosed with bladder cancer are over the age of 55. The average age at the time of diagnosis is 73 (American Cancer Society. (2019). *Key Statistics for Bladder Cancer*. Retrieved 2019 from https://www.cancer.org/cancer/bladder-cancer/about/key-statistics.html).

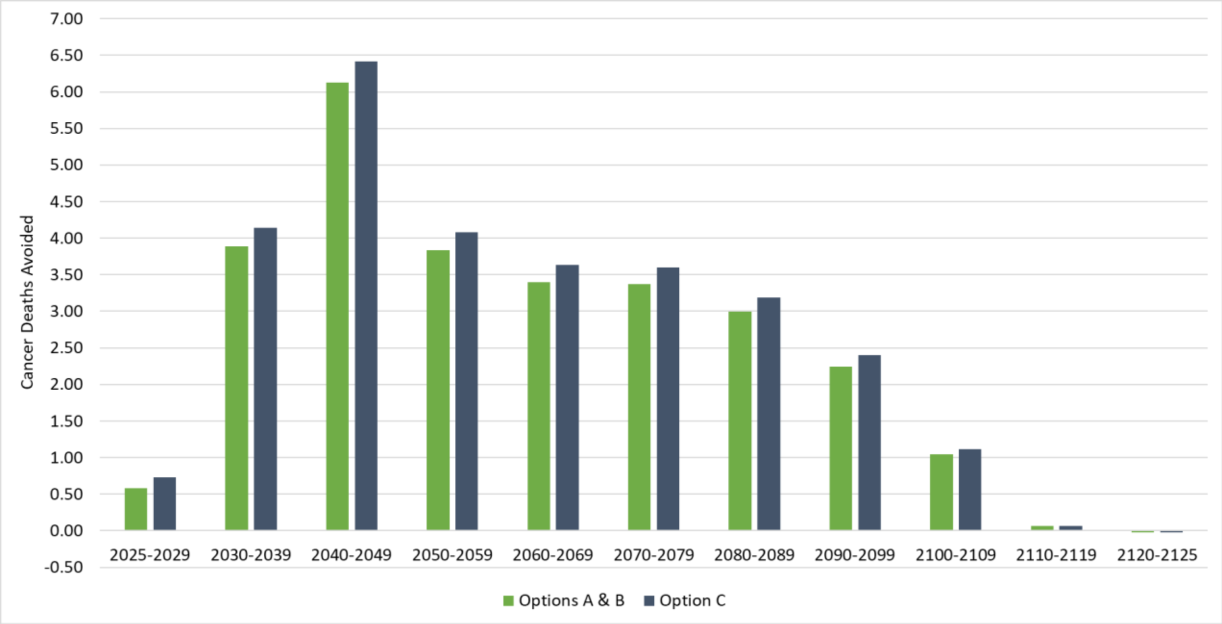
[72] The increase in cancer cases in the last decade is due to the connection between survival and cancer incidence. Lower estimated TTHM exposure due to reductions in bromide loadings under certain regulatory options reduces the estimated number of people developing bladder cancer during the earlier years of the analysis and increases overall survival rates. Higher estimated rates of survival lead to longer life spans and more people developing cancer later in life. This effect becomes more apparent closer to the end of the evaluation period, at which point there are fewer people estimated to be alive in the baseline population compared to the estimated number of people alive under certain regulatory option scenarios.

Figure 4-3: Estimated Number of Bladder Cancer Cases Avoided under the Regulatory Options.



Source: U.S. EPA Analysis, 2024.

Figure 4-4: Estimated Number of Cancer Deaths Avoided under the Regulatory Options.



Source: U.S. EPA Analysis, 2024.

Table 4-8 summarizes the estimated changes in the incidence of bladder cancer from exposure to TTHM due to the regulatory options and the value of benefits from avoided cancer cases, including avoided mortality and morbidity. The table provides the present value of benefits from changes in TTHM exposure in 2025-2049 for the period of analysis (2025-2049) and for the entire period with attributable benefits (through 2125).

Table 4-8: Estimated Bromide-related Bladder Cancer Mortality and Morbidity Monetized Benefits

Regulatory Option	Changes in cancer cases[a] from changes in TTHM exposure 2025-2049		Present value of discounted benefits[a] (million 2023$, discounted to 2024 at 2 percent)			Annualized[b] benefits (million 2023$, discounted to 2024 at 2 percent)		
	Total bladder cancer cases avoided	Total cancer deaths avoided	Avoided mortality	Avoided morbidity	Total	Avoided mortality	Avoided morbidity	Total
Option A	98	28	$225.8	$40.4	$266.2	$11.3	$2.0	$13.4
Option B (Final Rule)	98	28	$225.8	$40.4	$266.2	$11.3	$2.0	$13.4
Option C	104	29	$241.0	$43.1	$284.1	$12.1	$2.2	$14.3

[a] The values account for the persisting health effects (up until 2125) from changes in TTHM exposure during the period of analysis (2025-2049).

[b] Benefits are annualized over 25 years. The annualized benefits account for avoided mortality and morbidity during the period of analysis (2025-2049) as well as persisting health effects (up until 2125) from reduced TTHM exposure through 2049.

Source: U.S. EPA Analysis, 2024

4.5 Additional Measures of Human Health Effects from Exposure to Steam Electric Pollutants via Drinking Water Pathway

The regulatory options may result in relatively small changes to source water quality for additional parameters that can adversely affect human health (see Section 2.1.1). Many pollutants in steam electric power plant discharges have MCLs that set allowable levels in treated water. For some pollutants that have an MCL above the MCLG, there may be incremental benefits from reducing concentrations below the MCL. In addition to certain brominated DBPs discussed in the previous sections, there are no “safe levels” for lead and arsenic and therefore any reduction in exposure to these pollutants is expected to yield benefits.[73]

Estimated concentrations of arsenic and lead in downstream reaches that serve as drinking water sources do not exceed typical detection limits for these contaminants. The results show thallium concentrations in source waters that exceed levels detectable by standard methods (0.005 µg/L) in one source water reach during Period 1 but are below 0.005 µg/L in all other modeled source waters. Relative to baseline concentrations, the changes in arsenic, lead, and thallium concentrations are small (*e.g.*, less than 0.005 µg/L in Period 1 and less than 0.007 µg/L in Period 2 in source waters). Table 4-9 summarizes the direction of changes in arsenic, lead, and thallium concentrations under the regulatory options for the two analysis periods. The magnitude of the changes depends on the Period, regulatory option, source water reach, and PWS but is generally consistent with the changes in halogen loadings associated with FGD wastewater and bottom ash transport water under each analyzed regulatory option (see Table 3-1). During Period 1, all Options show either reductions or no changes in arsenic, lead, and thallium concentrations for all source waters and PWS. During Period 2, the three regulatory options also show estimated reductions in arsenic, lead, and thallium concentrations with both the magnitude and scope (the number of reaches, PWS, and population served) of the reductions larger than during Period 1.

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[73] Even in cases where the MCLG is equal to the MCL, there may be incremental health-related benefits associated with changes in concentrations arising from the regulatory options since detection of the pollutants is subject to imperfect monitoring and treatment may not remove all contaminants from the drinking water supplies, as evidenced by reported MCL violations for inorganic and other contaminants at community water systems (U.S. Environmental Protection Agency. (2013b). *Fiscal year 2011: Drinking water and ground water statistics*. (EPA 816-R-13-003). Washington, DC: U.S. Environmental Protection Agency, Office of Water).

To assess potential additional drinking water-related health benefits, EPA estimated the changes in the number of receiving reaches with drinking water intakes that have modeled pollutant concentrations exceeding MCLs or MCLGs. EPA did this analysis for all of the pollutants listed in Table 2-2, except bromate and TTHM.[74] This analysis showed no changes in the number of MCL or MCLG exceedances under the regulatory options during Period 1, when compared to the baseline. In addition, EPA found no reaches with drinking water intakes that had modeled lead, arsenic, or thallium concentrations in excess of MCLs or MCLGs under either the baseline or the regulatory options during Period 1, even where concentrations increased as summarized in Table 4-9.[75]

During Period 2, EPA found 182 reaches with drinking water intakes that had modeled arsenic concentrations in excess of the MCLG and 23 reaches with modeled lead concentrations in excess of the MCLG that showed improvements under at least one of the regulatory options. The Agency concluded, based on these screening analyses, that any additional benefits from changes in exposure to the pollutants examined in this analysis via the drinking water pathway would be relatively small.

Table 4-9: Estimated Distribution of Changes in Source Water and PWS-Level Arsenic, Lead, and Thallium Concentrations by Period and Regulatory Option, Compared to Baseline

Regulatory Option	Number of Source Water Reaches		Number of PWS[a]		Population Served by PWS (Millions)	
	Reduction	No Change	Reduction	No Change	Reduction	No Change
Period 1 (2025-2029)						
Arsenic						
Option A	215	13	849	67	28.0	1.1
Option B (Final Rule)	217	11	866	50	28.6	0.5
Option C	217	11	866	50	28.6	0.5
Lead						
Option A	118	26	464	79	13.8	3.1
Option B (Final Rule)	118	26	464	79	13.8	3.1
Option C	118	26	464	79	13.8	3.1
Thallium						
Option A	215	13	849	67	28.0	1.1
Option B (Final Rule)	217	11	866	50	28.6	0.5
Option C	217	11	866	50	28.6	0.5
Period 2 (2030-2049)						
Arsenic						
Option A	222	6	889	27	29.0	0.2
Option B (Final Rule)	223	5	894	22	29.1	0.1
Option C	223	5	894	22	29.1	0.1
Lead						
Option A	130	14	493	50	15.5	1.4
Option B (Final Rule)	130	14	493	50	15.5	1.4
Option C	131	13	505	38	16.0	0.9

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[74] EPA did not consider MCL or MCLG exceedances for bromate and TTHM because the background data on these contaminants in source waters is not readily available (*e.g.*, these contaminants are not included in the TRI dataset). Additionally, modeled discharges of bromate from steam electric plant effluent do not exceed EPA's MCL of 0.01 mg/L, but all exceed the MCLG of zero.

[75] EPA also found that there are no reaches with drinking water intakes that have pollutant concentrations exceeding human health ambient water quality criteria for either the consumption of water and organism or the consumption of organism only.

Table 4-9: Estimated Distribution of Changes in Source Water and PWS-Level Arsenic, Lead, and Thallium Concentrations by Period and Regulatory Option, Compared to Baseline

Regulatory Option	Number of Source Water Reaches		Number of PWS[a]		Population Served by PWS (Millions)	
	Reduction	No Change	Reduction	No Change	Reduction	No Change
Thallium						
Option A	222	6	889	27	29.0	0.2
Option B (Final Rule)	223	5	894	22	29.1	0.1
Option C	223	5	894	22	29.1	0.1

a. Includes systems potentially directly and/or indirectly affected by steam electric power plant discharges.

Source: U.S. EPA Analysis, 2024.

4.6 Limitations and Uncertainties

Table 4-10 summarizes principal limitations and sources of uncertainties associated with the estimated changes in pollutant levels in source waters downstream from steam electric power plant discharges. Additional limitations and uncertainties are associated with the estimation of pollutant loadings (see U.S. EPA, U.S. EPA, 2020g). Note that the effect on benefits estimates indicated in the second column of the table refers to the magnitude of the benefits rather than the direction (*i.e.*, a source of uncertainty that tends to underestimate benefits indicates expectation for either larger forgone benefits or larger realized benefits).

Table 4-10: Limitations and Uncertainties in the Analysis of Human Health Benefits from Changes in Discharges of Halogens and Other Pollutants Via the Drinking Water Pathway

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
Analysis does not account for births within the exposed population.	Underestimate	The analysis does not account for people born after 2025. This likely leads to an underestimate of benefits.
Analysis does not account for migration within the exposed population.	Uncertain	The analysis does not account for people leaving or moving into the service area. The overall effect of this factor on the estimated benefits is uncertain.
Bladder cancer risks are estimated for populations for which changes in TTHM exposures relative to baseline exposures start at different ages, including children.	Uncertain	The relative cancer potency of TTHM in children is unknown, which may bias benefits estimates either upward or downward. Past reviews found no clear evidence that children are at greater risk of adverse effects from bromoform or dibromochloromethane exposure (U.S. EPA, 2005a) although certain modes of action and health effects may be associated with exposure to TTHM during childhood (U.S. EPA, 2016c). Because bladder cancer incidence in children is very small, EPA assesses any bias to be negligible.
For PWS with multiple sources of water, the analysis uses equal contributions from each source.	Uncertain	Data on the flow rates of individual source facilities are not available and EPA therefore estimated that all permanent active sources contribute equally to a PWS's total supply. Effects of the regulatory option may be greater or smaller than estimated, depending on actual supply shares.

Table 4-10: Limitations and Uncertainties in the Analysis of Human Health Benefits from Changes in Discharges of Halogens and Other Pollutants Via the Drinking Water Pathway

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
Changes in bromide concentrations are analyzed for active permanent surface water intakes and reservoirs only.	Underestimate	The analysis includes only permanent active surface water facilities associated with non-transient PWS classified as "community water systems" that use surface water as primary source. To the extent that PWS using surface waters as secondary source or other non-permanent surface water facilities are affected, this approach understates the effects of the regulatory options.
Changes in TTHM formation depends only on changes in bromide levels.	Uncertain	The regulatory options are expected to affect bromide levels in source water. Other factors such as disinfection method, pH, temperature, and organic content affect TTHM formation. EPA assumes that PWS and source waters affected by steam electric power plant discharges have similar characteristics as those modeled in Regli et al. (2015).
Use of a national relationship from Regli et al. (2015) to relate changes in bromide concentration to changes in TTHM concentration.	Uncertain	EPA did not collect site-specific information on factors affecting TTHM formation at each potentially affected drinking water treatment plant, but instead used the median from a sample population of approximately 200 drinking water treatment systems. Use of the national relationship from Regli et al. (2015) could either understate or overstate actual changes in TTHM concentrations for a given change in bromide concentrations at any specific drinking water treatment system.
Change in risk is based on changes in exposure to TTHMs rather than to brominated trihalomethanes specifically.	Underestimate	Brominated species play a prominent role in the overall toxicity of DBP exposure. Given that the regulatory options predominantly affect the formation of brominated DBPs, the estimated changes in cancer risk resulting from regulatory options could be biased downward. EPA report provides additional information about health effects of DBPs (U.S. EPA, 2016c).
The analysis relies on public-access SEER 18 5-year relative bladder cancer survival data to model mortality patterns in the bladder cancer population.	Uncertain	Reliance on these data generates both a downward and an upward bias. The downward bias is due to the short, 5-year excess mortality follow-up window. Survival rates beyond 5 years following the initial diagnosis are likely to be lower. The upward bias comes from the inability to determine how many of the excess deaths were deaths from bladder cancer.
The dose-response function used to estimate risk assumes causality of bladder cancer from exposure to disinfected drinking water.	Overestimate	While the evidence supporting causality has increased since EPA's Stage 2 DBP Rule, the weight of evidence is still not definitive (see Regli et al. (2015)).

Table 4-10: Limitations and Uncertainties in the Analysis of Human Health Benefits from Changes in Discharges of Halogens and Other Pollutants Via the Drinking Water Pathway

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
The relationship from Regli et al. (2015) is a linear approximation of the odds ratios reported in Villanueva et al. (2004).	Uncertain	Given the uncertainty about the historical, location-specific TTHM baselines, Regli et al. (2015) provides a reasonable approximation of the risk. However, depending on the baseline TTHM exposure level, the impact computed based on Regli et al. (2015) may be larger or smaller than the impact computed using the Villanueva et al. (2004)-reported odds ratios directly.
The analysis does not account for the relationship between TTHM exposure and bladder cancer within certain subpopulations.	Overestimate	Epidemiological literature suggests that TTHM effects could be greatest for the smoker population, whose members are already at higher risk for bladder cancer. Smoking prevalence has declined in the United States and relationships estimated with data from the 1980s and 1990s may overestimate future bladder cancer impact. Robust synthesis estimates of the relationship between TTHM and bladder cancer in the smoker population are lacking, limiting EPA's ability to account for smoking when modeling health effects.
The change in risk for a given change in TTHM is uncertain for changes in TTHM concentrations that are less than 1 µg/L.	Uncertain	EPA notes that the majority of the regulatory options benefits are associated with PWS for which predicted changes in TTHM concentration are greater than 1 µg/L. Although there is greater uncertainty in the estimated changes in health risk associated with changes in TTHM concentrations less than 1 µg/L, EPA included these changes in the estimated benefits. Benefits from the regulatory options may be greater or smaller than estimated, depending on actual risk changes.
Health effects associated with DBP exposure other than bladder cancer are not quantified in this analysis.	Uncertain	An EPA report discusses potential linkages between DBP exposures and other health endpoints, *e.g.*, developmental effects (with a short-term exposure) and cancers other than bladder cancers (with a long-term exposure), but there is insufficient data to fully evaluate these endpoints (U.S. EPA, 2016c).
Discharge monitoring data for bromide from steam electric power plants are limited and demonstrate significant variability based on site-specific factors.	Uncertain	Limited bromide monitoring data are available to assess bromide source water concentration estimates.
The analysis does not consider pollutant sources beyond those associated with steam electric power plants or TRI dischargers.	Underestimate	The analysis of other pollutants does not account for natural background and anthropogenic sources that do not report to TRI. This results in a potential underestimate of the number of waters exceeding the MCL or MCLG.

Table 4-10: Limitations and Uncertainties in the Analysis of Human Health Benefits from Changes in Discharges of Halogens and Other Pollutants Via the Drinking Water Pathway

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
The analysis does not account for populations that consume bottled water as their primary drinking water source or populations that practice averting behaviors such as purchasing bottled water and filters in response to drinking water violations.	Uncertain	Studies indicate that between 13 percent and 33 percent of the U.S. population consumes bottled water as their primary drinking water source (Hu, Morton & Mahler, 2011; Rosinger et al., 2018; Vieux et al., 2020). Recent research also documents a relationship between sales of bottled water and violations of the SDWA (Allaire et al., 2019). The benefits models do not consider populations who consume bottled water as their primary drinking water source or populations that practice averting behaviors in response to poor drinking water quality. The overall effect of not considering these populations on the estimated benefits is uncertain.

5 Human Health Effects from Changes in Pollutant Exposure via the Fish Ingestion Pathway

EPA expects the regulatory options to affect human health risk by changing effluent discharges to surface waters and, as a result, ambient pollutant concentrations in the receiving reaches. The EA provides details on the health effects of steam electric pollutants (U.S. EPA, 2024b). Recreational and subsistence fishers (and their household members) who consume fish caught[76] in the reaches receiving steam electric power plant discharges could benefit from reduced pollutant concentrations in fish tissue. This chapter presents EPA's analysis of human health effects resulting from changes in exposure to pollutants in bottom ash transport water, FGD wastewater and CRL via the fish consumption pathway. The analyzed health effects include:

- Changes in exposure to lead: This includes changes in neurological and cognitive damages in children (ages 0-7) based on the impact of an additional IQ point on an individual's future earnings, and changes in cardiovascular disease (CVD) premature mortality for adults.
- Changes in exposure to mercury: Changes in neurological and cognitive damages in infants from exposure to mercury *in-utero* based on the impact of an additional IQ point on an individual's future earnings.
- Changes in exposure to arsenic: Changes in incidence of cancer cases and the COI associated with treating skin cancer.

The total quantified human health effects included in this analysis represent only a subset of the potential health effects estimated to result from the regulatory options. While additional adverse health effects are associated with pollutants in bottom ash transport water and FGD wastewater (such as kidney damage from cadmium or selenium exposure, gastrointestinal problems from zinc, thallium, or boron exposure, and others), the lack of data on dose-response relationships[77] between ingestion rates and these effects precluded EPA from quantifying the associated health effects.

EPA's analysis of the monetary value of human health effects utilizes data and methodologies described in Chapter 3 and in the EA (U.S. EPA, 2024b). The relevant data include the set of immediate and downstream reaches that receive steam electric power plant discharges (*i.e.*, affected reaches), as defined by the NHD COMID,[78] the estimated ambient pollutant concentrations in receiving reaches, and estimated fish consumption rates among different age and ethnic cohorts for affected recreational and subsistence fishers.

Section 5.1 describes how EPA identified the population potentially exposed to pollutants from steam electric power plant discharges via fish consumption. Section 5.2 describes the methods for estimating fish tissue pollutant concentrations and potential exposure via fish consumption in the affected population. Section 5.3 to Section 5.6 describe EPA's analysis of various human health endpoints potentially affected by the regulatory

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[76] As detailed in Section 5.2 and Section 5.9, for the subset of recreational and subsistence fishers who consume catch from affected reaches (*i.e.*, do not practice catch-and-release), EPA assumed that all fish consumed consists of self-caught fish. EPA assumed no exposure via fish consumption for all other households, including recreational and subsistence fishers who consume catch from other reaches.

[77] A dose response relationship is an increase in incidences of an adverse health outcome per unit increase in exposure to a toxin.

[78] A COMID is a unique numeric identifier for a given waterbody (reach), assigned by a joint effort of the United States Geological Survey and EPA.

options, which are then summarized in Section 5.7. Section 5.8 provides additional measures of human health benefits. Section 5.9 describes limitations and uncertainties.

5.1 Population in Scope of the Analysis

The population in scope of the analysis (*i.e.*, individuals potentially exposed to steam electric pollutants via consumption of contaminated fish tissue) includes recreational and subsistence fishers who fish reaches affected by steam electric power plant discharges (including receiving and downstream reaches), as well as their household members.[79] EPA estimated the number of people who are likely to fish affected reaches based on typical travel distances to a fishing site and presence of substitute fishing locations. EPA notes that the universe of sites potentially visited by recreational and subsistence fishers includes reaches subject to fish consumption advisories (FCA).[80] EPA expects that recreational fishers' responses to FCA presence are reflected in their catch and release practices, as discussed below.

Since fish consumption rates vary across different age, racial and ethnic groups, and fishing mode (recreational versus subsistence fishing), EPA estimated potential health effects separately for a number of age-, ethnicity-, and mode-specific cohorts. For each Census Block Group (CBG) within 50 miles of an affected reach, EPA assembled 2021 American Community Survey data on the number of people in 7 age categories (0 to 1, 2, 3 to 5, 6 to 10, 11 to 15, 16 to 21, and 21 years or higher) for the analysis of benefits to children from reductions in lead and mercury, and for cancer benefits from reductions in arsenic, and in 41 age categories for the analysis of adult lead benefits. EPA then subdivided each group according to 7 racial/ethnic categories:[81] 1) White non-Hispanic; 2) African-American non-Hispanic; 3) Tribal/Native Alaskan non-Hispanic; 4) Asian/Pacific Islander non-Hispanic; 5) Other non-Hispanic (including multiple races); 6) Mexican Hispanic; and 7) Other Hispanic.[82] Within each racial/ethnic group, EPA further subdivided the population according to recreational and subsistence fisher groups. The Agency assumed that the 95th percentile of the general population fish consumption rate is representative of the subsistence fisher consumption rate. Accordingly, the Agency assumed that 5 percent of the total fishers population practices subsistence fishing.[83] EPA also subdivided the affected population by income into poverty and non-poverty

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[79] The in-scope population excludes recreational and subsistence fishers who fish other reaches or certain affected waterbodies not covered by the water quality models (*i.e.*, Great Lakes and estuaries).

[80] Based on EPA's review of studies documenting fishers' awareness of FCA and their behavioral responses to FCA, 57.0 percent to 61.2 percent of fishers are aware of FCA, and 71.6 percent to 76.1 percent of those who are aware ignore FCA (Burger, J. (2004). Fish consumption advisories: knowledge, compliance and why people fish in an urban estuary. *Journal of Risk Research, 7*(5), 463-479. , Jakus, P. M., Downing, M., Bevelhimer, M. S., & Fly, J. M. (1997). Do sportfish consumption advisories affect reservoir anglers' site choice? *Agricultural and Resource Economics Review*, *26*(2), 196-204. ; Jakus, P. M., McGuinness, M., & Krupnick, A. J. (2002). *The benefits and costs of fish consumption advisories for mercury*. ; Williams, R. L., O'Leary, J. T., Sheaffer, A. L., & Mason, D. (2000). An examination of fish consumption by Indiana recreational anglers: an on-site survey. *West Lafayette, IN: Purdue University*.). Therefore, only 17.4 percent of fishers may adjust their behavior in response to FCA (U.S. Environmental Protection Agency. (2015a). *Benefit and Cost Analysis for the Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category*. (EPA-821-R-15-005).). The analysis reflects EPA's expectations that fishers responses to FCA are reflected in their catch and release practices.

[81] The racial/ethnic categories are based on available fish consumption data as well as the breakout of ethnic/racial populations in Census data, which distinguishes racial groups within Hispanic and non-Hispanic categories.

[82] The Mexican Hispanic and Hispanic block group populations were calculated by applying the Census tract percent Mexican Hispanic and Hispanic to the underlying block-group populations, since these data were not available at the block-group level.

[83] Data are not available on the share of the fishing population that practices subsistence fishing. EPA assumed that 5 percent of people who fish practice subsistence fishing, based on the assumed 95th percentile fish consumption rate for this population in EPA's Exposure Factors Handbook (see U.S. Environmental Protection Agency. (2011). *Exposure Factors Handbook, 2011 Edition (Final)*. (EPA-600-R-09-025F). U.S. Environmental Protection Agency, Washington, DC).

groups, based on the share of people below the federal poverty line.[84] After subdividing population groups by age, race, fishing mode, and poverty indicator, each CBG has 196 unique population cohorts (7 age groups × 7 ethnic/racial groups × 2 fishing modes [recreational versus subsistence fishing] × 2 poverty status designations) for the analysis of benefits to children from reductions in lead and mercury and cancer benefits from reductions in arsenic, and each CBG has 1,148 unique population cohorts (41 age groups × 7 ethnic/racial groups × 2 fishing modes [recreational versus subsistence fishing] × 2 poverty status designations) for the analysis of adult lead benefits.

EPA distinguished the exposed population by racial/ethnic group and poverty status to support analysis of potential environmental justice (EJ) considerations from baseline exposure to pollutants in steam electric power plant discharges, and to allow evaluation of the effects of the regulatory options on mitigating any EJ concerns. See EJA document for details of the EJ analysis. As noted below, distinguishing the exposed population in this manner allows the Agency to account for differences in exposure among demographic groups, where supported by available data.

Equation 5-1 shows how EPA estimated the population potentially exposed to steam electric pollutants, *ExPop(i)(s)(c)*, for CBG *i* in state *s* for cohort *c*.

Equation 5-1.

$$\boldsymbol{ExPop(i)(s)(c) = Pop(i)(c) \times \%Fish(s) \times CaR(c)}$$

Where:

Pop(i)(c) = Total CBG population in cohort c. Age and racial/ethnicity-specific populations in each CBG are based on data from the 2021 American Community Survey, which provides population numbers for each CBG broken out by age and racial/ethnic group. To estimate the population in each age- and ethnicity/race-specific group, EPA calculated the share of the population in each racial/ethnic group and applied those percentages to the population in each age group.

%Fish(s) = Fraction of people who live in households with fishers. To estimate what percentage of the total population participates in fishing, EPA used region-specific U.S. Fish and Wildlife Service (U.S. FWS, 2023) estimates of the population 16 and older who fish.[85] EPA assumed that the share of households that includes fishers is equal to the fraction of people over 16 who participate in recreational fishing.

CaR(c) = Adjustment for catch-and-release practices. According to U.S. FWS (U.S. FWS, 2006) data, approximately 23.3 percent of recreational fishers release all the fish they catch (“catch-and-release” fishers). Fishers practicing “catch-and-release” would not be exposed to steam electric pollutants via consumption of contaminated fish. For all recreational fishers, EPA reduced the affected population by 23.3 percent. EPA assumed that subsistence fishers do not practice “catch-and-release” fishing.

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[84] Poverty status is based on data from the Census Bureau’s American Community Survey which determines poverty status by comparing annual income to a set of dollar values called poverty thresholds that vary by family size, number of children, and the age of the householder.

[85] The share of the population who fishes ranges from 10 percent in the Pacific region to 22 percent in the West North Central region. Other regions include the Middle Atlantic (12 percent), New England (12 percent), Mountain (15 percent), South Atlantic (16 percent), East North Central (17 percent), West South Central (17 percent), and East South Central (20 percent).

Table 5-1 summarizes the population living within 50 miles of reaches affected by steam electric power plant discharges (see Section 5.2.1 for a discussion of this distance buffer) and EPA's estimate of the population potentially exposed to the pollutants via consumption of subsistence- and recreationally-caught fish (based on 2021 population data and not adjusted for population growth during the analysis period). Of the total population, 17 percent live within 50 miles of an affected reach and participate in recreational and/or subsistence fishing, and 13 percent are potentially exposed to fish contaminated by steam electric pollutants in bottom ash transport water, FGD wastewater, CRL, and legacy wastewater discharges.

Table 5-1: Summary of Population Potentially Exposed to Contaminated Fish Living within 50 Miles of Affected Reaches (as of 2021)

Total population	126,726,686
Total fishers population[a]	21,532,470
Population potentially exposed to contaminated fish[b, c]	16,766,257

a. Total population living within 50 miles of an affected reach multiplied by the state-specific share of the population who fishes based on U.S. FWS (2023; 2018; between 10 percent and 22 percent, depending on the state).

b. Total fishers population adjusted to remove fishers practicing catch-and-release and who therefore do not consume self-caught fish.

c. Analysis accounts for projected population growth so that the average population in scope of the analysis over the period of 2025 through 2049 is 10.8 percent higher than the population in 2021 presented in the table, or 18.6 million people. The analysis estimates that the fraction of the U.S. population engaged in recreational and subsistence fishing remains constant from 2025 through 2049.

Source: U.S. EPA Analysis, 2024

5.2 Pollutant Exposure from Fish Consumption

EPA calculated an average fish tissue concentration for each pollutant for each CBG based on a length-weighted average concentration for all reaches within 50 miles. Depending on the health endpoint used in the analysis, EPA calculated either the average daily dose (ADD) or lifetime average daily dose (LADD) for each combination of pollutant, cohort and CBG.

5.2.1 Fish Tissue Pollutant Concentrations

The set of reaches that may represent a source of contaminated fish for recreational and subsistence fishers in each CBG depends on the typical distance fishers travel to fish. EPA assumed that fishers typically travel up to 50 miles to fish,[86] and used this distance to estimate the relevant fishing sites for the population of fishers in each CBG.

Fishers may have several fishable sites to choose from within 50 miles of travel. To account for the effect of substitute sites, EPA assumed that fishing efforts are uniformly distributed among all the available fishing sites within 50 miles from the CBG (travel zone). For each CBG, EPA identified all fishable reaches within 50 miles (where distance was determined based on the Euclidean distance between the centroid of the CBG and the midpoint of the reach) and the reach length in miles.

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[86] Studies of fishers behavior and practices have made similar observations (*e.g.*, Sohngen, B., Zhang, W., Bruskotter, J., & Sheldon, B. (2015). Results from a 2014 survey of Lake Erie anglers. *Columbus, OH: The Ohio State University, Department of Agricultural, Environmental and Development Economics and School of Environment & Natural Resources*. and Sea Grant - Illinois-Indiana. (2018). Lake Michigan anglers boost local Illinois and Indiana economies. Retrieved 2019, from https://iiseagrant.org/lake-michigan-anglers-boost-illinois-and-indiana-local-economies/).

EPA then calculated, for each CBG within the 50-mile buffer of a fishable reach, the fish tissue concentration of As, Hg, and lead (Pb). Appendix E in U.S. EPA (2020b) describes the approach used to calculate fish tissue concentrations of steam electric pollutants in the baseline and under each of the regulatory options.

For each CBG, EPA then calculated the reach length ($Length_i$) weighted fish fillet concentration (C_{Fish_Fillet} *(CBG))* based on all fishable reaches within the 50-mile radius according to Equation 5-2. See Appendix E for additional details about the derivation of fish tissue concentration values.

Equation 5-2.

$$C_{Fish_{Fillet_e}}(CBG) = \frac{\sum_{i=1}^{n} C_{Fish_{Fillet}}(i) * Length_i}{\sum_{i=1}^{n} Length_i}$$

5.2.2 Average Daily Dose

Exposure to steam electric pollutants via fish consumption depends on the cohort-specific fish consumption rates. Table 5-2 summarizes the average fish consumption rates, expressed in daily grams per kilogram of body weight (BW), according to the race/ethnicity and fishing mode. The rates reflect recommended values for consumer-only intake of finfish in the general population from all sources, based on EPA's Exposure Factors Handbook (U.S. EPA, 2011). For more details on these fish consumption rates, see the EA (U.S. EPA, 2024b) and the uncertainty discussion in Section 5.9.

Table 5-2: Summary of Group-specific Consumption Rates for Fish Tissue Consumption Risk Analysis

Race/ Ethnicity[a]	EA Cohort Name[b]	Consumption Rate (g/kg BW/day)	
		Recreational	Subsistence
White (non-Hispanic)	Non-Hispanic White	0.67	1.9
African American (non-Hispanic)	Non-Hispanic Black	0.77	2.1
Asian/Pacific Islander (non-Hispanic)	Other, including Multiple Races	0.96	3.6
Tribal/Native Alaskan (non-Hispanic)	Other, including Multiple Races	0.96	3.6
Other non-Hispanic	Other, including Multiple Races	0.96	3.6
Mexican Hispanic	Mexican Hispanic	0.93	2.8
Other Hispanic	Other Hispanic	0.82	2.7

a. Each group is also subdivided into seven age groups (0-1, 2, 3-5, 6-10, 11-15, 16-20, Adult [21 or higher] and two income groups [above and below the poverty threshold]).

b. See EA for details (U.S. EPA, 2024b).

Source: U.S. EPA Analysis, 2024

Equation 5-3 and Equation 5-4 show the cohort- and CBG-specific ADD and LADD calculations based on fish tissue concentrations, consumption rates, and exposure duration and averaging periods detailed in the EA (U.S. EPA, 2024b.

Equation 5-3.

$$\boldsymbol{ADD(c)(i) = \frac{C_{fish\_fillet}(i) \times CR_{Fish}(c) \times F_{Fish}}{1000}}$$

Where:

$ADD(c)(i)$ = average daily dose of pollutant from fish consumption for cohort c in CBG i (milligrams[mg] per kilogram [kg] body weight [BW] per day)

$C_{fish\_fillet}(i)$ = average fish fillet pollutant concentration consumed by humans for CBG i (mg per kg)

$CR_{fish}(c)$ = consumption rate of fish for cohort c (grams per kg BW per day); see Table 5-2

F_{fish} = fraction of fish from reaches within the analyzed distance from the CBG (percent; estimated value of 100%)

Equation 5-4. $$LADD(c)(i) = \frac{ADD(c)(i) \times ED(c) \times EF}{AT \times 365}$$

Where:

LADD (*c*)(*i*) = lifetime average daily dose (mg per kg BW per day) for cohort *c* in CBG *i*

ADD (*c*)(*i*) = average daily dose (mg per kg BW per day) for cohort *c* in CBG *i*

ED(*c*) = exposure duration (years) for cohort *c*

EF = exposure frequency (days; set to 350)

AT = averaging time (years; set to 70)

EPA used the doses of steam electric pollutants as calculated above from fish caught through recreational and subsistence fishing in its analysis of benefits associated with the various human health endpoints described below.

5.3 Health Effects in Children from Changes in Lead Exposure

Lead is a highly toxic pollutant that can cause a variety of adverse health effects in children of all ages. In particular, elevated lead exposure may induce a number of adverse neurological effects in children, including decline in cognitive function, conduct disorders, attentional difficulties, internalizing behavior,[87] and motor skill deficits (see NTP, 2012; ATSDR, 2020; U.S. EPA, 2024d, 2019e, 2020g, and 2024d). Elevated blood lead level (BLL) in children may also slow postnatal growth in children ages one to 16, delay puberty in 8- to 17-year-olds, and decrease hearing and motor function (NTP, 2012; ATSDR, 2020; U.S. EPA, 2019e and 2024d). Lead exposure is also associated with adverse health outcomes related to the immune system, including atopic and inflammatory responses (*e.g.*, allergy and asthma) and reduced resistance to bacterial infections. Studies have also found a relationship between lead exposure in expectant mothers and lower birth weight in newborns (NTP, 2012; ATSDR, 2020; U.S. EPA, 2019e and 2024d; Zhu et al., 2010). For this final rule, EPA estimated the effects of changes in neurological and cognitive damages to children ages 0 to 7 using the dose-response relationship for IQ decrements (Crump et al., 2013).[88]

EPA estimated health effects from changes in exposure to lead to preschool children using BLL as a biomarker of lead exposure. EPA modeled BLL under the baseline and regulatory option scenarios, and then used a concentration-response relationship between BLL and IQ loss to estimate changes in IQ losses in the affected population of children and changes in incidences of extremely low IQ scores (less than 70, or two standard deviations below the mean). EPA calculated the monetary value of changes in children's health effects based on the impact of an additional IQ point on an individual's future earnings.

EPA used the methodology described in Section 5.1 to estimate the population of children from birth to age seven who live in recreational fisher and subsistence fisher households and are potentially exposed to lead via

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[87] Behavioral difficulties in children may include both externalizing behavior (*e.g.,* inattention, impulsivity, conduct disorders), and internalizing behaviors (*e.g.,* withdrawn behaviors, symptoms of depression, fearfulness, and anxiety).

[88] EPA also evaluated estimating the effects of changes in lead exposure on ADHD in children and low birthweight in infants, but given the small magnitude of IQ point effects for the final rule and the fact that regulatory analyses for other rules have shown avoided IQ losses to be larger than ADHD and birthweight effects, EPA did not quantify these additional benefits. For example, the 2023 Lead and Copper Rule Improvements (LCRI) proposed rulemaking showed the cognitive development benefits from avoided IQ losses to be 3 to 13 times ADHD benefits and 150 to 1,000 times low-birthweight benefits, depending on the scenario and discount rate (U.S. Environmental Protection Agency. (2023f). *Economic Analysis for the Proposed Lead and Copper Rule Improvements*.).

consumption of contaminated fish tissue. EPA notes that fish tissue is not the only route of exposure to lead among children. Other routes of exposure may include drinking water, dust, and other food. EPA used reference exposure values for these other routes of lead exposures and held these values constant for the baseline and regulatory options scenarios. Since this health effect applies to children up to the seventh birthday only, EPA restricted the analysis to the relevant age cohorts of fisher household members.

5.3.1 Data and Methodology

This analysis considers children who are born after implementation of the regulatory options and live in recreational fisher and subsistence fisher households. It relies on EPA's Integrated Exposure, Uptake, and Biokinetics (IEUBK) Model for Lead in Children (version 2; U.S. EPA, 2021a), which uses lead concentrations in a variety of media – including soil, dust, air, water, and diet – to estimate total exposure to lead for children in seven one-year age cohorts from birth through the seventh birthday. Based on the estimated total exposure, the model generates a predicted geometric mean BLL for a population of children exposed to similar lead levels. See the 2013 BCA report (U.S. EPA, 2013a) for details.

For each CBG, EPA used the cohort-specific ADD based on Equation 5-3. EPA then multiplied the cohort-specific ADD by the average body weight for each age group[89] to calculate the "alternative source" dietary input for the IEUBK model, which varied by option relative to the baseline. All other sources of lead were held constant. Lead bioavailability and uptake after consumption vary for different chemical forms. Many factors complicate the estimation of bioavailability, including nutritional status and timing of meals relative to lead intake. For this analysis, EPA used the default media-specific bioavailability factor for the "alternative source" provided in the IEUBK model, which is 50 percent for oral ingestion.

EPA used the IEUBK model to generate the geometric mean BLL for each cohort in each CBG under the baseline and post-technology implementation scenarios. The IEUBK model processes daily intake to two decimal places (µg/day). For this analysis, this means that some of the change between the baseline and regulatory options is not accounted for by using the model (*i.e.*, IEUBK treats these very small changes as zero). This aspect of the model contributes to potential underestimation of the lead-related health effects in children arising from the regulatory options, since the estimated changes in health effects are driven by small changes across large populations.

EPA used the Crump et al. (2013) dose-response function to estimate changes in IQ losses between the baseline and regulatory options. Comparing the baseline and regulatory option results provides the changes in IQ loss per child. Crump et al. (2013) concluded that there was statistical evidence that the exposure-response is non-linear over the full range of BLL. Equation 5-5 shows an exposure-response function that represents this non-linearity:

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[89] The average body weight values are 11.4 kg for ages 0 to 2, 13.8 kg for ages 2 to less than 3, 18.6 kg for ages 3 to less than 6, and 31.8 kg for ages 6 to 7.

Equation 5-5. $$\Delta \boldsymbol{IQ} = \beta_1 \times \boldsymbol{ln}(\boldsymbol{BLL} + \mathbf{1})$$

Where:

β_1 = -3.315 (log-linear regression coefficient on the lifetime blood lead level[90])

Multiplying the result by the number of affected pre-school children yields the total change in the number of IQ points for the affected population of children for the baseline and each regulatory option.

The IEUBK model estimates the mean of the BLL distribution in children, assuming a continuous exposure pattern for children from birth through the seventh birthday. The 2021 American Community Survey indicates that children ages 0 to 7 are approximately evenly distributed by age. To get an annual estimate of the number of children that would benefit from implementation of the regulatory options, EPA divided the estimated number of affected children by 7. This division adjusts the equation to apply only to children age 0 to 1. The estimated changes in IQ loss represent an annual value (*i.e.*, it would apply to the cohort of children born each year after implementation).[91] Equation 5-6 shows this calculation for the annual increase in total IQ points.

Equation 5-6. $$\Delta \boldsymbol{IQ}(\boldsymbol{i})(\boldsymbol{c}) = \left(\mathbf{ln}\big(\Delta \boldsymbol{GM}(\boldsymbol{i})(\boldsymbol{c})\big) \times \mathbf{CRF} \times \left(\frac{\boldsymbol{ExCh}(\boldsymbol{i})(\boldsymbol{c})}{\mathbf{7}}\right)\right)$$

Where:

Δ*IQ(i)(c)* = the difference in total IQ points between the baseline and regulatory option scenarios for cohort *c* in CBG *i*

*Ln(*Δ*GM(i)(c))* = the log-linear change in the average BLL in affected population of children (µg/dL) for cohort *c* in CBG *i*

CRF = -3.315, the log-linear regression coefficient from Crump et al. (2013)

ExCh(i)(c) = the number of affected children aged 0 to 7 for cohort *c* in CBG *i*

The available economic literature provides little empirical data on society's overall WTP to avoid a decrease in children's IQ. To estimate the value of avoided IQ losses, EPA used estimates of the changes in a child's future expected lifetime earnings per one IQ point reduction using the methodology presented in Salkever (1995) but with more recent data from the 1997 National Longitudinal Survey of Youth (U.S. EPA, 2019d). Updated results based on Salkever (1995) indicate that a one-point IQ reduction reduces expected lifetime earnings by 2.63 percent. Table 5-3 summarizes the estimated values of an IQ point based on the updated Salkever (1995) analysis using a 2 percent discount rate. For the lead analysis, the value is discounted to the third year of life to represent the midpoint of the exposed children population. For the mercury analysis (Section 5.5), the value of an IQ point is discounted to birth to better align the benefits of reducing exposure

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[90] The lifetime blood lead level in children ages 0 to 7 is defined as a mean from six months of age to present (Crump, K. S., Van Landingham, C., Bowers, T. S., Cahoy, D., & Chandalia, J. K. (2013). A statistical reevaluation of the data used in the Lanphear et al. pooled-analysis that related low levels of blood lead to intellectual deficits in children. *Critical reviews in toxicology, 43*(9), 785-799.).

[91] Dividing by seven undercounts overall benefits. Children from ages 1 to 7 (*i.e.*, born prior to the base year of the analysis) are not accounted for in the analysis, although they are also affected by changes in lead exposure.

to mercury with in-utero exposure (U.S. EPA, 2019f). EPA also used an alternative value of an IQ point from Lin, Lutter and Ruhm (2018) in a sensitivity analysis (see Appendix G).

Table 5-3: Value of an IQ Point (2023$) based on Expected Reductions in Lifetime Earnings, 2 Percent Discount Rate

Discount Age	Value of an IQ Point[a,b] (2023$)
Discounted to Age 3 (Lead)	$39,930
Discounted to Birth (Mercury)	$37,627

a. Values are adjusted for the cost of education.

b. EPA adjusted the value of an IQ point to 2023 dollars using the GDP deflator.

Source: U.S. EPA (2019d) re-analysis of data from Salkever (1995); 2 percent estimates calculated for U.S. EPA (2023f)

5.3.2 Results

Table 5-4 shows the benefits associated with changes in IQ losses from lead exposure via consumption of self-caught fish. Avoided IQ point losses over the entire in-scope population of children with changes in lead exposure is approximately 1 point. Estimated annualized benefits from avoided IQ losses are less than $0.01 million.

Table 5-4: Estimated Benefits from Avoided IQ Losses for Children Exposed to Lead under the Regulatory Options, Compared to Baseline

Regulatory Option	Average Annual Number of Children 0 to 7 in Scope of the Analysis[b]	Total Avoided IQ Point Losses, 2025 to 2049 in All Children 0 to 7 in Scope of the Analysis[c]	Annualized Value of Avoided IQ Point Losses[a] (Millions 2023$; 2% Discount Rate)
Option A	1,555,558	1	<$0.01
Option B (Final Rule)	1,555,558	1	<$0.01
Option C	1,555,558	1	<$0.01

a. Based on estimate that the loss of one IQ point results in the loss of 2.63 percent of lifetime earnings, following updated Salkever (1995) values from U.S. EPA (2019d).

b. The number of children in scope of the analysis is based on reaches analyzed across the regulatory options. Some of the children included in this count see no changes in exposure under some options.

c. EPA notes that the IEUBK model does not analyze BLL changes beyond two decimal points and therefore the analysis omits benefits from very small changes in lead exposure and resulting BLL changes.

Source: U.S. EPA Analysis, 2024

5.4 Health Effects in Adults from Changes in Lead Exposure

As described in Chapter 2 of this document and in the EA (U.S. EPA, 2024b), exposure to lead can result in numerous adverse health effects in adults, including increasing the incidence of cardiovascular disease premature mortality (*e.g.*, Aoki et al., 2016; Lanphear et al., 2018; Navas-Acien, 2021; U.S. EPA, 2023f; 2024d).

To analyze the benefits of reducing exposure to lead from the consumption of self-caught fish, EPA adapted the methodology used in the Agency’s analysis of the 2023 Lead and Copper Rule Improvements (LCRI) proposed rulemaking (U.S. EPA, 2023f) to reflect differences in exposure and affected populations. This methodology relies on concentration-response functions relating adult BLL level to CVD mortality.

5.4.1 Data and Methodology

The affected population is derived from that described in Section 5.1 and consists of adults aged 40 to 80 who live in recreational and subsistence fisher households near reaches affected by steam electric power plant discharges and who are potentially exposed to lead via consumption of contaminated fish tissue. To estimate total exposure to lead for individuals from 40 to age 80, EPA relied on the All Ages Lead Model (AALM),[92] which uses lead concentrations in a variety of media, including soil, dust, air, water, and food to predict lead concentration in body tissues and organs of hypothetical individuals based on a simulated lifetime of lead exposure (U.S. EPA, 2019a). EPA only varied lead intake via food to account for varying levels of lead exposure caused by consuming exposed fish and left all other media at their recommended default value. To estimate the "food" input for the AALM, EPA first estimated the cohort-specific ADD for each CBG based on Equation 5-3. EPA then multiplied the cohort-specific ADD by the average body weight for each age group in Table 5-5. Based on the estimated total exposure to lead, the model generates a predicted BLL geometric mean for a population of adults.

Table 5-5: Estimated Average Body Weights (kg) by Age and Gender

Age	Males	Females	Age	Males	Females
0 to 1	9.30	9.30	43 to 44	89.48	71.59
1 to 2	11.30	11.50	44 to 45	87.00	74.86
2 to 3	13.70	13.30	45 to 46	84.61	81.15
3 to 4	16.40	15.20	46 to 47	93.27	74.94
4 to 5	18.80	18.10	47 to 48	80.87	68.24
5 to 6	20.20	20.70	48 to 49	85.58	82.10
6 to 7	22.90	22.00	49 to 50	88.84	75.55
7to 8	28.10	26.00	50 to 51	90.09	83.22
8 to 9	31.90	30.80	51 to 52	90.63	76.89
9 to 10	36.10	36.00	52 to 53	90.62	80.89
10 to 11	39.50	39.40	53 to 54	92.42	76.12
11 to 12	42.00	47.20	54 to 55	90.51	75.19
12 to 13	49.40	51.60	55 to 56	84.84	79.87
13 to 14	54.90	59.80	56 to 57	84.48	80.68
14 to 15	65.10	59.90	57 to 58	86.02	73.07
15 to 16	68.20	63.40	58 to 59	89.11	71.21
16 to 17	72.50	63.40	59 to 60	83.82	76.28
17 to 18	75.40	59.90	60 to 61	89.53	75.97
18 to 19	74.80	65.00	61 to 62	86.04	77.01
19 to 20	80.10	68.70	62 to 63	84.46	75.78
20 to 21	80.00	66.30	63 to 64	86.51	77.95
21 to 22	73.84	65.89	64 to 65	91.45	76.75
22 to 23	89.62	67.27	65 to 66	89.46	72.95
23 to 24	83.39	73.58	66 to 67	90.40	79.00
24 to 25	80.26	71.81	67 to 68	85.34	77.76
25 to 26	87.47	71.64	68 to 69	84.48	73.28
26 to 27	72.11	78.09	69 to 70	92.35	69.94
27 to 28	85.78	72.48	70 to 71	81.91	70.50
28 to 29	88.04	76.18	71 to 72	79.65	66.22
29 to 30	84.02	71.88	72 to 73	84.67	76.89
30 to 31	80.10	74.00	73 to 74	89.70	72.75

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[92] The AALM is an outgrowth of the IEUBK model used in the analysis described in Section 5.3.

Table 5-5: Estimated Average Body Weights (kg) by Age and Gender

Age	Males	Females	Age	Males	Females
31 to 32	84.65	79.12	74 to 75	80.85	69.21
32 to 33	90.99	77.53	75 to 76	84.26	68.61
33 to 34	90.90	76.60	76 to 77	86.13	67.42
34 to 35	79.09	73.26	77 to 78	81.68	78.35
35 to 36	91.15	79.91	78 to 79	81.99	72.30
36 to 37	88.96	72.10	79 to 80	80.18	67.95
37 to 38	84.62	70.75	80 to 81	75.90	60.97
38 to 39	80.52	80.86	81 to 82	73.77	68.76
39 to 40	84.77	78.08	82 to 83	81.01	62.93
40 to 41	92.21	73.87	83 to 84	76.07	66.24
41 to 42	83.11	75.91	84 to 85	73.06	66.29
42 to 43	91.94	82.03	85+	74.10	59.68

Note: Data converted from ages in months to ages in years (*e.g.*, age 1–2 year represents ages from 12 to 23 months).

Source: Adapted from Table 8-24 in U.S. EPA (2011)

Because the AALM assumes a linear relationship between lead intake from food ingestion and BLL, EPA calculated age- and sex-specific slopes that approximate the linear relationship between lead intake from food ingestion and BLL, instead of running the AALM for each CBG and cohort-specific lead intakes.[93] EPA used the age- and sex-specific slopes to scale a cohort's BLL given their lead intake from fish ingestion for the two periods under the baseline and each regulatory option. EPA estimated small BLL changes during the period of analysis, ranging between zero and 0.001 µg/dL and with an average of 0.0007 µg/dL across the exposed population under Option C.

EPA relied on the relationship between BLL and CVD mortality from Aoki et al. (2016) and Lanphear et al. (2018) to link the estimated BLL to changes in CVD mortality. Both studies use regression models to relate log-transformed BLL to CVD mortality, as shown in Equation 5-7. To estimate the annual number of avoided CVD mortality cases, EPA multiplied the estimated change in CVD mortality risk by the affected population (Equation 5-8). Consistent with the methodology used in LCRI (U.S. EPA, 2023f), EPA assumed a 10-year window of exposure. Therefore, the BLL (x_2 and x_1 in Equation 5-7 and Equation 5-8) represent an individual's average BLL over the past ten years. EPA assumed that the change in lead intake, and resulting change in BLL, occur instantaneously.[94] Since the change in lead intake and BLL realistically occurs over time, this assumption tends to overstate the benefits from the change in exposure to lead in fish tissue.

Equation 5-7.

$$\Delta CVD\ Mortality = y_1\left(1 - e^{\beta \log_z\left(\frac{x_2}{x_1}\right)}\right)$$

Equation 5-8.

$$Deaths\ Avoided = y_1\left(1 - e^{\beta \log_z\left(\frac{x_2}{x_1}\right)}\right) * pop$$

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[93] This approach enables the analysis to remain sensitive to very small changes in BLL from changes in lead exposure.

[94] In the LCRI analysis, EPA assumed that lead intake, and resulting BLL, changed gradually.

Where:

y_1 = Hazard rate of CVD mortality in baseline scenario (*i.e.*, without the rule)

β = Beta coefficient, which represents the change in CVD mortality per unit change in BLL

Log_z = Log transformation to the base z (*i.e.*, $\log_{10}$)

x_2 = BLL associated with the regulatory option

x_1 = BLL associated with the baseline

pop = population for whom the change in BLL occurs

EPA obtained the baseline hazard rates of CVD mortality (y_1) used in Equation 5-7 and Equation 5-8 from the CDC's Wonder database (see Table 5-6).

Table 5-6: Baseline Hazard Rates of CVD Mortality by Age and Gender

Age	Male	Female
40-49	0.000786	0.000377
50-59	0.002186	0.000972
60-69	0.004598	0.002211
70-80	0.010802	0.006751

Source: U.S. EPA, 2023f, originally obtained from Centers for Disease Control and Prevention, 2014

EPA calculated low and high estimates of the effect of BLL on CVD mortality to reflect the uncertainty over the best functional form that describes the relationship between BLL and CVD mortality. The low estimate (β = 0.36) is based on Aoki et al. (2016) and the high estimate (β = 0.96) is based on Lanphear et al. (2018). Using these beta coefficients in Equation 5-7 and Equation 5-8, EPA calculated high and low estimates of the change in CVD mortality risk and the number annual deaths avoided under each regulatory option.

To value changes in CVD mortality, EPA used the VSL described in Section 4.3.4. The product of VSL and the estimated population level reduction in risk of CVD mortality in a given year represents the affected population's aggregate WTP to reduce the probability of CVD-related death in one year.

5.4.2 Results

Table 5-7 summarizes estimated benefits from avoided CVD mortality from reducing lead exposure via consumption of self-caught fish under each regulatory option. The estimated benefits of the final rule range from $0.16 million to $0.43 million.

Table 5-7: Estimated Benefits from Avoided CVD Deaths for Adults Aged 40-80 For All Regulatory Options, Compared to Baseline

Regulatory Option	Number of Adults in Scope of the Analysis[a]	Total CVD Deaths Avoided[b] 2025 to 2049 in All Adults in Scope of Analysis		Annualized Value of Avoided CVD Deaths (2% Discount Rate; Millions 2023$)	
		Low	High	Low	High
Option A	21,684,921	0.42	1.13	$0.16	$0.43
Option B (Final Rule)	21,684,921	0.42	1.13	$0.16	$0.43
Option C	21,684,921	0.45	1.20	$0.17	$0.45

a. The number of adults in scope of the analysis is based on reaches analyzed across the regulatory options. Some of the adults included in this count see no changes in exposure under some options. Benefits accrue to the subset of adults that experience changes in exposure under one or more options (576,537 adults in 2025). Under the assumption that fishers would share their catch with members of their household, EPA included household members in this subset.

b. Assumes that the distribution for the individuals experiencing lead-related CVD mortality is the same as the distribution of CVD mortality irrespective of the cause.

Source: U.S. EPA Analysis, 2024

5.5 Heath Effects in Children from Changes in Mercury Exposure

Mercury can have a variety of adverse health effects on adults (*e.g.*, vision defects, tremors, cerebellar changes, and mortality) and children (*e.g.*, neurological effects) (U.S. EPA, 2024b; Grandjean et al., 2014; Hollingsworth & Rudik, 2021; Mergler et al., 2007; CDC, 2009). The regulatory options may change the discharge of mercury to surface waters by steam electric power plants and therefore affect a range of human health outcomes. Due to data limitations, however, EPA estimated only the monetary value of the changes in IQ losses among children exposed to mercury *in-utero* as a result of maternal consumption of contaminated fish.

EPA identified the population of children exposed *in-utero* starting from the CBG-specific population in scope of the analysis described in Section 5.1. Therefore, this analysis only reflects health effects from consumption of self-caught fish by households. Also, because this analysis focuses only on infants born after implementation of the regulatory options, EPA further limited the analyzed population by estimating the number of women between the ages of 15 and 44 potentially exposed to contaminated fish caught in the affected waterbodies and multiplying the result by ethnicity-specific average fertility rates.[95] This yields the cohort-specific annual number of births for each CBG.

The U.S. Department of Health and Human Services provides fertility rates by race for 2021 in the National Vital Statistics Report (Osterman et al., 2023). The fertility rate measures the number of births occurring per 1,000 women between the ages of 15 and 44 in a particular year. Fertility rates were highest for Hispanic women at 63.4, followed by African Americans at 57.4, other race/ethnicities at 56.3, Caucasians at 54.4, Native Americans at 50.8, and Asians at 49.6.

5.5.1 Data and Methodology

EPA used the ethnicity- and mode-specific consumption rates shown in Table 5-2 and calculated the CBG- and cohort-specific mercury ADD based on Equation 5-3. As EPA is not aware of consumption rates specific

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[95] EPA acknowledges that fertility rates vary by age. However, the use of a single average fertility rate for all ages is not expected to bias results because the average fertility rate reflects the underlying distribution of fertility rates by age.

to pregnant women, the analysis uses the same consumption rates as in the general population within each analyzed cohort.

In this analysis, EPA used a linear dose-response relationship between maternal mercury hair content and subsequent childhood IQ loss from Axelrad et al. (2007). Axelrad et al. (2007) developed a dose-response function based on data from three epidemiological studies in the Faroe Islands, New Zealand, and Seychelle Islands. According to their results, there is a 0.18-point IQ loss for each 1 part-per-million (ppm) increase in maternal hair mercury.

To estimate maternal hair mercury concentrations based on the daily intake (see Section 5.2.2), EPA used the median conversion factor derived by Swartout and Rice (2000), who estimated that a 0.08 µg/kg body weight increase in daily mercury dose is associated with a 1 ppm increase in hair concentration. Equation 5-9 shows EPA’s calculation of the total annual IQ changes for a given receiving reach.

Equation 5-9.

$$\boldsymbol{IQL(i)(c) = InExPop(i)(c) * MADD(i)(c) * \left(\frac{1}{Conv}\right) * DRF}$$

Where:

IQL(i)(c) = IQ changes associated with *in-utero* exposure to mercury from maternal consumption of fish contaminated with mercury for cohort *c* in CBG *i*

InExPop(i)(c) = population of infants in scope of the analysis for cohort *c* in CBG *i* (the number of births)

MADD(i)(c) = maternal ADD for cohort *c* in CBG *i* (µg/kg BW/day)

Conv = conversion factor for hair mercury concentration based on maternal mercury exposure (0.08 µg/kg BW/day per 1 ppm increase in hair mercury)

DRF = dose response function for IQ decrement based on marginal increase in maternal hair mercury (0.18-point IQ decrement per 1 ppm increase in hair mercury)

Summing estimated IQ changes across all analyzed CBGs yields the total changes in the number of IQ points due to *in-utero* mercury exposure from maternal fish consumption under each analyzed regulatory option. The benefits of the regulatory options are calculated as the change in IQ points between the baseline and modeled post-technology implementation conditions under each of the regulatory options.

The available economic literature provides little empirical data on society’s overall WTP to avoid a decrease in children’s IQ. To estimate the value of avoided IQ losses, EPA used estimates of the changes in a child’s future expected lifetime earnings per one IQ point reduction, discounted to birth (Table 5-3). EPA also used an alternative value of an IQ point from Lin, Lutter and Ruhm (2018) in a sensitivity analysis (see Appendix G).

5.5.2 Results

Table 5-8 shows the estimated changes in IQ point losses for infants exposed to mercury in-utero and the corresponding monetary values. The final rule (Option B) results in 1,377 avoided IQ point losses over the entire in-scope population of infants with changes in mercury exposure. The annualized benefits of avoided IQ point losses are $1.98 million.

Table 5-8: Estimated Benefits from Avoided IQ Losses for Infants from Mercury Exposure under the Regulatory Options, Compared to Baseline

Regulatory Option	Number of Infants in Scope of the Analysis per Year[b]	Total Avoided IQ Point Losses, 2025 to 2049 in All Infants in Scope of the Analysis	Annualized Value of Avoided IQ Point Losses[a] (Millions 2023$; 2% Discount Rate)
Option A	201,850	1,190	$1.71
Option B (Final Rule)	201,850	1,377	$1.98
Option C	201,850	1,393	$2.00

a. Based on the estimate that the loss of one IQ point results in the loss of 2.63 percent of lifetime earnings discounted to birth, following updated Salkever (1995) values from U.S. EPA (2019f).

b. The number of infants in scope of the analysis is based on reaches analyzed across the regulatory options. Some of the children included in this count see no changes in exposure under some options.

Source: U.S. EPA Analysis, 2024

5.6 Estimated Changes in Cancer Cases from Arsenic Exposure

Among steam electric pollutants that can contaminate fish tissue and are analyzed in the EA, arsenic is the only confirmed carcinogen with a published dose response function (see U.S. EPA, 2010).[96] EPA used the methodology presented in Section 3.6 of the 2015 BCA (U.S. EPA, 2015a) to estimate the number of annual skin cancer cases associated with consumption of fish contaminated with arsenic from steam electric power plant discharges under the baseline and the change corresponding to each regulatory option and the associated monetary values. EPA's analysis shows negligible changes in skin cancer cases from exposure to arsenic via consumption of self-caught fish under the regulatory options.[97] Accordingly, the estimated benefits are also negligible under all regulatory options and are not included in the total monetized benefits.

5.7 Monetary Values of Estimated Changes in Human Health Effects

Table 5-9 presents the estimated benefits under the regulatory options of changes in adverse human health outcomes associated with the consumption of self-caught fish. The estimated benefits of the final rule (Option B) range from $2.14 million to $2.41 million. Changes in mercury exposure for children account for the majority of total monetary values from increases in adverse health outcomes.

Table 5-9: Estimated Benefits of Changes in Human Health Outcomes Associated with Fish Consumption under the Regulatory Options, Compared to Baseline (Millions of 2023$; 2% Discount Rate)

Regulatory Option	Changes in Lead Exposure for Children	Changes in Lead Exposure for Adults		Changes in Mercury Exposure for Children	Total	
		Low	High		Low	High
Option A	<$0.01	$0.16	$0.43	$1.71	$1.87	$2.14
Option B (Final Rule)	<$0.01	$0.16	$0.43	$1.98	$2.14	$2.41
Option C	<$0.01	$0.17	$0.45	$2.00	$2.17	$2.45

Source: U.S. EPA Analysis, 2024

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[96] Although other pollutants, such as cadmium, are also likely to be carcinogenic (see U.S. Department of Health and Human Services. (2012). *Toxicological Profile for Cadmium.*), EPA did not identify dose-response functions to quantify the effects of changes in these other pollutants.

[97] The analysis estimated a reduction in the incidence of arsenic-related skin cancer cases of 0.01 cases between 2025 and 2049 for all three regulatory options.

5.8 Additional Measures of Potential Changes in Human Health Effects

As noted in the introduction to this chapter, untreated pollutants in steam electric power plant discharges have been linked to additional adverse human health effects. EPA compared immediate receiving water concentrations to human health-based NRWQC in U.S. EPA (2020g). To provide an additional measure of the potential health effects of the regulatory options, EPA also estimated the changes in the number of receiving and downstream reaches with pollutant concentrations in excess of human health-based NRWQC. This analysis compares pollutant concentrations estimated for the baseline and each analyzed regulatory option in receiving reaches and downstream reaches to criteria established by EPA for protection of human health. EPA compared estimated in-water concentrations of antimony, arsenic, barium, cadmium, chromium, cyanide, copper, lead, manganese, mercury, nitrate-nitrite as N, nickel, selenium, thallium, and zinc to EPA's NRWQC protective of human health used by states and tribes (U.S. EPA, 2018c) and to MCLs.[98] Estimated pollutant concentrations in excess of these values indicate potential risks to human health. This analysis and its findings are not additive to the preceding analyses in this chapter, but instead represent another way of characterizing potential health effects resulting from changes in exposure to steam electric pollutants.

Table 5-10 shows the results of this analysis.[99] During Period 1, EPA estimates that with baseline steam electric pollutant discharges, concentrations of steam electric pollutants exceed human health criteria for at least one pollutant in 375 reaches based on the "consumption of water and organism" criteria, and 112 reaches based on the "consumption of organism only" criteria nationwide. During Period 2, concentrations of steam electric pollutants exceed human health criteria for at least one pollutant in 326 reaches based on the "consumption of water and organism" criteria, and 112 reaches based on the "consumption of organism only" criteria nationwide under the baseline scenario. The estimated number of reaches with exceedances of "consumption water and organism" criteria and with exceedances of "consumption of organism only" criteria during both Period 1 and Period 2 decreases under all regulatory options.[100] For example, Option C eliminates exceedances in 271 reaches (326-55) and reduces the number of exceedances in 237 reaches.

Table 5-10: Estimated Number of Reaches Exceeding Human Health Criteria for Steam Electric Pollutants

Regulatory Option	Number of Reaches with Ambient Concentrations Exceeding Human Health Criteria for at Least One Pollutant[a]		Number of Reaches with Lower Number of Exceedances, Relative to Baseline[b]	
	Consumption of Water + Organism	Consumption of Organism Only	Consumption of Water + Organism	Consumption of Organism Only
Period 1 (2025-2029)				
Baseline	375	112	Not applicable	Not applicable
Option A	308	70	73	42
Option B (Final Rule)	298	68	90	52
Option C	274	68	117	52

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[98] For pollutants that do not have NRWQC protective of human health, EPA used MCLs. These pollutants include cadmium, chromium, lead, and mercury.

[99] Only reaches designated as fishable (*i.e.*, Strahler Stream Order larger than 1) were included in the NRWQC exceedances analysis.

[100] EPA's analysis does not account for the fact that the NPDES permit for each steam electric power plant, like all NPDES permits, is required to have limits more stringent than the technology-based limits established by an ELG, wherever necessary to protect water quality standards. Because this analysis does not project where a permit will have more stringent limits than those required by the ELG, it may overestimate any negative impacts to aquatic ecosystems and T&E species, including impacts that will not be realized at all because the permits will be written to include limits as stringent as necessary to meet water quality standards as required by the CWA.

Table 5-10: Estimated Number of Reaches Exceeding Human Health Criteria for Steam Electric Pollutants

Regulatory Option	Number of Reaches with Ambient Concentrations Exceeding Human Health Criteria for at Least One Pollutant[a]		Number of Reaches with Lower Number of Exceedances, Relative to Baseline[b]	
	Consumption of Water + Organism	Consumption of Organism Only	Consumption of Water + Organism	Consumption of Organism Only
Period 2 (2030-2049)				
Baseline	326	112	Not applicable	Not applicable
Option A	180	38	140	67
Option B (Final Rule)	78	8	222	79
Option C	55	0	237	84

a. Pollutants for which there was at least one exceedance in the baseline or regulatory options include antimony, arsenic, chromium, cyanide, manganese, and thallium in Period 1 and arsenic, chromium, cyanide, manganese, and thallium in Period 2.

b. Pollutants for which there was at least one reach with lower number of exceedances relative to baseline include arsenic and chromium in Period 1 and arsenic, chromium, cyanide, manganese, and thallium in Period 2.

Source: U.S. EPA Analysis, 2024

5.9 Limitations and Uncertainties

The analysis presented in this chapter does not include all possible human health effects associated with post-technology implementation changes in pollutant discharges due to lack of data on a dose-response relationship between ingestion rates and potential adverse health effects. Therefore, the total quantified human health effects included in this analysis represent only a subset of the potential health effects estimated to result from the regulatory options. Section 2.1 provides a qualitative discussion of health effects omitted from the quantitative analysis.

The methodologies and data used in the analysis of adverse health outcomes due to consumption of fish contaminated with steam electric pollutants involve limitations and uncertainties. Table 5-11 summarizes the limitations and uncertainties and indicates the direction of the potential bias. Additional limitations and uncertainties associated with the environmental assessment analyses and data are discussed in the EA (see U.S. EPA, 2024b).

Table 5-11: Limitations and Uncertainties in the Analysis of Human Health Effects via the Fish Ingestion Pathway

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
Fishers are estimated to evenly distribute their activity over all available fishing sites within the 50-mile travel distance.	Uncertain	EPA estimated that all fishers travel up to 50 miles and distribute their visits over all fishable sites within the area. In fact, recreational and subsistence fishers may have preferred sites (*e.g.*, a site located closer to their home) that they visit more frequently. The characteristics of these sites, notably ambient water concentrations and fishing advisories, affects exposure to pollutants, but EPA does not have data to support a more detailed analysis of fishing visits. The impact of this approach on monetary estimates is uncertain since fewer/more fishers may be exposed to higher/lower fish tissue concentrations than estimated by EPA.

Table 5-11: Limitations and Uncertainties in the Analysis of Human Health Effects via the Fish Ingestion Pathway

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
The exposed population is estimated based on households in proximity to affected reaches and the fraction of the general population who fish.	Uncertain	EPA estimated the share of households that includes fishers to be equal to the fraction of people over 16 who are fishers. This may double-count households with more than one fisher over 16. However, the exposed population may also include non-household members who also consume the catch.
Fish intake rates used in estimating exposure are based on recommended values for the general consumer population.	Uncertain	The fish consumption rates used in the analysis are based on the general consumer population, which may understate or overstate the amount of fish consumed by fishers who may consume fish at higher or lower rates than the general population (*e.g.*, Burger, 2013; U.S. EPA, 2011, 2013c)
Fish intake rates used in estimating exposure do not reflect potential lower fish consumption by pregnant women.	Overestimate	To the degree that pregnant women reduce their consumption of self-caught fish when compared to women in the general population, then exposure in the baseline would be less and the final rule benefits from reduced exposure to mercury correspondingly lower.
100 percent of fish consumed by recreational fishers is self-caught.	Overestimate	The fish consumption rates used in the analysis account for all fish sources (*i.e.*, store-bought or self-caught fish). Assuming that recreational fishers consume only self-caught fish may overestimate exposure to steam electric pollutants from fish consumption. The degree of the overestimate is unknown as the fraction of fish consumed that is self-caught varies significantly across different locations and population subgroups (*e.g.*, U.S. EPA, 2013c).
The number of subsistence fishers was set to equal 5 percent of the total number of fishers fishing the affected reaches.	Uncertain	The magnitude of subsistence fishing in the United States or individual states is not known. Using 5 percent may understate or overstate the overall number of potentially affected subsistence fishers (and their households) and ignores potential variability in subsistence fishing rates across racial/ethnic groups and different geographic locations.
Value of an IQ point used to quantify benefits health effects from changes in lead and mercury exposure	Uncertain	EPA used two alternative estimates of the value of an IQ point in its analysis, following the methodology in U.S. EPA (2019d; 2019e, 2020b). EPA acknowledges recent research indicating higher IQ point values than those calculated based on Salkever (1995) and Lin, Lutter and Ruhm (2018). However, because the recent research was based on either non-U.S. populations (*e.g.*, Grönqvist, Nilsson & Robling, 2020) or unrepresentative subsets of the U.S. population (Hollingsworth et al., 2020; Hollingsworth & Rudik, 2021),EPA continued to use IQ point values based on Salkever (1995) and Lin, Lutter and Ruhm (2018).
There is a 0.18-point IQ loss for each 1 ppm increase in maternal hair mercury (*i.e.*, the relationship is assumed to be linear).	Uncertain	The exact form of the relationship between maternal body mercury burden and IQ losses is uncertain. Using a linear relationship may understate or overstate the IQ losses resulting from a given change in mercury exposure.

Table 5-11: Limitations and Uncertainties in the Analysis of Human Health Effects via the Fish Ingestion Pathway

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
For the mercury- and lead-related health impact analyses, EPA assessed IQ losses to be an appropriate endpoint for quantifying adverse cognitive and neurological effects resulting from childhood or in-utero exposures to lead and mercury (respectively).	Underestimate	IQ may not be the most sensitive endpoint. Additionally, there are deficits in cognitive abilities that are not reflected in IQ scores, including increased incidence of attention-related and problem behaviors (NTP, 2012; U.S. EPA, 2005d). To the extent that these impacts create disadvantages for children exposed to mercury and lead in the absence of (or independent from) measurable IQ losses, this analysis may underestimate the social welfare effects of the regulatory options of changes in lead and mercury exposure.
The IEUBK model processes daily intake from “alternative sources” to 2 decimal places (µg/day).	Underestimate	Since the fish-associated pollutant intakes are small, some variation is missed by using this model (*i.e.*, it does not capture very small changes between the baseline and regulatory options).
For the lead analysis in adults EPA assumed that fishers would share their catch with household members.	Overestimate	EPA used CBG-specific estimates of persons per household which range from 1.0 to 13.6 and average 2.6 members. Not all individuals within a household may be adults.
The AALM only models BLL from birth to age 60.	Uncertain	BLL for ages 61-80 were extrapolated, but because the simulation of BLL levels off and becomes very predictable after age 30 confidence in the extrapolation is high.
CVD mortality studies use a single measurement of adult BLL.	Uncertain	The CVD studies used to derive the beta coefficients used in Equation 5-7 and Equation 5-8 use a single measurement of adult BLL.
EPA does not adjust BLLs for hematocrit when using the Aoki CVD mortality function.	Overestimate	Based on example calculations conducted in Abt Associates (2023), which compared the two approaches using a hypothetical scenario, the use of whole blood BLLs appears to reasonable for scenarios such as the one in this analysis, where BLLs changes are expected to be small.
EPA estimates avoided CVD premature mortality impacts for adults ages 40 through 80 only.	Underestimate	EPA did not estimate avoided premature CVD deaths for populations younger than 40 or older than 80. This will underestimate benefits because benefits are directly proportional to the size of the affected population and baseline mortality rates.
Uncertainty in the shape of the dose-response function for CVD premature mortality.	Uncertain	The mathematical form of the dose-response function for lead CVD impacts is based on models that best fit the data from the selected epidemiological studies. However, uncertainty remains about the true shape of the function, particularly at very low blood lead levels, for which there are fewer historic data points. Estimating health impacts using alternative mathematical functions that reflect these alternative shapes is beyond the scope of this analysis. Depending on the shape tested, benefit results could be higher or lower.
Baseline CVD rates used in the analysis of lead-related CVD premature mortality in adults did not consider cause.	Uncertain	EPA assumed that the distribution for the age of the individuals experiencing lead-related CVD premature mortality is the same as the distribution of CVD mortality by age and sex for CVD premature mortality irrespective of the cause.

Table 5-11: Limitations and Uncertainties in the Analysis of Human Health Effects via the Fish Ingestion Pathway

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
EPA assumed that changes in lead intake for adults and the resulting change in BLL occur instantaneously.	Overestimate	Because change in BLL in adults resulting from reduction in lead intake realistically occurs over time, assuming an instantaneous change in BLL is likely to overestimate reduction in lead-related CVD premature mortality.
EPA did not monetize the health effects associated with changes in adult exposure to mercury.	Underestimate	The scientific literature suggests that exposure to mercury may have significant adverse health effects for adults (*e.g.*, Hollingsworth & Rudik, 2021; Mergler et al., 2007; Center for Disease Control and Prevention (CDC), 2009). If measurable effects are occurring at current exposure levels, excluding the effects of increased adult exposure results in an underestimate of benefits.
EPA did not quantify other health effects in children from exposure to lead or mercury.	Underestimate	As discussed in Section 2.1, exposure to lead could result in additional adverse health effects in children (*e.g.*, low birth weight and neonatal mortality from in-utero exposure to lead, or neurological effects in children exposed to lead after age seven) (NTP, 2012; U.S. EPA, 2024d; U.S. EPA, 2019e; U.S. EPA, 2023f). Additional neurological effects could also occur in children from exposure to mercury after birth (Mergler et al., 2007; CDC, 2009). If measurable effects are occurring at current exposure levels, excluding additional health effects of increased children exposure results in an underestimate of benefits.
EPA did not assess combined health risk of multiple pollutants.	Uncertain	The combined health risk of exposure to multiple pollutants could be greater than that to a single pollutant (Evans, Campbell & Naidenko, 2020). However, quantifying cumulative risk is challenging because a mixture of pollutants could affect a wide range of target organs and endpoints (ATSDR, 2004, 2009). For example, different carcinogens found in steam electric power plant discharges may affect different organs (*e.g.*, arsenic is linked to skin cancer while cadmium is linked to kidney cancer). Other synergistic effects may increase or lessen the risk. While there are no existing methods to fully analyze and monetize these effects, EPA quantified some of these effects in the EA (U.S. EPA, 2024b).

6 Nonmarket Benefits from Water Quality Changes

As discussed in the EA (U.S. EPA, 2024b), heavy metals, nutrients, and other pollutants discharged by steam electric power plants can have a wide range of effects on water resources downstream from the plants. These environmental changes affect environmental goods and services valued by humans, including recreation; commercial fishing; public and private property ownership; navigation; water supply and use; and existence services such as aquatic life, wildlife, and habitat designated uses. Some environmental goods and services (*e.g.*, commercially caught fish) are traded in markets, and thus their value can be directly observed. Other environmental goods and services (*e.g.*, recreation and support of aquatic life) are not bought or sold directly and thus do not have observable market values. This second type of environmental goods and services are classified as "nonmarket." The estimated changes in the nonmarket values of the water resources affected by the regulatory options (hereafter nonmarket benefits) are additive to market values (*e.g.*, avoided costs of producing various market goods and services).

The analysis of the nonmarket value of water quality changes resulting from the regulatory options follows the same approach EPA used in the analysis of the 2015 and 2020 rules and 2023 proposal (U.S. EPA, 2015a, 2020b, 2023c). This approach, which is briefly summarized below, involves:

1. Characterizing the change in water quality under the regulatory options relative to the baseline using a WQI and linking these changes to ecosystem services or potential uses that are valued by society (see Section 3.4.2), and

2. Monetizing changes in the nonmarket value of affected water resources under the regulatory options using a meta-analysis of surface water valuation studies that provide data on the public's WTP for water quality changes (see Section 6.1).

The analysis accounts for improvements in water quality resulting from changes in nutrient, sediment, and toxics concentrations in reaches potentially affected by bottom ash transport water and FGD wastewater discharges. The assessment uses the CBG as the geographic unit of analysis, assigning a radial distance of 100 miles from the CBG centroid. EPA estimates that households residing in a given CBG value water quality changes in all modeled reaches within this range, with all unaffected reaches being viable substitutes for affected reaches within the area around the CBG. Appendix E in U.S. EPA (2020b) provides additional details on EPA's approach.

6.1 Estimated Total WTP for Water Quality Changes

EPA estimated economic values of water quality changes at the CBG level using results of a meta-analysis of 189 estimates of total WTP (including both use and nonuse values) for water quality improvements, provided by 59 original studies conducted between 1981 and 2017.[101] The estimated econometric model allows calculation of total WTP for changes in a variety of environmental services affected by water quality and valued by humans, including changes in recreational fishing opportunities, other water-based recreation, and

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[101] Although the potential limitations and challenges of benefit transfer are well established (Desvousges, W. H., Smith, V. K., & Fisher, A. (1987). Option price estimates for water quality improvements: a contingent valuation study for the Monongahela River. *Journal of Environmental Economics and Management, 14*, 248-267. https://doi.org/https://doi.org/10.1016/0095-0696(87)90019-2), benefit transfers are a nearly universal component of benefit cost analyses conducted by and for government agencies. As noted by Smith, V. K., Van Houtven, G., & Pattanayak, S. K. (2002). Benefit transfer via preference calibration:"Prudential algebra" for policy. *Land Economics, 78*(1), 132-152. , "nearly all benefit cost analyses rely on benefit transfers, whether they acknowledge it or not."

existence services such as aquatic life, wildlife, and habitat designated uses. The model also allows EPA to adjust WTP values based on the core geospatial factors predicted by theory to influence WTP, including: scale (the size of affected resources or areas), market extent (the size of the market area over which WTP is estimated), and the availability of substitutes. The meta-analysis regression is based on two models: Model 1 provides EPA's main estimate of non-market benefits, and Model 2 is used in a sensitivity analysis to develop a range of estimates that account for uncertainty in the estimated WTP values (see Section 6.2 for Model 2 results). Appendix H provides details on how EPA used the meta-analysis to predict household WTP for each CBG and year as well as the estimated regression equation, intercept and variable coefficients for the two models used in this analysis. The appendix also provides names and definitions of the independent variable and assigned values.

Based on the meta-analysis results, EPA multiplied the coefficient estimates for each variable (see Model 1 and Model 2 in Table H-3) by the variable levels calculated for each CBG or fixed at the levels indicated in the "Assigned Value" column in Table H-3. The sum of these products represents the predicted natural log of the WTP for a one-point improvement on the WQI (*ln_OWTP*) for a representative household in each CBG. Equation 6-1 provides the equation used to calculate household benefits for each CBG.

Equation 6-1.

$$HWTP_{Y,B} = OWTP_{Y,B} \times \Delta WQI_B$$

where:

$HWTP_{Y,B}$	=	Annual household WTP in 2023$ in year *Y* for households located in the CBG (*B*),
$OWTP_{Y,B}$	=	WTP for a one-point improvement on the WQI for a given year (*Y*) and the CBG (*B*), estimated by the meta-analysis function and evaluated at the midpoint of the range over which water quality is changed,
ΔWQI_B	=	Estimated annual average water quality change for the CBG (*B*). See Section 3.4 and Appendix C for details about the WQI calculation methodology.

To estimate WTP for water quality improvements under the regulatory options, EPA first estimated water quality improvements for each year within Period 1 and Period 2 (see Section 3.2.1 for details) and then applied the meta-regression model (MRM) to estimate per household WTP for water quality improvements for each year in the analysis period (2024-2049). As summarized in Table 6-1, average annual household WTP estimates for the regulatory options, based on the main estimates from Model 1, range from $0.01 under Option A to $0.03 under Option C.

To estimate total WTP (TWTP) for water quality changes for each CBG, EPA multiplied the per-household WTP values for the estimated water quality change by the number of households within each CBG in a given year and calculated the present value (PV) of the stream of WTP over the 25 years in EPA's period of analysis. EPA then calculated annualized total WTP values for each CBG using a 2 percent discount rate as shown in Equation 6-2.

Equation 6-2.

$$TWTP_B = \left(\sum_{T=2025}^{2049} \frac{HWTP_{Y,B} \times HH_{Y,B}}{(1+i)^{Y-2024}} \right) \times \left(\frac{i \times (1+i)^n}{(1+i)^{n+1} - 1} \right)$$

where:

$TWTP_B$	=	Annualized total household WTP in 2023$ for households located in the CBG (*B*),
$HWTP_{Y,B}$	=	Annual household WTP in 2023$ for households located in the CBG (*B*) in year (*Y*),
$HH_{Y,B}$	=	the number of households residing in the CBG (*B*) in year (*Y*),
T	=	Year when benefits are realized
i	=	Discount rate (2 percent)
n	=	Duration of the analysis (25 years)[102]

EPA generated annual household counts for each CBG through the period of analysis based on projected population growth following the method described in Section 1.3.6. Table 6-1 presents the main analysis results, based on Model 1. For the final rule (Option B), the total annualized values of water quality changes resulting from changes in toxics, nutrient and sediment discharges in these reaches are $1.24 million.

Table 6-1: Estimated Household and Total Annualized Willingness-to-Pay for Water Quality Improvements under the Regulatory Options, Compared to Baseline (Main Estimates)

Regulatory Option	Number of Affected Households (Millions)[a]	Average Annual WTP Per Household (2023$)[b]	Total Annualized WTP (Millions 2023$; 2% Discount Rate)[b]
Option A	58.7	$0.01	$0.79
Option B (Final Rule)	58.9	$0.02	$1.24
Option C	59.6	$0.03	$1.68

a. The number of affected households varies across options because of differences in the number of reaches that have non-zero changes in water quality.

b. Estimates based on Model 1, which provides EPA's main estimate of non-market benefits.

Source: U.S. EPA Analysis, 2024

6.2 Sensitivity Analysis

Table 6-2 presents sensitivity analysis results produced from Model 2, including average annual household WTP and total annualized values, for water quality improvements resulting from all regulatory options. For the final rule (Option B), average annual household WTP estimates range from $0.02 to $0.05. Total annualized values range from $1.31 million to $2.68 million.

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[102] See Section 1.3.3 for details on the period of analysis.

Table 6-2: Estimated Household and Total Annualized Willingness-to-Pay for Water Quality Changes under the Regulatory Options, Compared to Baseline (Sensitivity Analysis)

Regulatory Option	Number of Affected Households (Millions)[a]	Average Annual WTP Per Household (2023$)[b]		Total Annualized WTP (Millions 2023$; 2% Discount Rate)[b]	
		Low	High	Low	High
Option A	58.7	$0.01	$0.03	$0.86	$1.76
Option B (Final Rule)	58.9	$0.02	$0.05	$1.31	$2.68
Option C	59.6	$0.03	$0.07	$1.78	$3.65

a. The number of affected households varies across options because of differences in the number of reaches that have non-zero changes in water quality.

b. Estimates based on Model 2, which provides a range of estimates that account for uncertainty in the WTP estimates as a sensitivity analysis. For the ∆WQI variable setting in Model 2-based sensitivity analysis, EPA used values of 20 units to develop low estimates and 7 units to develop high estimates (see Appendix H for details).

Source: U.S. EPA Analysis, 2024

6.3 Limitations and Uncertainties

Table 6-3 summarizes the limitations and uncertainties in the analysis of benefits associated with changes in surface water quality and indicates the direction of any potential bias.

Table 6-3: Limitations and Uncertainties in the Analysis of Nonmarket Water Quality Benefits

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
Use of 100-mile buffer for calculating water quality benefits for each CBG	Underestimate	The distance between surveyed households and the affected waterbodies is not well measured by any of the explanatory variables in the MRM. EPA would expect values for water quality changes to diminish with distance (all else equal) between the household and affected waterbody. The choice of 100 miles is based on typical driving distance to recreational sites (*i.e.*, 2 hours or 100 miles; Viscusi, Huber & Bell, 2008), which captures approximately 80 percent of recreational uses. However, it does not capture the full extent of recreational use or recreational use for multiday trips. It also does not capture the extent of market or population willingness to pay for nonuse value. EPA used 100 miles to approximate the distance decay effect on WTP values but acknowledges that distance decay effects could occur at varying distances (*i.e.,* closer or further than 100 miles) and may exhibit more complex spatial patterns than a simple radius approach. The analysis recognizes further uncertainty for people living farther than 100 miles and does not assign any value for water quality improvements in waters affected by this rulemaking despite literature that shows that while WTP tends to decline with distance from the waterbody, people value the quality of waters outside their region.

Table 6-3: Limitations and Uncertainties in the Analysis of Nonmarket Water Quality Benefits

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
Selection of the *lnquality_ch* variable value in Model 2 for estimating a range of WTP values (sensitivity analysis)	Uncertain	The value of an additional one-point improvement in WQI is expected to decline as the magnitude of the water quality change increases. To account for variability in WTP due to the magnitude of the valued water quality changes, EPA estimated a range of WTP values for a one-point improvement on the WQI using alternative settings for *lnquality_ch* (ΔWQI= 20 and 7 units, respectively). These values were based on the 25th and 75th percentile of water quality changes included in the meta-data. To ensure that the benefit transfer function satisfies the adding-up condition, this variable is treated as a methodological (fixed) variable. The negative coefficient for *lnquality_ch* implies that larger value settings produce smaller WTP estimates for a one-point improvement, which is consistent with economic theory; smaller value settings produce larger WTP estimates for a one-point improvement. The selected values may bias the estimated WTP values either upward or downward.
Potential hypothetical bias in underlying stated preference results	Uncertain	Following standard benefit transfer approaches, this analysis proceeds under the assumption that each source study provides a valid, unbiased estimate of the welfare measure under consideration (cf. Moeltner, Boyle & Paterson, 2007; Rosenberger and Phipps, 2007). To minimize potential hypothetical bias underlying stated preference studies included in meta-data, EPA set independent variable values to reflect best practices for stated preference (*e.g.*, the payment vehicle variable is set to a non-voluntary value because use of voluntary donations is prone to issues of free-riding).
Use of different water quality measures in the underlying meta-data	Uncertain	The estimation of WTP may be sensitive to differences in the presentation of water quality changes across studies in the meta-data. Studies that did not use the WQI were mapped to the WQI, so a comparison could be made across studies. To account for potential effects of the use of a different water quality metric (*i.e.*, index of biotic integrity (IBI)) on WTP values for a one-point improvement on the WQI, EPA used a dummy variable in the MRM (see Appendix H for details). In benefit transfer applications, the IBI variable is set to zero, which is consistent with using the WQI.
Transfer error	Uncertain	Transfer error may occur when benefit estimates from a study site are adopted to forecast the benefits of a policy site. Rosenberger and Stanley (2006) define transfer error as the difference between the transferred and actual, generally unknown, value. Although meta-analyses are often more flexible and accurate compared to other types of transfer approaches (*e.g.*, value transfers and benefit function transfers) due to the data synthesis from multiple source studies (Rosenberger and Phipps, 2007; Johnston et al., 2021), there is still a potential for transfer errors (Shrestha, Rosenberger & Loomis, 2007) and no transfer method is always superior relative to other benefit transfer methods (Johnston et al., 2021).
Omission of Great Lakes and estuaries from analysis of benefits from water quality changes	Underestimate	Five out of 92 (5 percent) steam electric power plants discharge to the Great Lakes or estuaries. Due to limitations of the water quality models used in the analysis of the regulatory options, these waterbodies were excluded from the analysis. This omission likely underestimates benefits of water quality changes from the regulatory options.

Table 6-3: Limitations and Uncertainties in the Analysis of Nonmarket Water Quality Benefits

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
The water quality model accounts for only a subset of sources of toxic pollutants contributing to baseline concentrations	Uncertain	The overall impact of this limitation on the estimated WTP for water quality changes is uncertain but is expected to be small. Toxic pollutants are grouped into one parameter out of the seven parameters included the WQI. Therefore, the effect of including additional toxic pollutants on the estimated change in WQI is likely to be small.

7 Impacts and Benefits to Threatened and Endangered Species

7.1 Introduction

T&E species are species vulnerable to future extinction or at risk of extinction in the near future, respectively. These designations reflect low or rapidly declining population levels, loss of essential habitat, or life history stages that are particularly vulnerable to environmental alteration or other stressors. In many cases, T&E species are given special protection due to inherent vulnerabilities to habitat modification, disturbance, or other impacts of human activities. This chapter examines the projected change in environmental impacts of steam electric power plant discharges on T&E species and the estimated benefits associated with the projected changes resulting from the regulatory options.

As described in the EA (U.S. EPA, 2024b), the untreated chemical constituents of steam electric power plant wastestreams can pose serious threats to ecological health due to the bioaccumulative nature of many pollutants, high concentrations, and high loadings. Pollutants such as selenium, arsenic and mercury have been associated with fish kills, disruption of growth and reproductive cycles and behavioral and physiological alterations in aquatic organisms. Additionally, high nutrient loads can lead to the eutrophication of waterbodies. Eutrophication can lead to increases in the occurrence and intensity of water column phytoplankton, including harmful algal blooms (*e.g.*, nuisance and/or toxic species), which have been found to cause fatal poisoning in other animals, fish, and birds. Eutrophication may also result in the loss of critical submerged rooted aquatic plants (or macrophytes), and reduced DO levels, leading to anoxic or hypoxic waters.

For species vulnerable to future extinction, even minor changes to growth and reproductive rates and small levels of mortality may represent a substantial portion of annual population growth. To quantify the estimated effects of the regulatory options compared to baseline, EPA conducted a screening analysis using as indicator of benefits the changes in projected attainment of freshwater NRWQC. Specifically, EPA identified the reaches that are projected to see changes in achievement of freshwater aquatic life NRWQC, assuming no more stringent controls are established to meet applicable water quality standards (*i.e.*, water-quality-based effluent limits issued under Section 301(b)(1)(C))). Using these projections, EPA then estimated the number of T&E species whose recovery could be affected based on the species' habitat range. Because NRWQC are recommended at levels to protect aquatic organisms, reducing the frequency at which aquatic life-based NRWQC are exceeded could translate into reduced risk to T&E species and potential improvements in species populations.[103]

In this chapter, EPA examines the current conservation status of species belonging to freshwater taxa and identifies the extent to which the regulatory options, independent of consideration of additional water quality-based controls, may benefit or adversely impact T&E species. The analysis generally follows the approach EPA used for the analyses of the 2015 and 2020 rules and 2023 proposal (U.S. EPA, 2015a, 2020b, 2023b), including updates EPA made over time to the methodology, assumptions, and inputs to address comments or

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[103] Criteria are developed based on the 1985 Guidelines methods (U.S. Environmental Protection Agency. (1985). *Guidelines for Deriving Numerical National Water Quality Criteria for the Protection Of Aquatic Organisms and Their Uses*. (PB85-227049). Retrieved from https://www.epa.gov/sites/production/files/2016-02/documents/guidelines-water-quality-criteria.pdf) and generally reflect high quality toxicity data from at least eight different taxa groups that broadly represent aquatic organisms. To the extent that more stringent levels are required to protect organisms in a particular location, that is addressed during the water quality standard development process for that location.

incorporate more recent data. As for the earlier analyses, this analysis provides a quantitative, but unmonetized proxy for the benefits associated with the regulatory options.

7.2 Baseline Status of Freshwater Fish Species

Reviews of aquatic species' conservation status over the past three decades have documented the effect of cumulative stressors on freshwater aquatic ecosystems, resulting in a significant decline in the biodiversity and condition of indigenous communities (Deacon et al., 1979; Williams et al., 1989; Williams et al., 1993; Taylor et al., 1996; Taylor et al., 2007; Jelks et al., 2008). Overall, aquatic species may be disproportionately imperiled relative to terrestrial species. For example, while 39 percent of freshwater and diadromous fish species are imperiled (Jelks et al., 2008), a similar status review found that only 7 percent of North American bird and mammal species are imperiled (Wilcove & Master, 2005). More recent studies of threats and extinction trends in freshwater taxa also concluded that biodiversity is much more at risk in freshwater compared to marine ecosystems (Winemiller, 2018).

Approximately 39 percent of described fish species in North America are imperiled, with 700 fish taxa classified as vulnerable (230), threatened (190), or endangered (280) in addition to 61 taxa presumed extinct or functionally extirpated from nature (Jelks et al., 2008). These data show that the number of T&E species has increased by 98 percent and 179 percent when compared to similar reviews conducted by the American Fisheries Society in 1989 (Williams et al., 1989) and 1979 (Deacon et al., 1979), respectively. Despite conservation efforts, including the listing of several species under the Endangered Species Act (ESA), only 6 percent of the fish taxa assessed in 2008 had improved in status since the 1989 inventory (Jelks et al., 2008).

Several families of fish have high proportions of T&E species. Approximately 46 percent and 44 percent of species within families Cyprinidae (carps and true minnows) and Percidae (darters and perches) are imperiled, respectively. Some families with few, wide-ranging species have even higher rates of imperilment, including the Acipenseridae (sturgeons; 88 percent) and Polyodontidae (paddlefish; 100 percent). Families with species important to sport and commercial fisheries have imperilment levels ranging from a low of 22 percent for Centrarchidae (sunfishes) to a high of 61 percent for Salmonidae (salmon) (Jelks et al., 2008).

7.3 T&E Species Potentially Affected by the Regulatory Options

To assess the potential effects of the regulatory options on T&E species, EPA used the U.S. FWS Environmental Conservation Online System (ECOS) to construct a database of species that have habitats that overlap with waters projected to improve due to reductions in pollutant discharge from steam electric power plants under the regulatory options. The source data include all animal species currently listed or proposed for listing under the ESA (U.S. FWS, 2020d).

7.3.1 Identifying T&E Species Potentially Affected by the Regulatory Options

To estimate the effects of the regulatory options on T&E species, EPA first compiled data on habitat ranges for all species currently listed or under consideration for listing under the ESA. EPA obtained the geographical distribution of T&E species in geographic information system (GIS) format from ECOS (U.S. FWS, 2020b).

EPA constructed a screening database using the spatial data on species habitat ranges and all NHD reaches downstream from steam electric power plants. This database included all T&E species whose habitat ranges intersect reaches immediately receiving or downstream of steam electric power plant discharges. EPA used a 200-meter buffer on either side of each reach when estimating the intersection to account for waterbody widths and any minor errors in habitat maps. EPA removed several species previously included in the analysis of the 2023 proposal because they were delisted from the ESA due to extinction, according to the USFWS (U.S. Fish & Wildlife Service, 2023). The analysis retained a total of 184 T&E species.

EPA then classified these species on the basis of their vulnerability to changes in water quality for the purpose of assessing potential impacts of the regulatory options. EPA obtained species life history data from a wide variety of sources to assess T&E species' vulnerability to water pollution. For the purpose of this analysis, species were classified as follows:

- Higher vulnerability – species living in aquatic habitats for several life history stages and/or species that obtain a majority of their food from aquatic sources.
- Moderate vulnerability – species living in aquatic habitats for one life history stage and/or species that obtain some of their food from aquatic sources.
- Lower vulnerability – species whose habitats overlap bodies of water, but whose life history traits and food sources are terrestrial.

Table 7-1 summarizes the results of this assessment. Appendix I lists all T&E species whose habitat ranges intersect reaches immediately receiving or downstream of steam electric power plant discharges.

Table 7-1: Number of T&E Species with Habitat Range Intersecting Reaches Immediately Receiving or Downstream of Steam Electric Power Plant Discharges, by Group

Species Group	Species Vulnerability			Species Count
	Lower	Moderate	Higher	
Amphibians	3	2	4	9
Arachnids	6	0	0	6
Birds	17	4	5	26
Clams	0	0	56	56
Crustaceans	0	0	5	5
Fishes	0	0	28	28
Insects	10	0	0	10
Mammals	13	1	1	15
Reptiles	13	0	6	19
Snails	1	0	9	10
Total	**63**	**7**	**114**	**184**

Source: U.S. EPA Analysis, 2024.

To estimate the potential impacts of the regulatory options, EPA focused the analysis on species with higher vulnerability potentials based upon life history traits. EPA's further review of this subset of species resulted in the removal from further analysis of those species endemic to isolated headwaters and natural springs, as these waters are unlikely to receive steam electric power plant discharges in the scope of the final rule (see Appendix I for details). A review of life history data for the remaining species shows pollution or water quality issues as factors influencing species decline. This suggests that water quality issues may be important to species recovery even if not emphasized explicitly in species recovery plans.

7.3.2 Estimating Effects of the Rule on T&E Species

EPA used the results of the water quality model described in Chapter 3 to flag those reaches where estimated pollutant concentrations exceed the freshwater NRWQC under the baseline or the regulatory options (see

Section 3.4.1.1). EPA estimated exceedances for two distinct periods (2025-2029 and 2030-2049) within the overall analysis period (2025-2049). As described in Section 3.2.1, Period 1 corresponds to transition years when the steam electric power plants would be installing treatment technologies to comply with the revised limits, whereas Period 2 reflects post-technology implementation conditions when all plants meet applicable revised limits.

EPA then linked the water quality model outputs with the species database described in the section above to identify potentially "affected T&E species habitats" where the reaches intersecting the habitat range of a T&E species do not meet the NRWQC under baseline conditions but do meet the NRWQC under one or more of the regulatory options (*i.e.*, potential positive benefits). EPA compared dissolved concentration estimates for eight pollutants to the freshwater acute and chronic NRWQC values[104] to assess the exceedance status of the reaches under the baseline and each regulatory option. Appendix I provides details on the number of exceedances from steam electric power plants affecting T&E species of all vulnerability levels. Overall, EPA's analysis indicates that 23 reaches intersecting the habitat ranges of 30 T&E species exceed NRWQC under the baseline conditions in Period 1 and 19 reaches intersecting the habitat ranges of 27 T&E species exceed NRWQC under the baseline conditions in Period 2. In Period 1 (2025-2029), exceedances improvements occur in four reaches under option A, and in 16 reaches under options B and C. In Period 2 (2030-2049), NRWQC exceedances are eliminated or reduced in two reaches under option A, in 16 reaches under option B, and in 19 reaches under option C.

Table 7-2, on the next page, provides additional details on the subset of species with higher vulnerability to water pollution for which the regulatory options reduce the number of exceedances in at least one Period and reach. EPA estimated that the improvements in water quality in Period 1 provide potential benefits to three T&E species under option A and ten T&E species under options B and C, as indicated by changes in the number of reaches with NRWQC exceedances. Improvements during Period 2 provide potential benefits to one T&E species under option A, 12 T&E species under option B, and 14 T&E species under option C.

While NRWQC do not translate into a quantifiable level of harm or improvement to wildlife species exposed to various contaminants, they may provide a useful proxy to indicate where significant improvements in water quality may occur, recognizing that these improvements may not necessarily benefit species to the same degree. Species have vastly different and unique life histories, and as a result, some may continue to face detrimental impacts even where NRWQC exceedances are eliminated, while other species may either not face detrimental impacts from water quality to begin with or may see benefits as the result of water quality improvements even without changes in exceedances. Furthermore, conditions that do not exceed NRWQC may still cause harm to species, especially those species with chronic exposure to contaminants such as heavy metals. Roughly 30 percent (56 of 184) of species with designated habitats intersecting reaches affected by steam electric power plant discharges are bivalves. Additionally, 15 percent (28 of 184) of species with designated habitats receiving steam electric power plant discharges are fish. Such taxonomic groups face consistent exposure to aquatic pollutants due to their entirely aquatic nature. Bivalves in particular fulfill vital ecological roles as ecosystem engineers (Hancock & Ermgassen, 2019). Freshwater bivalves are crucial filter feeders, removing metals, sediment, excess nutrients, and bacteria from surrounding water (Upper Midwest Environmental Sciences Center, 2020). Healthy populations of freshwater bivalve species help improve water quality and overall river/lake health by improving habitat for other aquatic invertebrates as well as finfish.

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[104] The eight pollutants are arsenic, cadmium, copper, lead, mercury, nickel, selenium, and zinc. For more information about the aquatic life NRWQC, see the EA (U.S. Environmental Protection Agency. (2024b). *Environmental Assessment for Supplemental Effluent Guidelines and Standards for the Steam Electric Power Generating Point Source Category*. (821-R-24-005).).

Species in which pollutants bioaccumulate may face detrimental or lethal effects at lower pollution levels over time. For example, bivalves feed by filtering large amounts of water and face extended exposure to pollutants over longer time spans compared to other species. As a result, populations of these species may suffer over time as negative effects of chronic exposure add up. Table 7-2 shows the Snuffbox mussel (*Epioblasma triquetra*), Sheepnose mussel (*Plethobasus cyphyus*), Spectaclecase mussel (*Cumberlandia monodonta*), and Pink Mucket (*Lampsilis abrupta*) all seeing improvements across many reaches intersecting their habitat ranges under the final rule (Option B). Publications from the USFWS warn that pollution and contamination are key threats to survival for each of these four species due to both acute and chronic toxic effects (Butler, 2007; U.S. Fish & Wildlife Service, 1997, 2012a, 2012b). Such cumulative effects on these species could further negatively impact local ecosystems by disrupting the filtering function provided by bivalves (Hancock & Ermgassen, 2019). Non-bivalve species could see benefits from improvements as well. Water contaminants, including metals, are a known threat to the survival of the Colorado Pikeminnow (*Ptychocheilus lucius*), and although the impacts of many contaminants are not quantified for this species, it demonstrates that this species could benefit from improvements to water quality (U.S. Fish & Wildlife Service, 2022). While the number of reaches with improvements are indicative of the benefits to T&E species provided by each option, it remains a rough indicator. However, for T&E species dependent on aquatic systems for survival, such as bivalves and fishes, any level of improvement that increases the ability of the species to survive and reproduce could enhance conservation and recovery efforts.

Table 7-2: Higher Vulnerability T&E Species Whose Habitat May be Affected by the Regulatory Options Compared to Baseline (Shading Highlights Change from Baseline)

Species Name	State(s)	Number of Reaches with NRWQC Exceedances for at Least One Pollutant			
		Baseline	Option A	Option B (Final Rule)	Option C
Period 1 (2025-2029)					
Clubshell (*Pleurobema clava*)	Kentucky	1	1	1	1
Colorado pikeminnow (*Ptychocheilus lucius*)	New Mexico	6	3	3	3
Fanshell (*Cyprogenia stegaria*)	Kentucky/West Virginia	11	11	1	1
Frosted Flatwoods salamander (*Ambystoma cingulatum*)	Florida	1	1	0	0
Humpback chub (*Gila cypha*)	Arizona	3	3	3	3
Orangefoot pimpleback (pearlymussel) (*Plethobasus cooperianus*)	Kentucky	1	1	1	1
Pink mucket (pearlymussel) (*Lampsilis abrupta*)	Kentucky/Ohio/West Virginia	12	12	2	2
Razorback sucker (*Xyrauchen texanus*)	New Mexico	3	0	0	0
Ring pink mussel (*Obovaria retusa*)	Kentucky	1	1	1	1
Rough pigtoe (*Pleurobema plenum*)	Kentucky	1	1	1	1
Sheepnose mussel (*Plethobasus cyphyus*)	West Virginia/Ohio	11	11	1	1
Snuffbox mussel (*Epioblasma triquetra*)	West Virginia	10	10	0	0
Spectaclecase mussel (*Cumberlandia monodonta*)	West Virginia	10	10	0	0
Topeka shiner (*Notropis topeka*)	Kansas	3	2	2	2
West Indian manatee (*Trichechus manatus*)	Florida	1	1	0	0

Table 7-2: Higher Vulnerability T&E Species Whose Habitat May be Affected by the Regulatory Options Compared to Baseline (Shading Highlights Change from Baseline)

Species Name	State(s)	Number of Reaches with NRWQC Exceedances for at Least One Pollutant			
		Baseline	Option A	Option B (Final Rule)	Option C
Period 2 (2030-2049)					
Clubshell (*Pleurobema clava*)	Kentucky	1	1	0	0
Colorado pikeminnow (*Ptychocheilus lucius*)	New Mexico	3	3	3	0
Fanshell (*Cyprogenia stegaria*)	Kentucky/West Virginia	11	11	0	0
Frosted Flatwoods salamander (*Ambystoma cingulatum*)	Florida	1	1	0	0
Humpback chub (*Gila cypha*)	Arizona	3	3	3	0
Orangefoot pimpleback (pearlymussel) (*Plethobasus cooperianus*)	Kentucky	1	1	0	0
Pink mucket (pearlymussel) (*Lampsilis abrupta*)	Kentucky/Ohio/West Virginia	12	12	0	0
Ring pink mussel (*Obovaria retusa*)	Kentucky	1	1	0	0
Rough pigtoe (*Pleurobema plenum*)	Kentucky	1	1	0	0
Sheepnose mussel (*Plethobasus cyphyus*)	West Virginia/Ohio	11	11	0	0
Snuffbox mussel (*Epioblasma triquetra*)	West Virginia	10	10	0	0
Spectaclecase mussel (*Cumberlandia monodonta*)	West Virginia	10	10	0	0
Topeka shiner (*Notropis topeka*)	Kansas	2	0	0	0
West Indian manatee (*Trichechus manatus*)	Florida	1	1	0	0

Source: U.S. EPA Analysis, 2024

7.4 Limitations and Uncertainties

One limitation of EPA's analysis of the regulatory options' impacts on T&E species and their habitat is the lack of data necessary to quantitively estimate population changes of T&E species and to monetize these effects. The data required to estimate the response of T&E species populations to improved habitats are rarely available. In addition, understanding the contribution of T&E species to ecosystem functions can be challenging because: (1) it is often difficult to locate T&E species, (2) experimental studies including rare or threatened species are limited; and (3) ecologists studying relationships between biodiversity and ecosystem functions typically focus on overall species diversity or estimate species contribution to ecosystem functions based on abundance (Dee et al., 2019). Finally, much of the wildlife economic literature focuses on recreational benefits (*i.e.*, use values) that are not relevant for many protected species and the existing T&E valuation studies tend to focus on species that many people consider to be "charismatic" (*e.g.*, spotted owl, salmon) (Richardson & Loomis, 2009). Although a relatively large number of economic studies have estimated WTP for T&E protection, these studies focused on estimating WTP to avoid species loss/extinction, reintroduction, increase in the probability of survival, or a substantial increase in species population (Subroy et al., 2019; Richardson & Loomis, 2009). In addition, use of the MRMs developed by Subroy et al. (2019) and Richardson and Loomis (2009) is not feasible for this analysis due to the challenges associated with estimating T&E population changes from the final rule.

Table 7-3 summarizes limitations and uncertainties known to affect EPA's assessment of the impacts of the final rule on T&E species. Note that the effect on benefits estimates indicated in the second column of the table refers to the direction and magnitude of the benefits (*i.e.*, a source of uncertainty that tends to underestimate benefits indicates expectation for larger realized benefits).

Table 7-3: Limitations and Uncertainties in the Analysis of T&E Species Impacts and Benefits

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
The analysis does not account for water quality based effluent limits	Overestimate	This screening analysis is intended to isolate possible effects of the regulatory options on T&E species, however, it does not consider the fact that the NPDES permits for each steam electric power plant, like all NPDES permits, are required to have limits more stringent than the technology-based limits established by an ELG wherever necessary to protect water quality standards. Because this analysis does not project where a permit will have more stringent limits than those required by the ELG, it may overestimate any negative impacts to T&E species in the baseline, and therefore overestimate benefits under the regulatory options.
Intersection of T&E species habitat with reaches affected by steam electric plant discharges is used as proxy for exposure to steam electric pollutants	Overestimate	EPA used the habitat range as the basis for assessing the potential for impacts to the species from water quality changes. This approach is reasonable given the lack of reach-specific population data to support a national-level analysis, but the Agency acknowledges that the habitat range of a species does not necessarily indicate that the species is found in individual reaches within the habitat range.
The change in T&E species populations due to improvement in water quality under the regulatory options is uncertain	Uncertain	Data necessary to quantitatively estimate population changes are unavailable. Therefore, EPA used the methodology described in Section 7.3.1 as a screening-level analysis to estimate whether the regulatory options could contribute to a change in the recovery of T&E species populations.
Only those T&E species listed as threatened or endangered under the ESA are included in the analysis	Underestimate	The databases used to conduct this analysis include only species protected under the ESA. Additional species may be considered threatened or endangered by scientific organizations but are not protected by the ESA (*e.g.*, the American Fisheries Society [Williams et al., 1993; Taylor et al., 2007; Jelks et al., 2008]). The magnitude of the underestimate is unknown. Although the proportion of imperiled freshwater fish and mussel species is high (*e.g.*, Jelks et al., 2008; Taylor et al., 2007), the geographic distribution of these species may or may not overlap with reaches affected by steam electric discharges.
The potential for impact to T&E species is also present for changes in pollutant concentrations that don't result in changes in NRWQC exceedances	Underestimate	EPA's analysis quantifies changes in whether a NRWQC is exceeded in a given reach that intersects T&E species habitat ranges. However, changes in pollutant concentrations have the potential to result in impacts to T&E species even where they do not result in changes in NRWQC exceedance status. There are also potential impacts to T&E species from changes in pollutants for which freshwater NRWQC are not available (*e.g.*, salinity).

Table 7-3: Limitations and Uncertainties in the Analysis of T&E Species Impacts and Benefits

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
EPA's water quality model does not capture all sources of pollutants with a potential to impact aquatic T&E species	Uncertain	EPA's water quality model focuses on toxic pollutant discharges from steam electric power plants and certain other point sources, but does not account for other pollution sources (*e.g.*, historical contamination) or background levels. Adding these other sources or background levels could result in additional NRWQC exceedances under the baseline and/or regulatory options, but it is uncertain how the regulatory options would change the exceedance status of the intersected reaches. Additionally, the water quality model does not capture synergistic relationships between pollutants, which may exacerbate adverse effects on T&E species.

8 Air Quality-Related Benefits

The regulatory options evaluated may affect air quality through three main mechanisms: 1) changes in energy used by steam electric power plants to operate wastewater treatment, ash handling, and other systems needed to meet the limitations and standards under the regulatory options; 2) transportation-related emissions due to the changes in trucking of CCR and other waste to on-site or off-site landfills; and 3) changes in the electricity generation profile from increases in wastewater treatment costs compared to the baseline and the resulting changes in EGU relative operating costs.

EPA estimated the climate-related benefits of changes in CO_2 and methane (CH_4) emissions, as well as the human health benefits resulting from changes in particulate matter and ozone ambient exposure due to net changes in emissions of NO_X, SO_2, and directly emitted fine particulate matter ($PM_{2.5}$), also referred to as primary $PM_{2.5}$ emissions.

8.1 Changes in Air Emissions

With respect to the third mechanism mentioned in the introduction and as discussed in the RIA, EPA used the Integrated Planning Model (IPM) to estimate the electricity market-level effects of the final rule (Option B). IPM projects generation from coal to decrease in all model years as a result of the final rule. Over the period of analysis, the reductions are largest in run years 2028 and 2035 (18.1 thousand GWh and 21.2 thousand GWh, respectively), are somewhat smaller in 2030 and 2040 (10.6 thousand GWh and 6.7 thousand GWh), and smallest in the last two run years of 2045 and 2050 (1.1 thousand GWh and 0.7 thousand GWh, respectively). These changes are offset in part by an increase in generation from natural gas, nuclear, and renewables. See details in Chapter 5 of the RIA (U.S. EPA, 2024e). The net effects of these changes in the generation mix are reductions in air emissions that reflect differences in EGU emissions rates for these other fuels or sources of energy, as compared to coal.

IPM outputs include estimated CO_2, NO_X, and SO_2 emissions to air from EGUs.[105] EPA also used IPM outputs to estimate EGU emissions of primary $PM_{2.5}$ based on the methodology described in U.S. EPA (2020c). Specifically, EPA estimated primary $PM_{2.5}$ emissions by multiplying the generation predicted for each IPM plant type (ultrasupercritical coal without carbon capture and storage, combined cycle, combustion turbine, etc.) by a type-specific empirical emission factor derived from the 2019 National Emissions Inventory (NEI) and other data sources. The emission factors reflect the fuel type (including coal rank), FGD controls, and state emission limits for each plant type, where applicable.

Comparing emissions projected under Option B to those projected for the baseline provides an assessment of the changes in air emissions resulting from changes in the profile of electricity generation under the final rule.[106] EPA used six of the seven IPM run years, shown in Table 8-1, to represent the period of analysis. IPM provides outputs starting in 2028 and EPA therefore estimated no changes in air emissions from changes in electricity generation in 2025 through 2027. The last run year (2055) falls outside of the analysis period of 2025-2049 and EPA does not include results for that year when estimating benefits.

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[105] EPA also estimated Hg, HCl and PM_{10} emissions but does not use these estimates for the benefits analysis.

[106] While EPA only ran IPM for the final rule (Option B), the Agency extrapolated the benefits estimated using these IPM outputs to Option A and Option C to provide insight on the potential air quality-related effects of the other regulatory options. See Section 8.4 for details.

Table 8-1: IPM Run Years

IPM Run Year	Years Represented
2028	2028-2029
2030	2030-2031
2035	2032-2037
2040	2038-2041
2045	2042-2047
2050	2048-2052
2055	2053-2059

Source: U.S. EPA, 2023e

As part of its analysis of non-water quality environmental impacts, EPA developed separate estimates of changes in energy requirements for operating wastewater treatment and ash handling systems, and changes in transportation needed to landfill solid waste and CCR (see TDD for details; U.S. EPA, 2024f). EPA estimated CO_2, NO_X, and SO_2 emissions associated with changes in energy requirements to power wastewater treatment systems by multiplying plant-specific changes in electricity consumption by plant- or North American Electric Reliability Corporation (NERC)-specific emission factors obtained from IPM for the baseline in run year 2035.[107] EPA estimated the changes in air emissions associated with changes in transportation by multiplying the increase in the number of miles traveled to dispose of CCR by average emission factors.

Table 8-2 and Table 8-3 respectively summarize the estimated changes in emissions associated with changes in power requirements to operate treatment systems and with the incremental transportation of CCR and solid waste under the regulatory options. For consistency, the tables present estimates for selected IPM model years. EPA modeled emissions in each year based on when each plant is estimated to implement technologies for each wastestream and any announced unit retirements. EPA estimates that changes in power requirements and transportation will increase emissions slightly, relative to the baseline. The variations across regulatory options reflect differences in treatment technologies and affected steam electric plants, whereas variations across model years for a given regulatory option reflect the timing of technology implementation and announced EGU retirements.[108]

Table 8-2: Estimated Changes in Air Pollutant Emissions Due to Increase in Power Requirements at Steam Electric Power Plants 2025-2049, Compared to Baseline

Year	CO_2 (Million Tons/Year)[a]	NOx (Thousand Tons/Year)[a]	SO_2 (Thousand Tons/Year)[a]	Primary $PM_{2.5}$ (Thousand Tons/Year)[a]	CH_4 (Million Tons/Year)[a]
Option A					
2028	0.034	0.015	0.020	Not estimated	Not estimated
2030	0.069	0.044	0.049	Not estimated	Not estimated
2035	0.069	0.044	0.049	Not estimated	Not estimated
2040	0.068	0.044	0.049	Not estimated	Not estimated
2045	0.068	0.044	0.049	Not estimated	Not estimated
2050	0.068	0.041	0.047	Not estimated	Not estimated

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[107] Applying grid emission factors developed for run year 2035 to the entire period of analysis may overstate emissions associated with power requirements for operating treatment systems since emission factors decline during the period of analysis.

[108] For the purpose of this analysis, EPA developed a time profile of air emissions changes based on plants' estimated technology implementation years during the period of 2025 through 2029, as well as announced EGU retirements during the period of analysis. For EGUs that retire during the analysis period, incremental power requirements and trucking associated with BA transport water and FGD wastewater treatment cease, but those associated with CRL continue even after the unit retires.

Table 8-2: Estimated Changes in Air Pollutant Emissions Due to Increase in Power Requirements at Steam Electric Power Plants 2025-2049, Compared to Baseline

Year	CO$_2$ (Million Tons/Year)[a]	NOx (Thousand Tons/Year)[a]	SO$_2$ (Thousand Tons/Year)[a]	Primary PM$_{2.5}$ (Thousand Tons/Year)[a]	CH$_4$ (Million Tons/Year)[a]
Option B (Final Rule)					
2028	0.073	0.043	0.066	Not estimated	Not estimated
2030	0.14	0.088	0.12	Not estimated	Not estimated
2035	0.14	0.088	0.12	Not estimated	Not estimated
2040	0.14	0.088	0.12	Not estimated	Not estimated
2045	0.14	0.087	0.12	Not estimated	Not estimated
2050	0.14	0.083	0.11	Not estimated	Not estimated
Option C					
2028	0.085	0.052	0.070	Not estimated	Not estimated
2030	0.16	0.10	0.12	Not estimated	Not estimated
2035	0.16	0.10	0.12	Not estimated	Not estimated
2040	0.16	0.10	0.12	Not estimated	Not estimated
2045	0.16	0.098	0.12	Not estimated	Not estimated
2050	0.16	0.094	0.12	Not estimated	Not estimated

a. Values rounded to two significant figures. Positive values indicate an increase in emissions.

Source: U.S. EPA Analysis, 2024

Table 8-3: Estimated Changes in Air Pollutant Emissions Due to Increase in Trucking at Steam Electric Power Plants 2025-2049, Compared to Baseline

Year	CO$_2$ (Million Tons/Year)[a]	NOx (Thousand Tons/Year)[a]	SO$_2$ (Thousand Tons/Year)[a]	Primary PM$_{2.5}$ (Thousand Tons/Year)[a]	CH$_4$ (Million Tons/Year)[a]
Option A					
2028	0.00041	0.00083	0.0000014	Not estimated	0.0000036
2030	0.00074	0.0016	0.0000025	Not estimated	0.0000070
2035	0.00074	0.0016	0.0000025	Not estimated	0.0000070
2040	0.00074	0.0016	0.0000025	Not estimated	0.0000070
2045	0.00074	0.0016	0.0000025	Not estimated	0.0000070
2050	0.00070	0.0015	0.0000024	Not estimated	0.0000066
Option B (Final Rule)					
2028	0.00047	0.00097	0.0000016	Not estimated	0.0000042
2030	0.00087	0.0019	0.0000029	Not estimated	0.0000083
2035	0.00087	0.0019	0.0000029	Not estimated	0.0000083
2040	0.00087	0.0019	0.0000029	Not estimated	0.0000083
2045	0.00087	0.0019	0.0000029	Not estimated	0.0000083
2050	0.00083	0.0018	0.0000028	Not estimated	0.0000079
Option C					
2028	0.00055	0.0012	0.0000019	Not estimated	0.0000050
2030	0.0012	0.0025	0.0000039	Not estimated	0.000011
2035	0.0012	0.0025	0.0000039	Not estimated	0.000011
2040	0.0012	0.0025	0.0000039	Not estimated	0.000011
2045	0.0011	0.0025	0.0000039	Not estimated	0.000011
2050	0.0011	0.0024	0.0000037	Not estimated	0.000010

a. Values rounded to two significant figures. Positive values indicate an increase in emissions.

Source: U.S. EPA Analysis, 2024

Table 8-4 summarizes the estimated changes in pollutant emissions from electricity generation under the final rule (*i.e.*, Option B).[109] Projected changes in the profile of electricity generation under Option B, compared to the baseline, generally lead to national-level reductions in emissions for all air pollutants modeled. The pattern of change follows the decline in coal generation described above. Thus, the largest declines in CO_2, NO_X, SO_2 and $PM_{2.5}$ emissions occur in model years 2028 through 2035 before tapering off in the latter run years of the analysis. Thus, at the national level, CO_2 emissions are estimated to decrease by between 11 million and 16 million tons during run years 2028 through 2035 under the final rule when compared to the baseline. Reductions in run years 2040 through 2050 are much smaller (0.7 million to 2.1 million tons per year). In relative terms, the largest effect is SO_2 emissions for the final rule is estimated to reduce baseline emissions by approximately 5 percent in model year 2035.

The impact on emissions varies across regions and by pollutant with emissions increasing in some and decreasing in other NERC regions, as detailed in the RIA (Table 5-4; U.S. EPA, 2024e).

Table 8-4: Estimated Changes in Pollutant Emissions Due to Changes in Electricity Generation Profile, Compared to Baseline

Regulatory Option	Year	CO_2 (Million Tons/Year)[a]	NOx (Thousand Tons/Year)[a]	SO_2 (Thousand Tons/Year)[a]	Primary $PM_{2.5}$ (Thousand Tons/Year)[a]	CH_4 (Million Tons/Year)[a]
Option B (Final Rule)	2028	-16	-8.9	-11	-0.63	Not estimated
	2030	-11	-7.4	-2.5	-0.38	Not estimated
	2035	-13	-8.8	-13	-0.25	Not estimated
	2040	-2.1	-3.2	-2.3	-0.16	Not estimated
	2045	-1.4	-0.7	-1.0	-0.093	Not estimated
	2050	-0.72	-0.45	-0.78	-0.12	Not estimated

a. Values rounded to two significant figures. Negative values indicate a reduction in emissions.

Source: U.S. EPA Analysis, 2024; See Chapter 5 in RIA for details on IPM (U.S. EPA, 2024e).

A comparison of estimated changes in emissions across the three mechanisms (Table 8-2, Table 8-3 and Table 8-4) for the final rule (Option B) shows that the largest effect on projected air emissions comes from the change in the emissions profile of electricity generation at the market level. Table 8-5 presents the net changes in emissions of the four pollutants compared to baseline. The next two sections quantify the climate change and human health benefits associated with changes in emissions under the final rule (Option B).

Table 8-5: Estimated Net Changes in Air Pollutant Emissions Due to Changes in Power Requirements, Trucking, and Electricity Generation Profile, Compared to Baseline

Regulatory Option	Year	CO_2 (Million Tons/Year)[a]	NOx (Thousand Tons/Year)[a]	SO_2 (Thousand Tons/Year)[a]	Primary $PM_{2.5}$ (Thousand Tons/Year)[a]	CH_4 (Million Tons/Year)[a]
Option B (Final Rule)	2028	-16	-8.9	-11	-0.63	0.0000042
	2030	-11	-7.3	-2.4	-0.38	0.0000083
	2035	-13	-8.7	-13	-0.25	0.0000083
	2040	-1.9	-3.1	-2.2	-0.16	0.0000083
	2045	-1.3	-0.63	-0.85	-0.093	0.0000083
	2050	-0.58	-0.37	-0.67	-0.12	0.0000079

a. Values rounded to two significant figures. Negative values indicate a net reduction in emissions.

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[109] EPA did not run IPM for Option A and Option C.

Table 8-5: Estimated Net Changes in Air Pollutant Emissions Due to Changes in Power Requirements, Trucking, and Electricity Generation Profile, Compared to Baseline

Regulatory Option	Year	CO_2 (Million Tons/Year)[a]	NOx (Thousand Tons/Year)[a]	SO_2 (Thousand Tons/Year)[a]	Primary $PM_{2.5}$ (Thousand Tons/Year)[a]	CH_4 (Million Tons/Year)[a]

Source: U.S. EPA Analysis, 2024

8.2 Climate Change Benefits

8.2.1 Data and Methodology

EPA estimated the climate benefits of the net CO_2 and CH_4 emission changes expected from this final rule using the estimates of the social cost of greenhouse gases (SC-GHG) – specifically, the social cost of carbon (SC-CO_2) and social cost of methane (SC-CH_4)[110] – that reflect recent advances in the scientific literature on climate change and its economic impacts and incorporate recommendations made by the National Academies of Science, Engineering, and Medicine (National Academies, 2017). EPA published and used these estimates in the RIA for the December 2023 Final Oil and Gas New Source Performance Standards (NSPS)/Emissions Guidelines (EG) Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review". EPA solicited public comment on the methodology and use of these estimates in the RIA for the agency's December 2022 Oil and Gas NSPS/EG Supplemental Proposal (U.S. EPA, 2023l) and has conducted an external peer review of these estimates, as described further below.

The SC-GHG is the monetary value of the net harm to society associated with emitting a metric ton of the GHG in question into the atmosphere in a given year, or the net benefit of avoiding that increase. In principle, the SC-GHG includes the value of all climate change impacts (both negative and positive), including (but not limited to) changes in net agricultural productivity, human health effects, property damage from increased flood risk and natural disasters, disruption of energy systems, risk of conflict, environmental migration, and the value of ecosystem services. The SC-GHG therefore reflects the societal value of reducing emissions of the gas in question by one metric ton and is the theoretically appropriate value to use in conducting benefit-cost analyses of policies that affect greenhouse gas emissions. In practice, data and modeling limitations restrain the ability of SC-GHG estimates to include all physical, ecological, and economic impacts of climate change, implicitly assigning a value of zero to the omitted climate damages. The estimates are, therefore, a partial accounting of climate change impacts and likely underestimate of the marginal benefits of abatement.

EPA and other Federal agencies began regularly incorporating SC-GHG estimates in their benefit-cost analyses conducted under E.O. 12866[111] since 2008, following a Ninth Circuit Court of Appeals remand of a rule for failing to monetize the benefits of reducing greenhouse gas emissions in that rulemaking process. The values used by EPA from 2009 to 2016, and since 2021 – including in the proposal for this rulemaking – have been consistent with those developed and recommended by the Interagency Working Group on the SC-GHG

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[110] Estimates of the social cost of greenhouse gases are gas specific (*e.g.*, social cost of carbon (SC-CO_2), social cost of methane (SC-CH_4), social cost of nitrous oxide (SC-N_2O)), but collectively they are referenced as the social cost of greenhouse gases (SC-GHG).

[111] E.O. 12866, released in 1993 and still in effect today, requires that for all economically significant regulatory actions, an agency provide an assessment of the potential costs and benefits of the regulatory action, and that this assessment include a quantification of benefits and costs to the extent feasible. For purposes of this action, monetized climate benefits are presented for purposes of providing a complete benefit-cost analysis under EO 12866 and other relevant executive orders. The estimates of change in GHG emissions and the monetized benefits associated with those changes play no part in the record basis for this action.

(IWG); and the values used from 2017 to 2020 were consistent with those required by E.O. 13783, which disbanded the IWG. During 2015-2017, the National Academies conducted a comprehensive review of the SC-CO_2 and issued a final report in 2017 recommending specific criteria for future updates to the SC-CO_2 estimates, a modeling framework to satisfy the specified criteria, and both near-term updates and longer-term research needs pertaining to various components of the estimation process (National Academies, 2017). The IWG was reconstituted in 2021 and E.O. 13990 directed it to develop a comprehensive update of its SC-GHG estimates, recommendations regarding areas of decision-making to which SC-GHG should be applied, and a standardized review and updating process to ensure that the recommended estimates continue to be based on the best available economics and science going forward.

EPA is a member of the IWG and is participating in the IWG's work under E.O. 13990. As noted in previous EPA RIAs, including in the proposal for this rulemaking, while that process continues, EPA is continuously reviewing developments in the scientific literature on the SC-GHG, including more robust methodologies for estimating damages from emissions, and looking for opportunities to further improve SC-GHG estimation [112] In the December 2022 Oil and Gas NSPS/EG Supplemental Proposal RIA, the Agency included a sensitivity analysis of the climate benefits of the Supplemental Proposal using a new set of SC-GHG estimates that incorporates recent research addressing recommendations of the National Academies (National Academies, 2017) in addition to using the interim SC-GHG estimates presented in the Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates under Executive Order 13990 (IWG, 2021) that the IWG recommended for use until updated estimates that address the National Academies' recommendations are available.

EPA solicited public comment on the sensitivity analysis and the accompanying draft technical report, External Review Draft of Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances, which explains the methodology underlying the new set of estimates, in the December 2022 Supplemental Oil and Gas Proposal. The response to comments document can be found in the docket for that action.

To ensure that the methodological updates adopted in the technical report are consistent with economic theory and reflect the latest science, EPA also initiated an external peer review panel to conduct a high-quality review of the technical report, completed in May 2023. See 88 FR at 26075/2 noting this peer review process. The peer reviewers commended the agency on its development of the draft update, calling it a much-needed improvement in estimating the SC-GHG and a significant step toward addressing the National Academies' recommendations with defensible modeling choices based on current science. The peer reviewers provided numerous recommendations for refining the presentation and for future modeling improvements, especially with respect to climate change impacts and associated damages that are not currently included in the analysis. Additional discussion of omitted impacts and other updates have been incorporated in the technical report to address peer reviewer recommendations. Complete information about the external peer review, including the peer reviewer selection process, the final report with individual recommendations from peer reviewers, and EPA's response to each recommendation is available on EPA's website.[113]

The remainder of this section provides an overview of the methodological updates incorporated into the SC-GHG estimates used in this analysis. A more detailed explanation of each input and the modeling process is

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[112] EPA strives to base its analyses on the best available science and economics, consistent with its responsibilities, for example, under the Information Quality Act.

[113] See https://www.epa.gov/environmental-economics/scghg

provided in the technical report, *Supplementary Material for the RIA: EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances* (U.S. EPA, 2023n). Appendix B shows the climate benefits of the final rule using the interim SC-GHG (IWG, 2021) estimates presented in the proposal BCA for comparison purposes.

The steps necessary to estimate the SC-GHG with a climate change integrated assessment model (IAM) can generally be grouped into four modules: socioeconomics and emissions, climate, damages, and discounting. The emissions trajectories from the socioeconomic module are used to project future temperatures in the climate module. The damage module then translates the temperature and other climate endpoints (along with the projections of socioeconomic variables) into physical impacts and associated monetized economic damages, where the damages are calculated as the amount of money the individuals experiencing the climate change impacts would be willing to pay to avoid them. To calculate the marginal effect of emissions, *i.e.*, the SC-GHG in year *t*, the entire model is run twice—first as a baseline and second with an additional pulse of emissions in year *t*. After recalculating the temperature effects and damages expected in all years beyond *t* resulting from the adjusted path of emissions, the losses are discounted to a present value in the discounting module. Many sources of uncertainty in the estimation process are incorporated using Monte Carlo techniques by taking draws from probability distributions that reflect the uncertainty in parameters.

The SC-GHG estimates used by EPA and many other federal agencies since 2009 have relied on an ensemble of three widely used IAMs: Dynamic Integrated Climate and Economy (DICE) (W. D. Nordhaus, 2010); Climate Framework for Uncertainty, Negotiation, and Distribution (FUND) (Anthoff & Tol, 2013a, 2013b); and Policy Analysis of the Greenhouse Gas Effect (PAGE) (Hope, 2013). In 2010, the IWG harmonized key inputs across the IAMs, but all other model features were left unchanged, relying on the model developers' best estimates and judgments. That is, the representation of climate dynamics and damage functions included in the default version of each IAM as used in the published literature was retained.

The SC-GHG estimates in U.S. EPA (2023l) no longer rely on the three IAMs (*i.e.*, DICE, FUND, and PAGE) used in previous SC-GHG estimates. Instead, EPA uses a modular approach to estimating the SC-GHG, consistent with the National Academies' near-term recommendations (National Academies, 2017). That is, the methodology underlying each component, or module, of the SC-GHG estimation process is developed by drawing on the latest research and expertise from the scientific disciplines relevant to that component. Under this approach, each step in the SC-GHG estimation improves consistency with the current state of scientific knowledge, enhances transparency, and allows for more explicit representation of uncertainty.

The socioeconomic and emissions module relies on a new set of probabilistic projections for population, income, and GHG emissions developed under the Resources for the Future (RFF) Social Cost of Carbon Initiative (Rennert et al., 2021). These socioeconomic projections (hereafter collectively referred to as the RFF-SPs) are an internally consistent set of probabilistic projections of population, GDP, and GHG emissions (CO_2, CH_4, and N_2O) to 2300. Based on a review of available sources of long-run projections necessary for damage calculations, the RFF-SPs stand out as being most consistent with the National Academies' recommendations. Consistent with the National Academies' recommendation, the RFF-SPs were developed using a mix of statistical and expert elicitation techniques to capture uncertainty in a single probabilistic approach, taking into account the likelihood of future emissions mitigation policies and technological developments, and provide the level of disaggregation necessary for damage calculations. Unlike other sources of projections, they provide inputs for estimation out to 2300 without further extrapolation assumptions. Conditional on the modeling conducted for the SC-GHG estimates, this time horizon is far enough in the future to capture the majority of discounted climate damages. Including damages beyond 2300 would increase the estimates of the SC-GHG. As discussed in U.S. EPA (2023n), the use of the RFF-SPs allows for capturing economic growth uncertainty within the discounting module.

The climate module relies on the Finite Amplitude Impulse Response (FaIR) model (IPCC, 2021b; Millar et al., 2017; Smith et al., 2018), a widely used Earth system model which captures the relationships between GHG emissions, atmospheric GHG concentrations, and global mean surface temperature. The FaIR model was originally developed by Richard Millar, Zeb Nicholls, and Myles Allen at Oxford University, as a modification of the approach used in IPCC AR5 to assess the GWP and GTP (Global Temperature Potential) of different gases. It is open source, widely used (*e.g.*, IPCC (2018, 2021a)), and was highlighted by the National Academies (2017) as a model that satisfies their recommendations for a near-term update of the climate module in SC-GHG estimation. Specifically, it translates GHG emissions into mean surface temperature response and represents the current understanding of the climate and GHG cycle systems and associated uncertainties within a probabilistic framework. The SC-GHG estimates used in this RIA rely on FaIR version 1.6.2 as used by the IPCC (2021a). It provides, with high confidence, an accurate representation of the latest scientific consensus on the relationship between global emissions and global mean surface temperature, offers a code base that is fully transparent and available online, and the uncertainty capabilities in FaIR 1.6.2 have been calibrated to the most recent assessment of the IPCC (which importantly narrowed the range of likely climate sensitivities relative to prior assessments). See U.S. EPA (2023n) for more details.

The socioeconomic projections and outputs of the climate module are inputs into the damage module to estimate monetized future damages from climate change.[114] The National Academies' recommendations for the damage module, scientific literature on climate damages, updates to models that have been developed since 2010, as well as the public comments received on individual EPA rulemakings and the IWG's February 2021 TSD, have all helped to identify available sources of improved damage functions. The IWG (*e.g.*, IWG, 2010; 2016b, 2021), the National Academies (2017), comprehensive studies (*e.g.*, Rose et al. (2014)), and public comments have all recognized that the damages functions underlying the IWG SC-GHG estimates used since 2013 (taken from DICE 2010 (W.D. Nordhaus, 2010); FUND 3.8 (Anthoff & Tol, 2013a, 2013b); and PAGE 2009 (Hope, 2012)) do not include all of important physical, ecological, and economic impacts of climate change. The climate change literature and the science underlying the economic damage functions have evolved, and DICE 2010, FUND 3.8, and PAGE 2009 now lag behind the most recent research.

The challenges involved with updating damage functions have been widely recognized. Functional forms and calibrations are constrained by the available literature and need to extrapolate beyond warming levels or locations studied in that literature. Research focused on understanding how these physical changes translate into economic impacts is still developing, and has received less public resources, relative to the research focused on modeling and improving our understanding of climate system dynamics and the physical impacts from climate change (Auffhammer, 2018). Even so, there has been a large increase in research on climate

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[114] In addition to temperature change, two of the three damage modules used in the SC-GHG estimation require global mean sea level (GMSL) projections as an input to estimate coastal damages. Those two damage modules use different models for generating estimates of GMSL. Both are based off reduced complexity models that can use the FaIR temperature outputs as inputs to the model and generate projections of GMSL accounting for the contributions of thermal expansion and glacial and ice sheet melting based on recent scientific research. Absent clear evidence on a preferred model, the SC-GHG estimates presented in this chapter retain both methods used by the damage module developers. See U.S. Environmental Protection Agency. (2023n). *Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review": EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances*. Retrieved from https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf for more details.

impacts and damages in the time since DICE 2010, FUND 3.8, and PAGE 2009 were published. Along with this growth, there continues to be variation in methodologies and scope of studies, such that care is required when synthesizing the current understanding of impacts or damages. Based on a review of available studies and approaches to damage function estimation, EPA uses three separate damage functions to form the damage module. They are:

1. a subnational-scale, sectoral damage function (based on the Data-driven Spatial Climate Impact Model (DSCIM) developed by the Climate Impact Lab (Carleton et al., 2022; Climate Impact Lab (CIL), 2023; Rode et al., 2021),
2. a country-scale, sectoral damage function (based on the Greenhouse Gas Impact Value Estimator (GIVE) model developed under RFF's Social Cost of Carbon Initiative (Rennert et al., 2022), and
3. a meta-analysis-based damage function (based on Howard & Sterner, 2017).

The damage functions in DSCIM and GIVE represent substantial improvements relative to the damage functions underlying the SC-GHG estimates used by EPA to date and reflect the forefront of scientific understanding about how temperature change and sea level rise lead to monetized net (market and nonmarket) damages for several categories of climate impacts. The models' spatially explicit and impact-specific modeling of relevant processes allows for improved understanding and transparency about mechanisms through which climate impacts are occurring and how each damage component contributes to the overall results, consistent with the National Academies' recommendations. DSCIM addresses common criticisms related to the damage functions underlying current SC-GHG estimates (*e.g.*, Pindyck (2017)) by developing multi-sector, empirically grounded damage functions. The damage functions in the GIVE model offer a direct implementation of the National Academies' near-term recommendation to develop updated sectoral damage functions that are based on recently published work and reflective of the current state of knowledge about damages in each sector. Specifically, the National Academies noted that "[t]he literature on agriculture, mortality, coastal damages, and energy demand provide immediate opportunities to update the [models]" (National Academies, 2017, p. 199), which are the four damage categories currently in GIVE. A limitation of both models is that the sectoral coverage is still limited, and even the categories that are represented are incomplete. Neither DSCIM nor GIVE yet accommodate estimation of several categories of temperature driven climate impacts (*e.g.*, morbidity, conflict, migration, biodiversity loss) and only represent a limited subset of damages from changes in precipitation. For example, while precipitation is considered in the agriculture sectors in both DSCIM and GIVE, neither model takes into account impacts of flooding, changes in rainfall from tropical storms, and other precipitation related impacts. As another example, the coastal damage estimates in both models do not fully reflect the consequences of sea level rise-driven salt-water intrusion and erosion, or sea level rise damages to coastal tourism and recreation. Other missing elements are damages that result from other physical impacts (*e.g.*, ocean acidification, non-temperature-related mortality such as diarrheal disease and malaria) and the many feedbacks and interactions across sectors and regions that can lead to additional damages.[115] See U.S. EPA (2023n) for more discussion of omitted damage categories and other modeling limitations. DSCIM and GIVE do account for the most commonly cited benefits associated with CO_2 emissions and climate change—CO_2 crop fertilization and declines in cold related mortality. As such, while the GIVE- and DSCIM-based results provide state-of-the-science assessments of

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[115] The one exception is that the agricultural damage function in DSCIM and GIVE reflects the ways that trade can help mitigate damages arising from crop yield impacts.

key climate change impacts, they remain partial estimates of future climate damages resulting from incremental changes in CO_2, CH_4, and N_2O.[116]

Finally, given the still relatively narrow sectoral scope of the recently developed DSCIM and GIVE models, the damage module includes a third damage function that reflects a synthesis of the state of knowledge in other published climate damages literature. Studies that employ meta-analytic techniques offer a tractable and straightforward way to combine the results of multiple studies into a single damage function that represents the body of evidence on climate damages that pre-date CIL and RFF's research initiatives.[117] The first use of meta-analysis to combine multiple climate damage studies was done by Tol (2009) and included 14 studies. The studies in Tol (2009) served as the basis for the global damage function in DICE starting in version 2013R (Nordhaus, 2014). The damage function in the most recent published version of DICE, DICE 2016, is from an updated meta-analysis based on a review of existing damage studies and included 26 studies published over 1994-2013 (Nordhaus & Moffat, 2017). Howard and Sterner (2017) provide a more recent published peer-reviewed meta-analysis of existing damage studies (published through 2016) and account for additional features of the underlying studies. This study addresses differences in measurement across studies by adjusting estimates such that the data are relative to the same base period. They also eliminate double counting by removing duplicative estimates. Howard and Sterner's final sample is drawn from 20 studies that were published through 2015. Howard and Sterner (2017) present results under several specifications, and their analysis shows that the estimates are somewhat sensitive to defensible alternative modeling choices. As discussed in detail in U.S. EPA (2023n), the damage module underlying the SC-GHG estimates in this analysis includes the damage function specification (that excludes duplicate studies) from Howard and Sterner (2017) that leads to the lowest SC-GHG estimates, all else equal.

The discounting module discounts the stream of future net climate damages to its present value in the year when the additional unit of emissions was released. Given the long time horizon over which the damages are expected to occur, the discount rate has a large influence on the present value of future damages. Consistent with the findings of National Academies (2017), the economic literature, OMB Circular A-4's guidance for regulatory analysis, and IWG recommendations to date (IWG, 2010, 2013; 2016a, 2016b, 2021), EPA continues to conclude that the consumption rate of interest is the theoretically appropriate discount rate to discount the future benefits of reducing GHG emissions and that discount rate uncertainty should be accounted for in selecting future discount rates in this intergenerational context. OMB's Circular A-4 points out that "the analytically preferred method of handling temporal differences between benefits and costs is to adjust all the benefits and costs to reflect their value in equivalent units of consumption before discounting them." (OMB, 2023)[118] The damage module described above calculates future net damages in terms of

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[116] One advantage of the modular approach used by these models is that future research on new or alternative damage functions can be incorporated in a relatively straightforward way. DSCIM and GIVE developers have work underway on other impact categories that may be ready for consideration in future updates (*e.g.,* morbidity and biodiversity loss).

[117] Meta-analysis is a statistical method of pooling data and/or results from a set of comparable studies of a problem. Pooling in this way provides a larger sample size for evaluation and allows for a stronger conclusion than can be provided by any single study. Meta-analysis yields a quantitative summary of the combined results and current state of the literature.

[118] The previous version of OMB's Circular A-4 similarly pointed out that "the analytically preferred method of handling temporal differences between benefits and costs is to adjust all the benefits and costs to reflect their value in equivalent units of consumption and to discount them at the rate consumers and savers would normally use in discounting future consumption benefits" (U.S. Office of Management and Budget. (2023). *Circular A-4: Regulatory Analysis*. Retrieved from https://www.whitehouse.gov/wp-content/uploads/2023/11/CircularA-4.pdf, ibid.).

reduced consumption (or monetary consumption equivalents), and so an application of this guidance is to use the consumption discount rate to calculate the SC-GHG.[119]

For the SC-GHG estimates used in this analysis, EPA relies on a dynamic discounting approach that more fully captures the role of uncertainty in the discount rate in a manner consistent with the other modules. Based on a review of the literature and data on consumption discount rates, the public comments received on individual EPA rulemakings, and the February 2021 TSD (IWG, 2021), and the National Academies (2017) recommendations for updating the discounting module, the SC-GHG estimates rely on discount rates that reflect more recent data on the consumption interest rate and uncertainty in future rates. Specifically, rather than using a constant discount rate, the evolution of the discount rate over time is defined following the latest empirical evidence on interest rate uncertainty and using a framework originally developed by Ramsey (1928) that connects economic growth and interest rates. The Ramsey approach explicitly reflects (1) preferences for utility in one period relative to utility in a later period and (2) the value of additional consumption as income changes. The dynamic discount rates used to develop the SC-GHG estimates applied in this analysis have been calibrated following the Newell, Pizer and Prest (2022) approach, as applied in Rennert et al. (2022). This approach uses the Ramsey (1928) discounting formula in which the parameters are calibrated such that (1) the decline in the certainty-equivalent discount rate matches the latest empirical evidence on interest rate uncertainty estimated by Bauer and Rudebusch (2020, 2023) and (2) the average of the certainty-equivalent discount rate over the first decade matches a near-term consumption rate of interest. Uncertainty in the starting rate is addressed by using three near-term target rates (1.5, 2.0, and 2.5 percent) based on multiple lines of evidence on observed market interest rates.

The resulting dynamic discount rate provides a notable improvement over the constant discount rate framework used for SC-GHG estimation in EPA regulatory impact analyses to date. Specifically, it provides internal consistency within the modeling and a more complete accounting of uncertainty consistent with economic theory (Arrow et al., 2013; Cropper et al., 2014) and the National Academies' (2017) recommendation to employ a more structural, Ramsey-like approach to discounting that explicitly recognizes the relationship between economic growth and discounting uncertainty. This approach is also consistent with the National Academies (2017) recommendation to use three sets of Ramsey parameters that reflect a range of near-term certainty-equivalent discount rates and are consistent with theory and empirical evidence on consumption rate uncertainty. Finally, the value of aversion to risk associated with net damages from GHG emissions is explicitly incorporated into the modeling framework following the economic literature. See U.S. EPA (2023n) for a more detailed discussion of the entire discounting module and methodology used to value risk aversion in the SC-GHG estimates.

Taken together, the methodologies adopted in this SC-GHG estimation process allow for a more holistic treatment of uncertainty than in past estimates by EPA. The updates incorporate a quantitative consideration of uncertainty into all modules and use a Monte Carlo approach that captures the compounding uncertainties across modules. The estimation process generates nine separate distributions of discounted marginal damages per metric ton — the product of using three damage modules and three near-term target discount rates — for each gas in each emissions year. These distributions have long right tails reflecting the extensive evidence in

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[119] See the discussion of the inappropriateness of discounting consumption-equivalent measures of benefits and costs using a rate of return on capital in Circular A-4 (ibid., ibid.). Note that under the previous version of OMB's Circular A-4 EPA also concluded that the use of the social rate of return on capital (7 percent under the 2003 OMB Circular A-4 guidance), which does not reflect the consumption rate, to discount damages estimated in terms of reduced consumption would inappropriately underestimate the impacts of climate change for the purposes of estimating the SC-GHG.

the scientific and economic literature that shows the potential for lower-probability but higher-impact outcomes from climate change, which would be particularly harmful to society. The uncertainty grows over the modeled time horizon. Therefore, under cases with a lower near-term target discount rate – that give relatively more weight to impacts in the future – the distribution of results is wider. To produce a range of estimates that reflects the uncertainty in the estimation exercise while also providing a manageable number of estimates for policy analysis, EPA combines the multiple lines of evidence on damage modules by averaging the results across the three damage module specifications. The full results generated from the updated methodology for methane and other greenhouse gases (SC-CO_2, SC-CH_4, and SC-N_2O) for emissions years 2020 through 2080 are provided in U.S. EPA (2023n).

Table 8-6 presents the resulting averaged certainty-equivalent SC-CO_2 and SC-CH_4 estimates for emissions occurring in 2025 to 2049 under each near-term discount rate that are used to estimate the climate benefits of the CO_2 and CH_4 changes expected from the final rule. These estimates are reported in 2023 dollars but are otherwise identical to those presented in U.S. EPA (2023l). The SC-GHG increases over time within the models — *i.e.*, the societal harm from one metric ton emitted in 2030 is higher than the harm caused by one metric ton emitted in 2025 — because future emissions produce larger incremental damages as physical and economic systems become more stressed in response to greater climatic change, and because GDP is growing over time and many damage categories are modeled as proportional to GDP. EPA estimated the climate benefits of the net CO_2 and CH_4 emission changes for each analysis year between 2025 and 2049 by applying the annual SC-CO_2 and SC-CH_4 estimates, shown in Table 8-6, to the estimated changes in CO_2 and CH_4 emissions in the corresponding year under the regulatory options.

Table 8-6: Estimates of the Social Cost of Greenhouse Gas by Year and Near-Term Ramsey Discount Rate, 2025–2049

Year	Social Cost of CO2 (2023$/Metric Tonne CO_2)			Social Cost of CH_4 (2023$/Metric Tonne CH_4)		
	1.5%	2.0%	2.5%	1.5%	2.0%	2.5%
2025	$150	$250	$430	$1,800	$2,300	$3,200
2026	$150	$250	$420	$1,900	$2,400	$3,300
2027	$160	$250	$430	$2,000	$2,500	$3,400
2028	$160	$260	$440	$2,100	$2,600	$3,500
2029	$160	$260	$440	$2,200	$2,700	$3,600
2030	$170	$270	$450	$2,200	$2,800	$3,700
2031	$170	$270	$450	$2,300	$2,900	$3,800
2032	$170	$270	$460	$2,400	$3,000	$3,900
2033	$180	$280	$460	$2,500	$3,100	$4,000
2034	$180	$280	$470	$2,600	$3,200	$4,100
2035	$180	$290	$470	$2,700	$3,300	$4,300
2036	$190	$290	$480	$2,800	$3,400	$4,400
2037	$190	$300	$480	$2,900	$3,500	$4,500
2038	$190	$300	$490	$3,000	$3,600	$4,600
2039	$200	$310	$490	$3,000	$3,700	$4,700
2040	$200	$310	$500	$3,100	$3,800	$4,800
2041	$200	$310	$510	$3,200	$3,900	$5,000
2042	$210	$320	$510	$3,300	$4,000	$5,100
2043	$210	$320	$520	$3,400	$4,100	$5,200
2044	$220	$330	$520	$3,500	$4,200	$5,300
2045	$220	$330	$530	$3,600	$4,400	$5,500
2046	$220	$340	$540	$3,700	$4,500	$5,600
2047	$230	$340	$540	$3,800	$4,600	$5,700
2048	$230	$350	$550	$3,900	$4,700	$5,900

Table 8-6: Estimates of the Social Cost of Greenhouse Gas by Year and Near-Term Ramsey Discount Rate, 2025–2049

Year	Social Cost of CO2 (2023$/Metric Tonne CO_2)			Social Cost of CH_4 (2023$/Metric Tonne CH_4)		
	1.5%	2.0%	2.5%	1.5%	2.0%	2.5%
2049	$230	$350	$550	$4,000	$4,800	$6,000

Note: Values shown are rounded to two significant figures, but the unrounded values were used in the calculations and are available in the Appendix to U.S. EPA (2023n). These SC-GHG values are identical to those reported in U.S. EPA (2023n) adjusted for inflation to 2023 dollars using the annual GDP Implicit Price Deflator values in the U.S. Bureau of Economic Analysis' (BEA) National Income and Product Accounts Table 1.1.9 (U.S. BEA, 2023; U.S. BEA, 2024), which are 122.262 and 105.381, respectively for 2023 and 2020. SC-CO_2 and SC-CH_4 values are stated in $/metric tonne CO_2 and CH_4, respectively (1 metric tonne equals 1.102 short tons) and vary depending on the year of emissions.

Source: U.S. EPA Analysis, 2024 based on U.S. EPA (2023l; U.S. EPA (2023n).

The methodological updates incorporated in U.S. EPA (2023l) and summarized above represent a major step forward in bringing SC-GHG estimation closer to the frontier of climate science and economics and address many of the near-term recommendations by the National Academies (2017). Nevertheless, the SC-GHG estimates presented in Table 8-6 still have several limitations, as would be expected for any modeling exercise that covers such a broad scope of scientific and economic issues across a complex global landscape. There are still many categories of climate impacts and associated damages that are only partially or not reflected yet in these estimates and sources of uncertainty that have not been fully characterized due to data and modeling limitations. For example, the modeling omits most of the consequences of changes in precipitation, damages from extreme weather events, the potential for nongradual damages from passing critical thresholds (*e.g.*, tipping elements) in natural or socioeconomic systems, and non-climate mediated effects of GHG emissions. The SC-CH_4 estimates do not account for the direct health and welfare impacts associated with tropospheric ozone produced by methane. Importantly, the updated SC-GHG methodology does not yet reflect interactions and feedback effects within, and across, Earth and human systems. For example, it does not explicitly reflect potential interactions among damage categories, such as those stemming from the interdependencies of energy, water, and land use. These, and other, interactions and feedbacks were highlighted by the National Academies as an important area of future research for longer-term enhancements in the SC-GHG estimation framework.

8.2.2 Results

Table 8-7 presents the undiscounted annual monetized climate benefits in selected years for Option B, the final rule. Benefits are calculated using the three different estimates of the SC-GHG from Table 8-6 based on the near-term Ramsey discount rates. EPA first mapped IPM emissions changes to corresponding years within the period of analysis 2025-2049 based on Table 8-1 and assuming no changes in air emissions from electricity generation between 2025 and 2027. For trucking and energy use, EPA estimated changes in air emissions corresponding to the year each plant is estimated to implement changes in technology. Net CO_2 and CH_4 changes each year are then multiplied by the SC-CO_2 or SC-CH_4 estimates for that year. EPA calculated the present value of climate benefits as of the expected rule promulgation year of 2024 by discounting each year-specific value to the year 2024 using the same near-term Ramsey discount rate used to calculate the corresponding SC-GHG.[120] That is, future climate benefits estimated with the SC-GHG at the 2.5 percent,

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[120] As discussed in U.S. Environmental Protection Agency. (2023n). *Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review": EPA Report on the Social Cost of Greenhouse Gases: Estimates*

2 percent, and 1.5 percent Ramsey rate are discounted to the base year of the analysis using a constant 2.5, 2, and 1.5 percent rate, respectively.

The profile of benefits is the result of both ELG effects and other factors. Thus, the larger benefits beginning in 2028 coincide with the timing of compliance with the revised ELGs and impacts of the rule on the generation mix, whereas the decline starting around 2038 coincide with emissions reductions already projected in Base Case due to factors external to the revised ELGs. See Chapter 5 in the RIA for details on IPM Base Case projections (U.S. EPA, 2024e).

Table 8-7: Estimated Undiscounted and Total Present Value of Climate Benefits from Changes in CO_2 and CH_4 Emissions under the Final Rule, Compared to Baseline (Millions of 2023$)

Regulatory Option	Year	Climate Benefits[a, b]		
		SC-GHG based on 1.5% near term Ramsey discount rate	**SC-GHG based on 2% near-term Ramsey discount rate**	**SC-GHG based on 2.5% near-term Ramsey discount rate**
Option B (Final Rule)	2025	$0.0	$0.0	$0.0
	2026	-$5.7	-$9.2	-$15.7
	2027	-$8.4	-$13.5	-$22.9
	2028	$2,393.4	$3,839.8	$6,457.1
	2029	$2,424.2	$3,885.6	$6,533.2
	2030	$1,642.7	$2,623.8	$4,380.6
	2031	$1,677.0	$2,669.4	$4,437.7
	2032	$1,993.3	$3,149.4	$5,235.7
	2033	$2,033.2	$3,202.6	$5,288.9
	2034	$2,059.8	$3,255.7	$5,355.4
	2035	$2,099.6	$3,295.6	$5,421.8
	2036	$2,139.5	$3,348.8	$5,475.0
	2037	$2,179.4	$3,401.9	$5,541.4
	2038	$340.5	$528.2	$860.5
	2039	$346.7	$536.3	$868.7
	2040	$352.8	$544.5	$878.9
	2041	$358.9	$552.7	$889.2
	2042	$242.4	$372.3	$597.1
	2043	$246.4	$377.8	$603.9
	2044	$251.9	$383.2	$610.7
	2045	$255.9	$388.6	$617.5
	2046	$260.0	$394.1	$625.7
	2047	$264.2	$401.0	$632.7
	2048	$121.7	$183.5	$288.7
	2049	$123.6	$186.0	$291.9
	Total present value	**$18,774.7**	**$31,019.9**	**$53,649.9**
	Annualized value	**$994.1**	**$1,557.7**	**$2,551.0**

a. Values rounded to two significant figures.

Incorporating Recent Scientific Advances. Retrieved from https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf, the error associated with using a constant discount rate rather than the certainty-equivalent rate path to calculate the present value of a future stream of monetized climate benefits is small for analyses with moderate time frames (*e.g.*, 30 years or less). Ibid. also provides an illustration of the amount that climate benefits from reductions in future emissions will be underestimated by using a constant discount rate relative to the more complicated certainty-equivalent rate path.

Table 8-7: Estimated Undiscounted and Total Present Value of Climate Benefits from Changes in CO_2 and CH_4 Emissions under the Final Rule, Compared to Baseline (Millions of 2023$)

Regulatory Option	Year	Climate Benefits[a, b]		
		SC-GHG based on 1.5% near term Ramsey discount rate	SC-GHG based on 2% near-term Ramsey discount rate	SC-GHG based on 2.5% near-term Ramsey discount rate

b. Climate benefits are based on changes in CO_2 and CH_4 emissions and are calculated using three different estimates of the SC-GHG (1.5 percent, 2 percent, and 2.5 percent near-term Ramsey discount rates).

Source: U.S. EPA Analysis, 2024

Table 8-8 shows the annualized climate benefits associated with changes in CO_2 and CH_4 emissions over the 2025-2049 period under each discount rate for the final rule by category of emissions. EPA annualized the climate benefits to enable consistent reporting across benefit categories (*e.g.*, benefits from improvement in water quality). As noted above, the IPM model run provides outputs starting in 2028. For the years 2025 through 2027, EPA assumed no change in air emissions from changes in the profile of electricity generation. For trucking and energy use, EPA estimated changes in air emissions corresponding to the year each plant is estimated to implement changes in technology. For each SC-GHG estimate, EPA then calculated the annualized benefits from the perspective of 2024 by discounting each year-specific value to the year 2024 using the same near-term discount rate used to calculate the SC-GHG. Using the SC-GHG values for the 2 percent near-term discount rate and using a 2 percent discount to annualize the benefits yields annualized benefits of $1,558 million.

Table 8-8: Estimated Annualized Climate Benefits from Changes in CO_2 and CH_4 Emissions under the Final Rule during the Period of 2025-2049 by Categories of Air Emissions and SC-GHG Estimates, Compared to Baseline (Millions of 2023$)

Regulatory Option	Category of Air Emissions	Annualized Climate Benefits[a,b]		
		1.5% Discount Rate	2.0% Discount Rate	2.5% Discount Rate
Option B (Final Rule)	Electricity generation	$1,014.0	$1,589.1	$2,602.8
	Trucking	-$0.1	-$0.2	-$0.3
	Energy use	-$19.7	-$31.2	-$51.4
	Total	**$994.2**	**$1,557.7**	**$2,551.1**

a. Values rounded to two significant figures. Negative values indicate forgone benefits whereas positive values indicate positive benefits.

b. Climate benefits are based on changes CO_2 and CH_4 emissions and are calculated using three different estimates of the SC-CO_2 and SC-CH_4 (1.5 percent, 2.0 percent, and 2.5 percent near-term Ramsey discount rates).

Source: U.S. EPA Analysis, 2024

Unlike many environmental problems where the causes and impacts are distributed more locally, GHG emissions are a global externality making climate change a true global challenge. GHG emissions contribute to damages around the world regardless of where they are emitted. Because of the distinctive global nature of climate change, in the BCA for this final rule EPA centers attention on a global measure of climate benefits from GHG reductions. Consistent with all IWG recommended SC-GHG estimates to date, the SC-GHG values presented in Table 8-6 above provide a global measure of monetized damages from GHG emissions and Tables 8-7 and 8-8 present the monetized global climate benefits of the GHG emission changes expected from the final rule. This approach is the same as that taken in EPA regulatory analyses from 2009 through 2016 and since 2021. It is also consistent with guidance in Circular A-4 (OMB, 2003) that recommends reporting of important international effects.[121] EPA also notes that EPA's cost estimates in RIAs, including the cost estimates contained in this BCA, regularly do not differentiate between the share of compliance costs expected to accrue to U.S. firms versus foreign interests, such as to foreign investors in regulated entities.[122] A global perspective on climate effects is therefore consistent with the approach EPA takes on costs. There are many reasons, as summarized in this section – and as articulated by OMB and in IWG assessments (IWG, 2010, 2013; 2016a, 2016b, 2021), the 2015 Response to Comments (IWG, 2015) and in detail in U.S. EPA (2023n) and in Appendix A of the Response to Comments document for the December 2023 Final Oil and Gas NSPS/EG Rulemaking – why EPA focuses on the global value of climate change impacts when analyzing policies that affect GHG emissions.

International cooperation and reciprocity are essential to successfully addressing climate change, as the global nature of greenhouse gases means that a ton of GHGs emitted in any other country harms those in the United States just as much as a ton emitted within the territorial United States. Assessing the benefits of U.S. GHG mitigation activities requires consideration of how those actions may affect mitigation activities by other countries, as those international mitigation actions will provide a benefit to U.S. citizens and residents by mitigating climate impacts that affect U.S. citizens and residents. This is a classic public goods problem because each country's reductions benefit everyone else, and no country can be excluded from enjoying the benefits of other countries' reductions. The only way to achieve an efficient allocation of resources for emissions reduction on a global basis — and so benefit the United States and its citizens and residents — is for all countries to base their policies on global estimates of damages. A wide range of scientific and

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[121] The 2003 version of OMB Circular A-4 states when a regulation is likely to have international effects, "these effects should be reported"; while OMB Circular A-4 recommends that international effects we reported separately, the guidance also explains that "[d]ifferent regulations may call for different emphases in the analysis, depending on the nature and complexity of the regulatory issues." (U.S. Office of Management and Budget. (2003). *Circular A-4: Regulatory Analysis*. Retrieved from https://www.whitehouse.gov/sites/whitehouse.gov/files/omb/circulars/A4/a-4.pdf). The 2023 update to Circular A-4 states that "In certain contexts, it may be particularly appropriate to include effects experienced by noncitizens residing abroad in your primary analysis. Such contexts include, for example, when:

- assessing effects on noncitizens residing abroad provides a useful proxy for effects on U.S. citizens and residents that are difficult to otherwise estimate;
- assessing effects on noncitizens residing abroad provides a useful proxy for effects on U.S. national interests that are not otherwise fully captured by effects experienced by particular U.S. citizens and residents (e.g., national security interests, diplomatic interests, etc.);
- regulating an externality on the basis of its global effects supports a cooperative international approach to the regulation of the externality by potentially inducing other countries to follow suit or maintain existing efforts; or
- international or domestic legal obligations require or support a global calculation of regulatory effects" (U.S. Office of Management and Budget. (2023). *Circular A-4: Regulatory Analysis*. Retrieved from https://www.whitehouse.gov/wp-content/uploads/2023/11/CircularA-4.pdf).
- Due to the global nature of the climate change problem, the OMB recommendations of appropriate contexts for considering international effects are relevant to the CO_2 emission reductions expected from the final rule. For example, as discussed in this RIA, a global focus in evaluating the climate impacts of changes in CO_2 emissions supports a cooperative international approach to GHG mitigation by potentially inducing other countries to follow suit or maintain existing efforts, and the global SC-CO_2 estimates better capture effects on U.S. citizens and residents and U.S. national interests that are difficult to estimate and not otherwise fully captured.

[122] For example, in the RIA for the 2018 Proposed Reconsideration of the Oil and Natural Gas Sector Emission Standards for New, Reconstructed, and Modified Sources, EPA acknowledged that some portion of regulatory costs will likely "accru[e] to entities outside U.S. borders" through foreign ownership, employment, or consumption (U.S. Environmental Protection Agency. (2018d). *Regulatory Impact Analysis for the Proposed Reconsideration of the Oil and Natural Gas Sector Emission Standards for New, Reconstructed, and Modified Sources*. (EPA-452/R-18-001). Retrieved from https://www.epa.gov/sites/default/files/2018-09/documents/oil_and_natural_gas_nsps_reconsideration_proposal_ria.pdf, p. 3-13). In general, a significant share of U.S. corporate debt and equities are foreign-owned, including in the oil and gas industry.

economic experts have emphasized the issue of international cooperation and reciprocity as support for assessing global damages of GHG emission in domestic policy analysis. Using a global estimate of damages in U.S. analyses of regulatory actions allows the U.S. to continue to actively encourage other nations, including emerging major economies, to also assess global climate damages of their policies and to take steps to reduce emissions. For example, many countries and international institutions have already explicitly adapted the global SC-GHG estimates used by EPA in their domestic analyses (*e.g.*, Canada, Israel) or developed their own estimates of global damages (*e.g.*, Germany), and recently, there has been renewed interest by other countries to update their estimates since the draft release of the updated SC-GHG estimates presented in the December 2022 Oil and Gas NSPS/EG Supplemental Proposal RIA.[123] Several recent studies have empirically examined the evidence on international GHG mitigation reciprocity, through both policy diffusion and technology diffusion effects. See U.S. EPA (2023n) for more discussion.

For all of these reasons, EPA believes that a global metric is appropriate for assessing the climate benefits of avoided GHG emissions in this final RIA. In addition, as emphasized in the National Academies' recommendations, "[i]t is important to consider what constitutes a domestic impact in the case of a global pollutant that could have international implications that impact the United States." (National Academies, 2017) The global nature of GHG pollution and its impacts means that U.S. interests are affected by climate change impacts through a multitude of pathways and these need to be considered when evaluating the benefits of GHG mitigation to U.S. citizens and residents. The increasing interconnectedness of global economy and populations means that impacts occurring outside of U.S. borders can have significant impacts on U.S. interests. Examples of affected interests include direct effects on U.S. citizens and assets located abroad, international trade, and tourism, and spillover pathways such as economic and political destabilization and global migration that can lead to adverse impacts on U.S. national security, public health, and humanitarian concerns. Those impacts point to the global nature of the climate change problem and are better captured within global measures of the social cost of greenhouse gases.

In the case of these global pollutants, for the reasons articulated in this section, the assessment of global net damages of GHG emissions allows EPA to fully disclose and contextualize the net climate benefits of GHG emission changes expected from this final rule. EPA disagrees with public comments received on the December 2022 Oil and Gas NSPS/EG Supplemental Proposal that suggested that EPA can or should use a metric focused on benefits resulting solely from changes in climate impacts occurring within U.S. borders. The global models used in the SC-GHG modeling described above do not lend themselves to be disaggregated in a way that could provide sufficiently robust information about the distribution of the rule's climate benefits to citizens and residents of particular countries, or population groups across the globe and within the U.S. Two of the models used to inform the damage module, the GIVE and DSCIM models, have spatial resolution that allows for some geographic disaggregation of future climate impacts across the world. This permits the calculation of a partial GIVE and DSCIM-based SC-GHG measuring the damages from four or five climate impact categories projected to physically occur within the U.S., respectively, subject to caveats. As discussed at length in U.S. EPA (2023n), these damage modules are only a partial accounting and do not capture all of the pathways through which climate change affects public health and welfare. Thus, they only cover a subset of potential climate change impacts. Furthermore, the damage modules do not capture

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[123] In April 2023, the government of Canada announced the publication of an interim update to their SC-GHG guidance, recommending SC-GHG estimates identical to EPA's updated estimates presented in the December 2022 Supplemental Proposal RIA. The Canadian interim guidance will be used across all Canadian federal departments and agencies, with the values expected to be finalized by the end of the year. https://www.canada.ca/en/environment-climate-change/services/climate-change/science-research-data/social-cost-ghg.html.

spillover or indirect effects whereby climate impacts in one country or region can affect the welfare of residents in other countries or regions—such as how economic and health conditions across countries will impact U.S. business, investments, and travel abroad.

Additional modeling efforts can and have shed further light on some omitted damage categories. For example, the Framework for Evaluating Damages and Impacts (FrEDI) is an open-source modeling framework developed by EPA[124] to facilitate the characterization of net annual climate change impacts in numerous impact categories within the contiguous U.S. and monetize the associated distribution of modeled damages (Sarofim et al., 2021; U.S. EPA, 2021c). The additional impact categories included in FrEDI reflect the availability of U.S.-specific data and research on climate change effects. As discussed in U.S. EPA (2023n) results from FrEDI show that annual damages resulting from climate change impacts within the contiguous U.S. (CONUS) (*i.e.*, excluding Hawaii, Alaska, and U.S. territories) and for impact categories not represented in GIVE and DSCIM are expected to be substantial. As discussed in U.S. EPA (2021c), results from FrEDI show that annual damages resulting from climate change impacts within the contiguous U.S. (CONUS) (*i.e.*, excluding Hawaii, Alaska, and U.S. territories) and for impact categories not represented in GIVE and DSCIM are expected to be substantial. For example, FrEDI estimates a partial SC-CO_2 of \$47/mtCO_2 for damages physically occurring within CONUS for 2030 emissions, under a 2 percent near-term Ramsey discount rate)[125] (Hartin et al., 2023), compared to a GIVE and DSCIM-based U.S.-specific SC-CO_2 of \$19/mtCO2 and \$21/mtCO_2, respectively, for 2030 emissions.[126]

While the FrEDI results help to illustrate how monetized damages physically occurring within CONUS increase as more impacts are reflected in the modeling framework, they are still subject to many of the same limitations associated with the DSCIM and GIVE damage modules, including the omission or partial

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[124] The FrEDI framework and Technical Documentation have been subject to a public review comment period and an independent external peer review, following guidance in EPA Peer-Review Handbook for Influential Scientific Information (ISI). Information on the FrEDI peer-review is available at EPA Science Inventory (https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryID=360384&Lab=OAP).

[125] As explained in U.S. Environmental Protection Agency. (2023n). *Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review": EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances*. Retrieved from https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf, Hartin, C., McDuffie, E. E., Noiva, K., Sarofim, M., Parthum, B., Martinich, J., Barr, S., . . . Fawcett, A. (2023). Advancing the estimation of future climate impacts within the United States. *Earth Syst. Dynam.*, *14*(5), 1015-1037. https://doi.org/10.5194/esd-14-1015-2023 present partial SC-CO2, SC-CH4, and SC-N2O estimates for a 2020 emissions pulse year. This same methodology was applied in U.S. Environmental Protection Agency. (2023n). *Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review": EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances*. Retrieved from https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf to calculate the FrEDI-based partial SC-GHG values for 2030 emissions. Updated the values from ibid. to 2023 dollars using the GDP deflator.

[126] Updated the values from U.S. Environmental Protection Agency. (2023n). *Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review": EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances*. Retrieved from https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf to 2023 dollars using the GDP deflator. FrEDI estimates a partial SC-CH_4 of \$684/mtCH_4 for damages physically occurring within CONUS for 2030 emissions (under a 2 percent near-term Ramsey discount rate) (Hartin, C., McDuffie, E. E., Noiva, K., Sarofim, M., Parthum, B., Martinich, J., Barr, S., . . . Fawcett, A. (2023). Advancing the estimation of future climate impacts within the United States. *Earth Syst. Dynam.*, *14*(5), 1015-1037. https://doi.org/10.5194/esd-14-1015-2023) compared to a GIVE and DSCIM-based U.S.-specific SC-CH_4 of \$321/mtCH_4 and \$87/mtCH_4, respectively, for 2030 emissions.

modeling of important damage categories.[127] Finally, none of these modeling efforts – GIVE, DSCIM, and FrEDI – reflect non-climate mediated effects of GHG emissions experienced by U.S. populations (other than CO_2 fertilization effects on agriculture). As one example of new research on non-climate mediated effects of methane emissions, McDuffie et al. (2023) estimate the monetized increase in respiratory-related human mortality risk from the ozone produced from a marginal pulse of methane emissions. Using the socioeconomics from the RFF-SPs and the 2 percent near-term Ramsey discounting approach, this additional health risk to U.S. populations is on the order of approximately \$417/mtCH_4 for 2030 emissions.[128]

Applying the U.S.-specific partial SC-GHG estimates derived from the multiple lines of evidence described above to the GHG emissions changes expected under the final rule would yield substantial benefits. For example, the present value of the climate benefits of the final rule over 2025-2049 as measured by FrEDI from climate change impacts in CONUS are estimated to be $4.8 billion (under a 2 percent near-term Ramsey discount rate). However, the numerous explicitly omitted damage categories and other modeling limitations discussed above and throughout U.S. EPA (2023n) make it likely that these estimates underestimate the benefits to U.S. citizens and residents of the GHG reductions from the final rule; the limitations in developing a U.S.-specific estimate that accurately captures direct and spillover effects on U.S. citizens and residents further demonstrates that it is more appropriate to use a global measure of climate benefits from GHG reductions. EPA will continue to review developments in the literature, including more robust methodologies for estimating the magnitude of the various damages to U.S. populations from climate impacts and reciprocal international mitigation activities, and explore ways to better inform the public of the full range of GHG impacts.

8.3 Human Health Benefits

8.3.1 Data and Methodology

As summarized in Table 8-5, the final rule is estimated to influence the level of pollutants emitted in the atmosphere that adversely affect human health, including directly emitted $PM_{2.5}$, as well as SO_2 and NO_X, which are both precursors to ambient $PM_{2.5}$. NO_X emissions are also a precursor to ambient ground-level ozone. The change in emissions alters the ambient concentrations, which in turn leads to changes in

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[127] Another method that has produced estimates of the effect of climate change on U.S.-specific outcomes uses a top-down approach to estimate aggregate damage functions. Published research using this approach include total-economy empirical studies that econometrically estimate the relationship between GDP and a climate variable, usually temperature. As discussed in U.S. Environmental Protection Agency. (2023n). *Supplementary Material for the Regulatory Impact Analysis for the Final Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review": EPA Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances*. Retrieved from https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf the modeling framework used in the existing published studies using this approach differ in important ways from the inputs underlying the SC-GHG estimates described above (*e.g.*, discounting, risk aversion, and scenario uncertainty). Hence, we do not consider this line of evidence in the analysis for this RIA. Updating the framework of total-economy empirical damage functions to be consistent with the methods described in this RIA and ibid. would require new analysis. Finally, because total-economy empirical studies estimate market impacts, they do not include any non-market impacts of climate change (*e.g.*, heat related mortality) and therefore are also only a partial estimate. EPA will continue to review developments in the literature and explore ways to better inform the public of the full range of GHG impacts.

[128] See ibid. for more details. Updated to 2023 dollars using the GDP deflator.

population exposure. EPA estimated the changes in the human health impacts associated with $PM_{2.5}$ and ozone.[129]

This section summarizes EPA's approach to estimating the incidence and economic value of the $PM_{2.5}$ and ozone-related benefits estimated for the final rule (Option B). The approach entails two major steps: (1) developing baseline and Option B spatial fields of air quality across the U.S. using nationwide photochemical modeling and related analyses; and (2) using these spatial fields in BenMAP-CE[130] to quantify the benefits under Option B as compared to the baseline. In this approach, EPA used IPM projections of EGU air emissions for the baseline and Option B (final rule).

8.3.1.1 Air Quality Modeling Methodology

As described in Appendix J, spatial fields of annual ozone and $PM_{2.5}$ concentrations representing the baseline and Option B were obtained from ozone source and PM source apportionment modeling. These $PM_{2.5}$ and ozone spatial fields were used as input to BenMAP-CE which, in turn, was used to quantify the benefits from this rule.

EPA prepared spatial fields of air quality for the baseline and for Option B for two health-impact metrics: annual mean $PM_{2.5}$ and April through September seasonal average 8-hour daily maximum (MDA8) ozone (AS-MO3). The EGU emissions for the baseline and Option B, consisting of total NO_X, SO_2, and primary $PM_{2.5}$ emissions summarized by year and state, were obtained from the outputs of the IPM run, as described above and in Chapter 5 of the RIA (U.S. EPA, 2024e). As such, the spatial fields do not account for changes in emissions associated with power requirements to operate treatment systems or with transportation. See Section 8.3.1 regarding limitations and uncertainty associated with the analysis of air quality related benefits.

The basic methodology for determining air quality changes is the same as that used in the RIAs from multiple previous rules (U.S. EPA, 2019i; 2020b; 2020a, 2021b; 2022c). Appendix J provides an overview of the air quality modeling and the methodologies EPA used to develop spatial fields of seasonal ozone and annual $PM_{2.5}$ concentrations. The appendix also provides selected figures showing the geographical and temporal distribution of air quality changes.

EPA used air quality modeling to estimate health benefits associated with changes in ozone and $PM_{2.5}$ concentrations that may occur because of Option B of the final rule relative to the baseline. Air quality surfaces of the baseline reflect projected 2026 emission from all sources other than EGUs but reflect year-specific projected emissions for EGUs for 2028, 2030, 2035, 3040, 2045 and 2050.[131] While the CAMx air quality modeling includes a range of pollution sources, contributions from non-EGU point sources, on-road vehicles, non-road mobile equipment and marine vessels are held constant in this analysis, and the only

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[129] Ambient concentrations of both SO_2 and NO_X also pose health risks independent of $PM_{2.5}$ and ozone, though EPA does not quantify these impacts in this analysis (U.S. Environmental Protection Agency. (2016b). *Integrated Science Assessment for Oxides of Nitrogen: Health Criteria*. (EPA/600/R-15/068). Retrieved from http://ofmpub.epa.gov/eims/eimscomm.getfile?p_download_id=526855, U.S. Environmental Protection Agency. (2017b). *Integrated Science Assessment for Sulfur Oxides: Health Criteria*. (EPA/600/R-17/451). Retrieved from http://ofmpub.epa.gov/eims/eimscomm.getfile?p_download_id=533653)

[130] The Environmental Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE) is described and found at: https://www.epa.gov/benmap.

[131] The air quality modeling techniques used for this analysis reflect non-EGU emissions as of 2026, so implementation or effects of any changes in non-EGU emissions expected to occur after 2026 are not accounted for in this analysis. However, the effect of non-EGU emissions on changes in pollution concentrations due to the final rule is likely to be small.

changes are those associated with the projected impacts of the rule on the profile of electricity generation and EGU emissions, as compared to the baseline. The modeled air quality changes do not include other potential effects of the rule, such as changes in power requirements to run treatment systems or changes in CCR transportation, which were estimated separately as described in Section 8.1 and were found to be negligible as described in section 8.4.

8.3.1.2 $PM_{2.5}$ and Ozone Related Health Impacts

EPA estimated the benefits of Option B using the open-source environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP-CE) (Sacks et al., 2018). The *Estimating $PM_{2.5}$- and Ozone-Attributable Health Benefits* Technical Support Document (TSD) fully describes the Agency's approach for identifying those health endpoints to evaluate as well as quantifying their number and value (U.S. EPA, 2023p). In the TSD, the reader can find the rationale for selecting health endpoints to quantify; the demographic, health and economic data used; modeling assumptions; and our techniques for quantifying uncertainty.

Estimating the health benefits of reductions in $PM_{2.5}$ and ozone exposure begins with estimating the change in exposure for each individual and then estimating the change in each individual's risks for those health outcomes affected by exposure. The dollar benefit of reducing the risk of each adverse effect is based on the exposed individual's willingness to pay (WTP) for the risk change, assuming that each outcome is independent of one another. The greater the magnitude of the risk reduction from a given change in concentration, the greater the individual's WTP, all else equal. The social benefit of the change in health risks equals the sum of the individual WTP estimates across all of the affected individuals residing in the United States. We conduct this analysis by adapting primary research—specifically, air pollution epidemiology studies and economic value studies—from similar contexts. This approach is sometimes referred to as "benefits transfer." Below we describe the procedure we follow for: (1) selecting air pollution health endpoints to quantify; (2) calculating counts of air pollution effects using a health impact function; (3) specifying the health impact function with concentration-response parameters drawn from the epidemiological literature.

The BenMAP-CE tool quantifies the number and value of air pollution-attributable premature deaths and illnesses resulting from changes in $PM_{2.5}$ and ozone concentrations. Table 8-9 reports the ozone and $PM_{2.5}$-related human health impacts effects EPA quantified and those the Agency did not quantify in this analysis of the final rule. The list of benefit categories not quantified is not exhaustive. And, among the effects quantified, it might not have been possible to quantify completely either the full range of human health impacts or economic values.

Table 8-9: Human Health Effects of Ambient Ozone and $PM_{2.5}$

Category	Effect	Effect Quantified	Effect Monetized	More Information
Premature mortality from exposure to $PM_{2.5}$	Adult premature mortality based on cohort study estimates and expert elicitation estimates (age 65-99 or age 30-99)	✓	✓	PM ISA
	Infant mortality (age <1)	✓	✓	PM ISA
Morbidity from exposure to $PM_{2.5}$	Heart attacks (age > 18)	✓	✓	PM ISA
	Hospital admissions—cardiovascular (ages 65-99)	✓	✓	PM ISA
	Emergency department visits— cardiovascular (age 0-99)	✓	✓	PM ISA
	Hospital admissions—respiratory (ages 0-18 and 65-99)	✓	✓	PM ISA
	Emergency room visits—respiratory (all ages)	✓	✓	PM ISA

Table 8-9: Human Health Effects of Ambient Ozone and PM$_{2.5}$

Category	Effect	Effect Quantified	Effect Monetized	More Information
	Cardiac arrest (ages 0-99; excludes initial hospital and/or emergency department visits)	✓	✓	PM ISA
	Stroke (ages 65-99)	✓	✓	PM ISA
	Asthma onset (ages 0-17)	✓	✓	PM ISA
	Asthma symptoms/exacerbation (6-17)	✓	✓	PM ISA
	Lung cancer (ages 30-99)	✓	✓	PM ISA
	Allergic rhinitis (hay fever) symptoms (ages 3-17)	✓	✓	PM ISA
	Lost work days (age 18-65)	✓	✓	PM ISA
	Minor restricted-activity days (age 18-65)	✓	✓	PM ISA
	Hospital admissions—Alzheimer’s disease (ages 65-99)	✓	✓	PM ISA
	Hospital admissions—Parkinson’s disease (ages 65-99)	✓	✓	PM ISA
	Other cardiovascular effects (*e.g.*, other ages)	—	—	PM ISA[b]
	Other respiratory effects (*e.g.*, pulmonary function, non-asthma ER visits, non-bronchitis chronic diseases, other ages and populations)	—	—	PM ISA[b]
	Other nervous system effects (*e.g.*, autism, cognitive decline, dementia)	—	—	PM ISA[b]
	Metabolic effects (*e.g.*, diabetes)	—	—	PM ISA[b]
	Reproductive and developmental effects (*e.g.*, low birth weight, pre-term births)	—	—	PM ISA[b]
	Cancer, mutagenicity, and genotoxicity effects	—	—	PM ISA[b]
Mortality from exposure to ozone	Premature mortality based on short-term study estimates (age 0-99)	✓	✓	Ozone ISA
	Premature mortality based on long-term study estimates (age 30–99)	✓	✓	Ozone ISA[a]
Morbidity from exposure to ozone	Hospital admissions—respiratory causes (ages 0-99)	✓	✓	Ozone ISA
	Emergency department—respiratory (ages 0-99)	✓	✓	Ozone ISA
	Asthma onset (0-17)	✓	✓	Ozone ISA
	Asthma symptoms/exacerbation (asthmatics age 2-17)	✓	✓	Ozone ISA
	Allergic rhinitis (hay fever) symptoms (ages 3-17)	✓	✓	Ozone ISA
	Minor restricted-activity days (age 18–65)	✓	✓	Ozone ISA
	School absence days (age 5–17)	✓	✓	Ozone ISA
	Decreased outdoor worker productivity (age 18–65)	—	—	Ozone ISA[b]
	Metabolic effects (*e.g.*, diabetes)	—	—	Ozone ISA[b]
	Other respiratory effects (*e.g.*, premature aging of lungs)	—	—	Ozone ISA[b]
	Cardiovascular and nervous system effects	—	—	Ozone ISA[b]
	Reproductive and developmental effects	—	—	Ozone ISA[b,c]

a. EPA assesses these benefits qualitatively due to data and resource limitations for this analysis. In other analyses EPA quantified these effects as a sensitivity analysis.

b. EPA assesses these benefits qualitatively because of insufficient confidence in available data or methods.

c. EPA assesses these benefits qualitatively because current evidence is only suggestive of causality or there are other significant concerns over the strength of the association.

Source: EPA Analysis, 2024

Counts of attributable effects are quantified using a health impact function, which combines information regarding the: concentration-response relationship between air quality changes and the risk of a given adverse outcome; population exposed to the air quality change; baseline rate of death or disease in that population; and air pollution concentration to which the population is exposed. When used to quantify PM$_{2.5}$- or ozone-related effects, the functions combine effect estimates (*i.e.*, the β coefficients) from epidemiological studies, which portray the relationship between a change in air quality and a health effect, such as mortality, associated with changes in estimated $PM_{2.5}$ or ozone concentrations (supplied using the IPM market model simulations described above), population data, and baseline death rates for each county in each year. After having quantified $PM_{2.5}$- and ozone-attributable cases of premature death and illness, EPA estimated the economic value of these cases using willingness to pay (WTP) and cost of illness (COI) measures.

EPA estimated the number of $PM_{2.5}$-attributable premature deaths using effect estimates from two epidemiology studies examining two large population cohorts: an analysis of Medicare beneficiaries (Wu et al., 2020) and the National Health Interview Survey (NHIS) (Pope et al., 2019). For ozone-related premature deaths, EPA uses one epidemiological study that examines the relationship between long-term exposure to ozone and mortality (Turner et al., 2016) and two studies that examine the relationship between short-term exposure to ozone and mortality (Katsouyanni et al., 2009; Zanobetti & Schwartz, 2008).

EPA quantifies and monetizes effects the Integrated Science Assessment (ISA) identifies as having either a causal or likely-to-be-causal relationship with the pollutant. Relative to the 2015 ISA, the 2020 ISA for Ozone reclassified the casual relation between short-term ozone exposure and total mortality, changing it from "likely to be causal" to "suggestive of, but not sufficient to infer, a causal relationship." The 2020 Ozone ISA separately classified short-term O3 exposure and respiratory outcomes as being "causal" and long-term exposure as being "likely to be causal." When determining whether there existed a causal relationship between short- or long-term ozone exposure and respiratory effects, EPA evaluated the evidence for both morbidity and mortality effects. The ISA identified evidence in the epidemiologic literature of an association between ozone exposure and respiratory mortality, finding that the evidence was not entirely consistent and there remained uncertainties in the evidence base.

EPA continues to quantify premature respiratory mortality attributable to both short- and long-term exposure to ozone because doing so is consistent with: (1) the evaluation of causality noted above; and (2) EPA's approach for selecting and quantifying endpoints described in the TSD "Estimating PM2.5- and Ozone-Attributable Health Benefits," which was recently reviewed by the U.S. EPA Science Advisory Board (U.S. EPA, 2023p; U.S. EPA Science Advisory Board, 2024).

Projected impacts of the final rule (Option B) show both decreased and increased levels of $PM_{2.5}$ and ozone, depending on the year and location, compared to the baseline (see maps in Appendix J for details). Some portion of the air quality and health benefits from the final rule occur in areas not attaining the $PM_{2.5}$ or Ozone National Ambient Air Quality Standards (NAAQS). The analysis does not account for possible interactions between NAAQS compliance and the final rule, which introduces uncertainty into the benefits (and forgone benefits) estimates. If the final rule increases or decreases primary $PM_{2.5}$, SO_2 and NO_X emissions and consequentially $PM_{2.5}$ and/or ozone concentrations, these changes may affect compliance with existing NAAQS standards and subsequently affect the actual benefits (and forgone benefits) of the final rule.

8.3.2 Results

EPA reports below the estimated number of avoided $PM_{2.5}$ and ozone-related premature deaths and illnesses in each year for Option B, the final rule, relative to the baseline along with the 95 percent confidence interval (see Table 8-10). The number of avoided premature deaths and illnesses under the final rule are calculated from the sum of individual reduced mortality and illness risk across the population in a given year. Table 8-11 reports the estimated economic value of avoided premature deaths and illness for each analysis year relative to the baseline.

Table 8-10: Estimated Avoided $PM_{2.5}$ and Ozone-Related Premature Deaths and Illnesses by Year for the Final Rule (Option B), Compared to Baseline (95 Percent Confidence Interval)

Category and Basis		2028[a]	2030[a]	2035[a]	2040[a]	2045[a]	2050[a]
Avoided premature death among adults[b]							
$PM_{2.5}$	Wu et al. (2020)	67	19	100	29	8.5	8.2
		(59 to 75)	(16 to 21)	(91 to 120)	(25 to 32)	(7.5 to 9.5)	(7.2 to 9.1)
	Pope III et al. (2019)	140	38	210	57	17	16
		(100 to 180)	(27 to 48)	(150 to 270)	(41 to 73)	(12 to 22)	(12 to 21)
Avoided infant mortality							
$PM_{2.5}$	Woodruff, Darrow & Parker, 2008	0.16	0.034	0.2	0.052	0.016	0.015
		(-0.10 to 0.42)	(-0.022 to 0.088)	(-0.12 to 0.51)	(-0.033 to 0.13)	(-0.010 to 0.041)	(-0.0092 to 0.037)
Ozone (O_3)	Katsouyanni et al. (2009)[c,d] and Zanobetti et al. (2008)[d] pooled	2.1	2	2.9	1.3	0.38	0.18
		(0.83 to 3.3)	(0.80 to 3.1)	(1.2 to 4.5)	(0.52 to 2.0)	(0.15 to 0.60)	(0.074 to 0.29)
	Turner et al. (2016)[c]	46	44	63	29	8.4	4.1
		(32 to 59)	(31 to 57)	(44 to 82)	(20 to 37)	(5.8 to 11)	(2.8 to 5.3)
All other morbidity effects							
Acute Myocardial Infarcation		2.3	0.57	3.5	0.95	0.29	0.29
		(1.3 to 3.2)	(0.33 to 0.79)	(2.0 to 4.9)	(0.55 to 1.3)	(0.17 to 0.40)	(0.17 to 0.40)
Hospital admissions—cardiovascular ($PM_{2.5}$)		9.9	2.7	15	4.2	1.3	1.2
		(7.2 to 13)	(2.0 to 3.4)	(11 to 19)	(3.0 to 5.3)	(0.91 to 1.6)	(0.89 to 1.6)
Hospital admissions—respiratory ($PM_{2.5}$)		6.9	1.5	9.6	2.6	0.81	0.82
		(2.4 to 11)	(0.50 to 2.5)	(3.2 to 16)	(0.87 to 4.3)	(0.28 to 1.3)	(0.28 to 1.3)
Hospital admissions—respiratory[d] (O_3)		6	5.7	8.1	3.6	1.1	0.59
		(-1.6 to 13)	(-1.5 to 13)	(-2.1 to 18)	(-0.95 to 8.1)	(-0.29 to 2.5)	(-0.15 to 1.3)
Hospital admissions—Alzheimer's Disease ($PM_{2.5}$)		37	8	57	16	5	5.2
		(28 to 46)	(5.9 to 9.9)	(42 to 71)	(12 to 20)	(3.8 to 6.3)	(3.9 to 6.5)
Hospital admissions— Parkinson's Disease ($PM_{2.5}$)		4.6	1.3	6.6	1.8	0.51	0.51
		(2.3 to 6.7)	(0.66 to 1.9)	(3.4 to 9.8)	(0.90 to 2.6)	(0.26 to 0.75)	(0.26 to 0.75)
ED visits—cardiovascular ($PM_{2.5}$)		21	5.3	30	8.3	2.6	2.5
		(-8.0 to 48)	(-2.0 to 12)	(-12 to 70)	(-3.2 to 19)	(-0.99 to 6.0)	(-0.97 to 5.9)
ED visits—respiratory ($PM_{2.5}$)		41	11	56	15	4.8	4.6
		(8.1 to 86)	(2.1 to 23)	(11 to 120)	(2.9 to 31)	(0.95 to 10)	(0.91 to 9.7)
ED visits—respiratory[f] (O_3)		110	96	140	62	20	9.7
		(31 to 240)	(26 to 200)	(38 to 290)	(17 to 130)	(5.6 to 43)	(2.7 to 20)
Cardiac Arrest ($PM_{2.5}$)		1	0.28	1.5	0.39	0.12	0.12
		(-0.42 to 2.3)	(-0.11 to 0.63)	(-0.59 to 3.3)	(-0.16 to 0.89)	(-0.050 to 0.28)	(-0.048 to 0.27)
Stroke ($PM_{2.5}$)		4.2	1.2	6	1.6	0.48	0.47
		(1.1 to 7.1)	(0.30 to 2.0)	(1.5 to 10)	(0.41 to 2.7)	(0.13 to 0.83)	(0.12 to 0.81)

Table 8-10: Estimated Avoided $PM_{2.5}$ and Ozone-Related Premature Deaths and Illnesses by Year for the Final Rule (Option B), Compared to Baseline (95 Percent Confidence Interval)

Category and Basis	2028[a]	2030[a]	2035[a]	2040[a]	2045[a]	2050[a]
Lung Cancer ($PM_{2.5}$)	4.7	1.3	7	2	0.61	0.59
	(1.4 to 7.8)	(0.39 to 2.2)	(2.1 to 12)	(0.59 to 3.3)	(0.18 to 1.0)	(0.18 to 0.98)
Hay Fever/Rhinitis ($PM_{2.5}$)	1,000	250	1,300	370	120	110
	(240 to 1,700)	(60 to 430)	(320 to 2,300)	(89 to 640)	(28 to 200)	(27 to 190)
Hay Fever/Rhinitis[g] (O_3)	2,000	1,700	2,300	1,000	320	150
	(1,000 to 2,900)	(900 to 2,500)	(1,200 to 3,400)	(550 to 1,500)	(170 to 470)	(78 to 220)
Asthma Onset ($PM_{2.5}$)	160	38	200	56	18	17
	(150 to 160)	(36 to 39)	(200 to 210)	(54 to 58)	(17 to 19)	(16 to 18)
Asthma onset[e] (O_3)	340	290	400	180	55	25
	(300 to 390)	(250 to 330)	(340 to 450)	(150 to 200)	(48 to 63)	(22 to 29)
Asthma symptoms-- Albuterol use ($PM_{2.5}$)	29,000	7,200	40,000	11,000	3,400	3,300
	(-14,000 to 71,000)	(-3,500 to 18,000)	(-19,000 to 96,000)	(-5,200 to 26,000)	(-1,700 to 8,300)	(-1,600 to 8,000)
Asthma symptoms (O_3)	64,000	55,000	74,000	33,000	10,000	4,700
	(-7,900 to 130,000)	(-6,800 to 110,000)	(-9,100 to 150,000)	(-4,100 to 69,000)	(-1,300 to 21,000)	(-580 to 9800)
Minor restricted-activity days ($PM_{2.5}$)	45,000	11,000	61,000	17,000	5,400	5,200
	(37,000 to 53,000)	(9,200 to 13,000)	(49,000 to 72,000)	(13,000 to 20,000)	(4,300 to 6,300)	(4,300 to 6,200)
Minor restricted-activity days[d,f] (O_3)	30,000	26,000	35,000	16,000	5,000	2,400
	(12,000 to 47,000)	(10,000 to 40,000)	(14,000 to 55,000)	(6,300 to 25,000)	(2,000 to 8,000)	(950 to 3,800)
Lost work days ($PM_{2.5}$)	7,700	1,900	10,000	2,800	910	890
	(6,500 to 8,800)	(1,600 to 2,200)	(8,700 to 12,000)	(2,400 to 3,200)	(760 to 1,000)	(750 to 1,000)
School absence days (O_3)	23,000	20,000	27,000	12,000	3,700	1,700
	(-3,200 to 48,000)	(-2,800 to 41,000)	(-3,800 to 56,000)	(-1,700 to 25,000)	(-520 to 7,700)	(-240 to 3,600)

a. Values rounded to two significant figures. Negative values indicate forgone benefits (*i.e.*, the number of avoided cases under the final rule is smaller than in the baseline). Lower bound of confidence interval represents the 95 percent confidence estimate that is lower in value than the point estimate, while upper bound represents the estimate that is higher in value than the point estimate.

b. EPA also quantified changes in premature infant mortality from exposure to $PM_{2.5}$ but the estimated change was less than 1 for all years analyzed.

c. Applied risk estimate derived from April-September exposures to estimates of ozone across the May-September warm season.

d. Converted ozone risk estimate metric from MDA1 to MDA8.

e. Applied risk estimate derived from June-August exposures to estimates of ozone across the May-September warm season.

f. Applied risk estimate derived from full year exposures to estimates of ozone across the May-September warm season.

g. Converted ozone risk estimate metric from DA24 to MDA8

Source: U.S. EPA Analysis, 2024

Table 8-11: Estimated Discounted Economic Value of Avoided Ozone and $PM_{2.5}$-Attributable Premature Mortality and Illness for Option B (millions of 2023$)

Year	2% Discount Rate[a]		
2028	$1,100	*and*	$2,600
2030	$390	*and*	$1,200
2035	$1,600	*and*	$3,900
2040	$500	*and*	$1,300
2045	$150	*and*	$380
2050	$140	*and*	$310

[a] Values rounded to two significant figures. The two benefits estimates are separated by the word "and" to signify that they are two separate estimates. The estimates do not represent lower- and upper-bound estimates and should not be summed.

Source: U.S. EPA Analysis, 2024

8.4 Annualized Air Quality-Related Benefits of Regulatory Options

EPA calculated the present value (discounted to 2024) of estimated air quality-related benefits over the analysis period of 2025-2049 and annualized these values to provide a measure that is comparable to the way other benefit categories and social costs are reported.

Section 8.2.1 provides benefit estimates for Option B, the final rule, based on the changes in the electricity generation profile projected in IPM. EPA mapped changes in emissions due to changes in electricity generation for each IPM run year to individual years within the analysis period of 2025-2049 (see Table 8-1). Because IPM outputs are available only for 2028 onward, EPA conservatively assumed no benefits associated with changes in the profile of electricity generation between 2025 and 2027. However, changes in the profile of electricity generation and EGU emissions are likely to occur as steam electric power generating plants start incurring costs to comply with the revised ELG between 2025 and 2029, and assuming no emission reductions for the first three years of this period understates the air quality-related benefits of the final rule.

For energy use and trucking, EPA estimated changes in air emissions corresponding to the year each plant is estimated to implement changes in technology. These emissions are included in the analysis of climate change benefits. As discussed in Section 8.3.1.1, however, the analysis of human health benefits does not account for other changes in pollutant emissions associated with power requirements to operate wastewater treatment systems or transport CCR or other solid waste. EPA considered adjusting the estimated benefits in proportion to the average ratio between total air emissions of NO_X and SO_2 (Table 8-5) and EGU emissions associated with changes in the electricity generation profile (Table 8-4) but concluded that such an adjustment would have a negligible effect on the estimated human health benefit estimates given the comparably small emissions changes associated with power requirements and trucking. Therefore, EPA is presenting unadjusted values for the final rule below.

For the climate change benefits, EPA used the same discount rate used to develop SC-GHG values. For the human health benefits, EPA used the LT mortality benefit estimate at a 2 percent discount rate from Table 8-11.

Table 8-12: Total Annualized Air Quality-Related Benefits of Final Rule (Option B), Compared to the Baseline, 2025-2049 (Millions of 2023$)

SC-GHG near-term discount rate	Climate Change Benefits[a]	$PM_{2.5}$ and Ozone Related Human Health Benefits at 2% Discount Rate[a]	Total[a]
1.5%	$990	$1,600	$2,600
2.0%	$1,600	$1,600	$3,200
2.5%	$2,600	$1,600	$4,200

a. Values rounded to two significant figures.

b. Values calculated based on the LT mortality benefits estimates at a 2 percent discount rate.

Source: U.S. EPA Analysis, 2024

Because EPA did not run IPM for Options A and C, EPA did not analyze climate and human health benefits for these regulatory options. To provide insight into the potential air quality-related benefits across regulatory options, EPA estimated benefits for Options A and C by scaling Option B benefits in proportion to the total social costs of the respective options (see Chapter 11 in this document). Specifically, EPA calculated the ratio of the benefits to total social costs for Option B, then multiplied total social costs for Options A and C by this ratio. The scaling factor provides an order of magnitude approximation of the benefits by assuming proportionality between air-related benefits and total social costs.[132] While air-related benefits are expected to be driven primarily by changes in the profile of electricity generation (see Table 8-4 and Table 8-5) and the generation profile is affected most directly by the incremental technology implementation costs, the effects may not be linear.

Table 8-13 summarizes the annualized air quality-related benefits of the regulatory options for the climate change benefits estimated using the SC-GHG under the 2 percent near-term Ramsey discount rate and for human health benefits discounted using a 2 percent discount rate.

Table 8-13: Total Annualized Air Quality-Related Benefits of Regulatory Options Based on Extrapolation from Option B, Compared to the Baseline, 2025-2049 (Millions of 2023$)

Regulatory Option	Climate Change Benefits (SC-GHG 2% near-term discount rate)[a]	$PM_{2.5}$ and Ozone Related Human Health Benefits at 2% Discount Rate[a,b]	Total[a]
Option A[c]	$1,200	$1,200	$2,400
Option B (Final Rule)	$1,600	$1,600	$3,200
Option C[c]	$1,900	$2,000	$3,900

a. Values rounded to two significant figures.

b. These values reflect the air-related human health benefits based on the LT mortality benefits estimates from changes in $PM_{2.5}$ and ozone levels.

c. EPA estimated air quality-related benefits for Options A and C by multiplying the total social costs for each option (see Section 11.2) by the ratio of [air quality-related benefits / total social costs] for Option B. For the purpose of scaling benefits, EPA used the subset of social costs associated with the wastestreams modeled in the benefits analyses.

Source: U.S. EPA Analysis, 2024

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[132] For the 2015 final rule, EPA analyzed two options using IPM and therefore had air-related benefits for both options. Using the benefit/cost ratio of one option to estimate benefits of the other option resulted in benefits that were ±7 percent than benefits derived from the IPM outputs.

8.5 Limitations and Uncertainties

Table 8-14 summarizes the limitations and uncertainties associated with the analysis of the air quality-related benefits. The second column of the table provides a conclusion of how the limitation affects the magnitude of the benefits estimate relative to expected actual benefits (*i.e.*, a source of uncertainty that has the effect of underestimating benefits indicates an expectation that expected actual benefits are larger than the estimate). The analysis also incorporates uncertainties associated with IPM modeling, which are discussed in Chapter 5 in the RIA (U.S. EPA, 2024e). See Appendix J for additional discussions of the uncertainty associated with the air quality modeling methodology.

Table 8-14: Limitations and Uncertainties in Analysis of Air Quality-Related Benefits

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
EPA extrapolated Option B benefits to Options A and C.	Uncertain	EPA ran IPM only for the final rule (Option B) and used the results to extrapolate benefits of Options A and C, based on the ratios of annualized benefits and annualized social costs. Air emissions and air quality changes are unlikely to follow differences in social costs in a linear fashion, however, given how marginal changes in operating costs for individual units may affect dispatch of EGUs within the broader regional and national electricity markets. Because benefits are dependent on magnitude and, for human health benefits, the spatial distribution of emissions changes, projected benefits for Options A and C are uncertain.
EPA assumed no changes in air emissions associated with shifts in the mix of electricity generation in 2025-2027 relative to baseline	Underestimate	The first IPM year is 2028. Changes in the profile of electricity generation and EGU emissions are likely to occur as steam electric power generating plants start incurring costs to comply with the revised ELG between 2025 and 2029, and assuming no emission reductions for the first three years of this technology implementation period understates the air quality-related benefits of the final rule. This is even though the changes in air emissions predicted in IPM are modest in 2028.
The modeled air quality assumes a static apportionment of EGU sources and static emissions from other sources.	Uncertain	As discussed in Appendix J, the source apportionment contributions are informed by the spatial and temporal distribution of the emissions from each source tag as they occur in the future year modeled case. Thus, the contribution modeling results do not consider the effects of any changes to spatial distribution of EGU emissions within a state-fuel tag between the future year modeled case and the baseline and final rule scenarios analyzed in this RIA.
The modeled air quality surfaces used in the analysis of human health benefits only reflect changes in emissions associated with changes in the electricity generation profile.	Uncertain	EPA developed the spatial fields based on IPM projected emissions changes for Option B. These projections do not include additional changes in NO_X and SO_2 emissions associated with power requirements to operate wastewater treatment systems or trucking to transport CCR and other solid waste. While these emissions changes could affect human health benefit estimates, such effects are expected to be small overall given that these emissions generally represent less than 2 percent of total NO_X and SO_2 emissions changes.

Table 8-14: Limitations and Uncertainties in Analysis of Air Quality-Related Benefits

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
The methodology used to create ozone and $PM_{2.5}$ Air Quality surfaces do not account for nonlinear impacts of precursor emissions changes	Uncertain	Appendix J provides further details on this limitation.
All fine particles, regardless of their chemical composition, are equally potent in causing premature mortality.	Uncertain	The PM ISA concluded reaffirmed the conclusion reached in the 2009 ISA that "many PM2.5 components and sources are associated with many health effects and that the evidence does not indicate that any one source or component is consistently more strongly related with health effects than PM2.5 mass." (U.S. EPA, 2009c, 2022d).
Assumed "Cessation" lag between the change in $PM_{2.5}$ and ozone exposures and the total realization of changes in long-term mortality effects.	Uncertain	The approach distributes the incidences of premature mortality related to $PM_{2.5}$ exposures over the 20 years following exposure based on the advice of EPA's Science Advisory Board Health Effect Subcommittee (SAB-HES) (U.S. EPA, 2004a). This distribution is also assumed for long-term mortality from ozone exposure. This distribution affects the valuation of mortality benefits at different discount rates. The actual distribution of effects over time is uncertain.
Climate changes may affect ambient concentrations of pollutants.	Uncertain	Estimated health benefits do not account for the influence of future changes in the climate on ambient concentrations of pollutants (U.S. Global Change Research Program, 2016). For example, recent research suggests that future changes to climate may create conditions more conducive to forming ozone; the influence of changes in the climate on $PM_{2.5}$ concentrations are less clear (Fann et al., 2015). The estimated health benefits also do not consider the potential for climate-induced changes in temperature to modify the relationship between ozone and the risk of premature death (Jhun et al., 2014; Ren, Williams, Mengersen, et al., 2008; Ren, Williams, Morawska, et al., 2008). Modeling used to estimate air quality changes from this final rule used meteorological fields representing conditions that occurred in 2016.
EPA did not analyze all benefits of changes in exposure to NO_X, SO_2, and other pollutants emitted by EGUs.	Underestimate	The analysis focused on adverse health effects related to $PM_{2.5}$ and ozone levels. There are additional benefits from changes in levels of NO_X, SO_2 and other air pollutants emitted by EGUs (*e.g.*, mercury, HCl). These include health benefits from changes in ambient NO_2 and SO_2 exposure, health benefits from changes in mercury deposition, ecosystem benefits associated with changes in emissions of NO_X, SO_2, PM, and mercury, and visibility impairment.

9 Estimated Changes in Drinking Water Treatment and Dredging Costs

By reducing pollutant loads in receiving and downstream waters, the regulatory options have the potential to reduce costs associated with uses of these waters. For example, numerous studies have shown an unequivocal link between source water quality and the cost of drinking water treatment and changes in sediment deposition has the potential to affect the cost of maintaining reservoirs and navigational waterways. This chapter provides EPA's analysis of the changes in drinking water treatment and dredging costs associated with the regulatory options.

9.1 Changes in Drinking Water Treatment Costs

As summarized in Chapter 2, the regulatory options have the potential to affect drinking water treatment costs by reducing loadings of steam electric pollutants to surface waters used for drinking water supply. EPA implemented a treatment cost elasticity approach to quantify avoided treatment costs from reductions in total nitrogen (TN) and total suspended solids (TSS). The treatment cost elasticity approach has been used in recent research estimating the social cost of nutrient pollution (Andarge, 2022), and it is supported by the economics literature on drinking water treatment costs (see Price and Heberling (2018) for a review of 15 U.S. and 9 non-U.S. studies that estimate quantitative relationships between source water quality and drinking water treatment costs).

The treatment cost elasticity approach differs from the work breakdown structure models that are more frequently used to estimate changes in drinking water treatment costs as part of EPA regulatory analysis (Khera, Ransom & Speth, 2013). In comparison to treatment cost elasticity approaches, work breakdown structure models require more information on drinking water system treatment practices, source water parameters, and how treatment process costs vary with changes in source water characteristics at different production levels. In contrast, treatment cost elasticities are based on empirical studies of water system behavior and observed costs, and thus they make fewer assumptions on how water systems respond to changes in source water characteristics.

Given the relatively small drinking water treatment savings expected to accrue from this rule, EPA implemented the more straightforward treatment cost elasticity approach to estimate the magnitude of impacts to drinking water systems. The use of a treatment cost elasticity approach in regulatory analysis may provide a rationale for academic researchers to develop additional treatment cost elasticities for application in future regulatory impact assessments.

9.1.1 Data and Methodology

EPA applied the following steps to calculate avoided drinking water treatment costs associated with reductions in TN and TSS:

1. Identify water systems with surface water intakes downstream of steam electric power plant discharges.
2. Estimate TN and TSS baseline levels and reductions in source waters using SPARROW modelling.
3. Convert TSS levels and reductions to turbidity levels and reductions following U.S. EPA (2009b).

4. Compute the percent change in TN and turbidity for each regulatory option and all regulatory periods.

5. Estimate drinking water treatment costs at affected water systems using the median cost by system size and source type according to responses to the 2006 Community Water System Survey.

6. Estimate the percent change in drinking water treatment costs associated with reductions in TN and turbidity levels using the elasticities in Price and Heberling (2018).

Further detail on the identification of water systems with affected intakes and SPARROW modelling is provided in Chapter 3. For this analysis, EPA excludes water systems that purchase their water from affected systems to avoid potentially double-counting benefits, although this assumption likely underestimates true cost savings across all affected systems as discussed in the limitations section of this chapter. In addition, EPA assumes that the blending ratio across intakes is uniform, such that a water system with multiple affected intakes will see the average loadings change across all intakes. Intakes that are not affected by steam electric power plant discharges in the baseline are assumed to have loadings changes of zero. Table 9-1 summarizes the average annual changes in TSS, TN, and TP loadings at 233 directly affected water systems.

Table 9-1: Average Percent Change in Source Water Concentrations of TN, TP, and TSS Compared to Baseline

Regulatory Option	Period 1 (2025-2029)			Period 2 (2030 -2049)		
	TSS	TN	TP	TSS	TN	TP
Option A	-0.0006	-0.008	-0.004	-0.0012	-0.009	-0.004
Option B (Final Rule)	-0.0006	-0.008	-0.004	-0.0013	-0.009	-0.004
Option C	-0.0009	-0.010	-0.005	-0.0015	-0.009	-0.005

Source: U.S. EPA Analysis, 2024.

Next, EPA incorporated expenditure data from the 2006 Community Water System Survey (CWWS, U.S. EPA, 2009a) to assign drinking water systems baseline treatment expenditures. The CWSS was specifically designed to support regulatory and policy analysis. It collected revenue and expenditure information from 1,314 community water systems using a stratified random sampling procedure to ensure representativeness across water system types; the surveyors ensured data accuracy by sending experts to smaller systems to assist completion of certain information fields (U.S. EPA, 2009a). The 2006 CWSS is the most recently available survey of water systems that collected information needed to estimate drinking water treatment costs separately from other types of expenditure category that are unlikely to vary with source water characteristics. In addition, the survey data has been used in the academic literature to assess the importance of source-water characteristics on drinking water treatment costs (Price & Heberling, 2020).

EPA uses only variable treatment cost expenditures in this analysis because the regulatory options are anticipated to reduce loadings of pollutants that affect ongoing treatment costs rather than all system cost categories. In particular, while systems may have already invested in costly capital equipment to address baseline pollutant loadings from steam electric power plant effluents, EPA assumes that these capital expenditures are largely irreversible. For example, some systems may have already invested in ion exchange treatment processes to contend with nitrates (Khera et al., 2021). The assumption of irreversibility of certain costs leads to an underestimate of true cost savings, as discussed in the limitations section of this chapter.

After removing observations with missing values, treatment cost information was available in the CWSS for 418 drinking water systems. Treatment expenditure information was updated from 2006 to 2023 price levels using the Consumer Price Index. Treatment costs are presented across system source type and population served category in Table 9-2, which also lists the count of systems affected by the regulation.

Table 9-2: Median Drinking Water Treatment Expenditures by System Size and Source Category

System Size	Groundwater		Surface Water		Affected Systems Count
	Median Treatment Cost	**CWSS System Count**	**Median Treatment Cost**	**CWSS System Count**	
Population <100	$27,740	14	$20,890	18	11
Population 101–500	$19,272	10	$279,412	21	8
Population 501–3,300	$49,137	19	$436,572	24	27
Population 3,301–10,000	$840,203	11	$1,679,000	27	47
Population 10,001–50,000	$660,920	25	$3,108,194	36	80
Population 50,001–100,000	$3,237,274	14	$2,263,000	38	23
Population 100,001–500,000	$9,927,596	16	$11,101,192	104	27
Population >500,00	$16,371,051	2	$90,992,030	39	10

Notes: Surface-water systems include systems sourcing from groundwater under the influence of surface water. Dollars estimated to 2023$

Source: 2006 CWWS, U.S. EPA, 2009a.

The treatment cost information for 418 systems in Table 9-2 with available cost data in the CWSS demonstrate that water systems sourcing from surface water tend to have higher treatment costs than water systems that source from groundwater. In addition, for every system size category there are at least 18 water systems that source from surface water with which to infer cost data for systems affected by this regulation. In general, median treatment costs tend to increase with system size, with the exception of surface-water systems serving a population of 50,001-100,000. The CWSS masks identifiers for specific water systems, and so it is not possible to link any surveyed systems to the systems that are affected by this regulatory action. As such, EPA assigns median cost values to water systems based on their size and source category. All directly affected systems source primarily from surface water. Median treatment costs are used instead of average treatment costs to reduce the influence of outlier observations.

Finally, EPA computes avoided drinking water treatment costs $\Delta Cost_{itp}$ for drinking water system *i*, period *t*, and each water quality parameter p as:

$$\Delta Cost_{itp} = \eta_p * \frac{\Delta Concentration_{itp}}{Concentration_{itp}} * Cost_{it}$$

Where η_p represents the elasticity between source water concentrations of water quality parameter p and drinking water treatment costs. EPA uses a range of total nitrogen elasticity values from 0.05 to 0.06 to represent average elasticity values in Price and Heberling (2018). The elasticity of 0.05 is derived from a non-U.S. study without key controls, but it is included as a possible low-range elasticity estimate to better characterize uncertainty. For TSS, EPA uses the range of turbidity elasticity estimates of 0.10 to 0.12 from the same study to represent low and high estimates, where these values are derived exclusively from studies with controls for key confounders.

9.1.2 Results

Annualized avoided costs across all drinking water systems affected by the regulatory options for TN, TSS, and both parameters combined are summarized at the 2 percent discount rate in Table 9-3 (EPA provides summaries at the 3 percent and 7 percent discount rates in Appendix B). Annualized cost savings related to TN loadings reductions under the final rule range from $357,000 to $429,000. For TSS, annualized cost savings range from $103,000 to $124,000 under the final rule (Option B). Under the final rule, total cost savings to drinking water systems range from $460,000 to $552,000. Further details on methods specific to TN and TSS are described in turn below.

Table 9-3: Annualized Estimated Drinking Water Treatment Cost Savings under the Regulatory Options, Compared to Baseline (Million 2023$, 2 Percent Discount Rate)

Regulatory Option	TN		TSS		Combined	
	Low Estimate	High Estimate	Low Estimate	High Estimate	Low Estimate	High Estimate
Option A	$0.357	$0.429	$0.092	$0.111	$0.449	$0.539
Option B (Final Rule)	$0.357	$0.429	$0.103	$0.124	$0.460	$0.552
Option C	$0.460	$0.552	$0.133	$0.160	$0.592	$0.711

Source: U.S. EPA Analysis, 2024.

9.1.2.1 Nutrients

As described in Chapter 2, the incremental cost of treating drinking water to address excess nutrients can be substantial. Price and Heberling (2018) combined prior studies of the effect of nutrients on drinking water treatment costs, showing that a 1 percent change in nitrogen (as nitrate) concentration in source water leads to a 0.05 - 0.06 percent change in drinking water treatment costs, depending on whether the studies control for key confounders. Similarly, the authors show that a 1 percent increase in phosphorus loadings increases drinking water treatment costs by 0 – 0.02 percent, where findings of zero represent a null statistical relationship between phosphorus loadings and drinking water treatment costs. Given the uncertainty in the treatment cost elasticities for phosphorus and the possibility of double-counting cost savings across nitrogen and phosphorus, EPA does not calculate cost changes with respect to phosphorus loading reductions. To characterize uncertainty in the relationship between source water TN and drinking water treatment costs, EPA employed a low elasticity estimate of 0.05 and a high elasticity estimate of 0.06, representing the range of values reported in Price and Heberling (2018).

Table 9-4 presents illustrative average cost savings from reductions in TN across all years in the regulatory analysis and for all drinking water systems in each size category. These values are intended to illustrate the magnitude of impacts across system size, and as such they are only averaged across all years in the regulatory period and not annualized or discounted. For most system size categories, the average annual cost savings are relatively small both in absolute terms and in relation to annual drinking water treatment costs, ranging from roughly 0.01 percent to 0.03 percent of drinking water treatment costs. These small impacts are in part due to the small impacts of the regulatory options on source water concentrations of TN as reported in Table 9-1.

Table 9-4: Estimated Average System-Level Annual Changes in Drinking Water Treatment Costs for TN under the Regulatory Options, Compared to Baseline (2023$)

System Size	Low Estimate			High Estimate		
	Option A	Option B (Final Rule)	Option C	Option A	Option B (Final Rule)	Option C
Population <100	-5	-5	-8	-6	-6	-9
Population 101–500	-57	-57	-93	-69	-69	-111

Table 9-4: Estimated Average System-Level Annual Changes in Drinking Water Treatment Costs for TN under the Regulatory Options, Compared to Baseline (2023$)

System Size	Low Estimate			High Estimate		
	Option A	Option B (Final Rule)	Option C	Option A	Option B (Final Rule)	Option C
Population 501–3,300	-353	-353	-387	-423	-423	-464
Population 3,301–10,000	-481	-481	-482	-578	-578	-578
Population 10,001–50,000	-1,527	-1,527	-1,692	-1,833	-1,833	-2,030
Population 50,001–100,000	-230	-230	-430	-276	-276	-516
Population 100,001–500,000	-914	-914	-1,338	-1,097	-1,097	-1,606
Population >500,00	-17,526	-17,526	-23,804	-21,031	-21,031	-28,565

Notes: The presented annual cost changes by system size are not discounted or annualized and represent only changes to system treatment costs averaged over each year of the regulatory analysis period. Treatment costs include only ongoing operation and maintenance costs and exclude investments in irreversible capital equipment.

Source: U.S. EPA Analysis, 2024.

9.1.2.2 Total Suspended Solids

Reducing TSS from steam electric power plant effluent is expected to affect the turbidity of source waters used by drinking water systems. Water systems address TSS using chemical treatment with coagulants such as alum or ferrous sulfate. Coagulant application varies in dosage depending on the influent concentrations of TSS, and thus water system variable costs for coagulant purchases vary with TSS in source water. Treatment for TSS also produces coagulated sediment in proportion to the influent concentration of TSS and the quantity of coagulant added, and disposal of this coagulated sediment results in additional variable costs for drinking water systems.

The impacts of TSS on drinking water treatment costs have been quantified in prior EPA regulatory analyses including the 2004 Meat and Poultry Products Effluent Limitation Guidelines as well as the 2009 Effluent Limitation Guidelines and Standards for the Construction and Development Industry (see U.S. EPA, 2004b, 2009b). To calculate the changes in drinking water treatment costs associated with TSS, EPA first converts TSS to turbidity and then applies the elasticity for turbidity from Price and Heberling (2018).

EPA uses the elasticity associated with turbidity in Price and Heberling (2018) instead of TSS because the elasticity with respect to TSS is based on only one study with key controls and three studies overall. In addition, two of the underlying studies informing the TSS elasticity date from 1987 and 1988, and this relationship may have changed significantly since these studies were conducted. Further, the range of elasticity values for TSS is more disperse and less certain, suggesting that a 1 percent change in sediment loads could lead to a 0.05 to 0.24 percent change in treatment costs. In contrast, Price and Heberling (2018) calculate an elasticity with respect to turbidity that is much more precisely estimated across twelve studies; these studies suggest that a 1 percent increase in turbidity leads to an increase in drinking water costs of 0.10 to 0.14 percent. Aside from quality of underlying elasticity estimates, EPA follows the precedent set in in U.S. EPA (2009b) by estimating TSS-related changes to drinking water costs via changes in turbidity.

EPA converted TSS concentrations into nephelometric turbidity units (NTUs) using the method employed in U.S. EPA (2009b). In the prior analysis, TSS was converted to turbidity using Equation 9-1.

Equation 9-1.

$$Turbidity = \frac{TSS}{b}$$

Where turbidity is measured in NTUs and TSS is measured in mg/L. In U.S. EPA (2009b), *b* was set to a constant equal to 0.8, 1.5, or 2.2 to reflect low, medium, and high estimates of the relationship between TSS and turbidity. For this analysis, EPA produces a range of plausible TSS-turbidity conversions using only the low and high constants of 0.8 and 2.2. EPA also selected a range of elasticities of 0.10 and 0.12 based on studies that include key controls for confounding variables as reported in Price and Heberling (2018).

Table 9-5 presents illustrative average cost savings from reductions in TSS and associated turbidity across all years in the regulatory analysis and for all drinking water systems in each size category. These values are intended to illustrate the magnitude of impacts across system size, and as such they are only averaged across all years in the regulatory period and not annualized or discounted. The average annual system-level cost changes are relatively small in comparison to typical system-level treatment costs across all size categories.

Table 9-5: Estimated Average System-Level Annual Changes in Drinking Water Treatment Costs for TSS under the Regulatory Options, Compared to Baseline (2023$)

System Size	Low Estimate			High Estimate		
	Option A	Option B (Final Rule)	Option C	Option A	Option B (Final Rule)	Option C
Population<100	-1	-1	-1	-1	-2	-2
Population 101–500	-17	-21	-22	-20	-26	-27
Population 501–3,300	-67	-81	-82	-80	-97	-99
Population 3,301–10,000	-406	-415	-531	-487	-498	-638
Population 10,001–50,000	-258	-291	-308	-309	-349	-370
Population 50,001–100,000	-78	-90	-110	-94	-107	-133
Population 100,001–500,000	-628	-697	-932	-754	-838	-1,119
Population >500,00	-3,291	-3,821	-5,312	-3,970	-4,610	-6,401

Notes: The presented annual cost changes by system size are not discounted or annualized and represent only changes to system treatment costs averaged over each year of the regulatory analysis period. Treatment costs include only ongoing operation and maintenance costs and exclude investments in irreversible capital equipment.

Source: U.S. EPA Analysis, 2024.

9.2 Changes in Dredging Costs

As summarized in Chapter 2 and in Table 3-1, the regulatory options could result in relatively small changes in suspended solid discharges by steam electric power plants, which could have an impact on the rate of sediment deposition in affected reaches, including navigable waterways and reservoirs that require dredging for maintenance.

Navigable waterways, including rivers, lakes, bays, shipping channels and harbors, are an integral part of the United States' transportation network. They are prone to reduced functionality due to sediment build-up, which can reduce the navigable depth and width of the waterway (Clark, Haverkamp & Chapman, 1985; Ribaudo, 2011). In many cases, costly periodic dredging is necessary to keep them passable. The regulatory options could increase or reduce costs for government and private entities responsible for maintenance of navigable waterways by changing the need for dredging.

Reservoirs serve many functions, including water storage for drinking, irrigation, and hydropower uses, flood control, and recreation. Streams and rivers carry sediment into reservoirs, where it can settle and build up at a recorded average rate of 1.2 billion kilograms per reservoir every year (USGS, 2009). Sedimentation reduces reservoir capacity (Graf et al., 2010) and the useful life of reservoirs unless measures such as dredging are taken to reclaim capacity (Clark, Haverkamp & Chapman, 1985; Hargrove et al., 2010; Miranda, 2017).

9.2.1 Data and Methodology

In this analysis, EPA followed the same general methodology for estimating changes in costs associated with changes in sediment depositions in navigational waterways and reservoirs that EPA used in the 2020 rule and 2023 proposal (U.S. EPA, 2020b, 2023b).[133] The methodology utilizes information on historic dredging locations, frequency of dredging, the amount of sediment removed, and dredging costs in conjunction with the estimated changes in net sediment deposition (sedimentation minus erosion) in dredged waterways and reservoirs under the regulatory options. Benefits are equal to avoided costs, calculated as the difference from historical averages in total annualized dredging costs due to changes between the baseline and the regulatory options.

9.2.2 Results

9.2.2.1 Estimated Changes in Navigational Dredging Costs

EPA identified 128 unique dredging jobs and 400 dredging occurrences[134] within the affected reaches. This corresponds to approximately 8 percent of the dredging occurrences with coordinates reported in the Dredging Information System (U.S. Army Corps of Engineers, 2013). The recurrence interval for dredging jobs ranged from one to 17 years across affected reaches and averaged 13 years. Dredging costs vary considerably across geographic locations and dredging jobs from less than $1 per cubic yard at the Ohio River (open channel)[135] in Louisville, Kentucky to $534 per cubic yard at Herculaneum in St. Louis, Missouri.[136] The median unit cost of dredging for the entire conterminous United States is $3.75 per cubic yard.

Table 9-6 presents low and high estimates of dredged sediment volume and dredging costs during the period of 2025 through 2049 in navigational waterways that may be affected by steam electric plant discharges, based on historical averages. EPA generated low and high estimates for navigational dredging by varying the projected future dredging occurrence, including dredging frequency and job start as well as cost of dredging for locations that did not report location specific costs (see U.S. EPA, 2015a, Appendix K for details). Estimated total navigational dredging costs based on historical averages range from $57.3 million to $130.8 million per year.

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[133] For the 2020 rule analysis, EPA made two improvements to the methodology used in 2015. First, dredging occurrences were considered part of a single dredging job if the latitude and longitude coordinates were identical to within two decimal places. Second, the 10th percentile and 90th percentile of costs and sediment dredged for dredging occurrences within USACE districts were used to fill in missing values in the Low and High scenarios. EPA also made one change to the methodology used to estimate net sediment deposition at any given location in the reach network by using the *TOTAL_YIELD* output variable from the SPARROW models instead of *INC_TOTAL_YIELD*. This change was implemented to be more inclusive of the upstream impacts to affected COMIDs (*INC_TOTAL_YIELD* excluded upstream impacts).

[134] Dredging jobs refer to unique sites/locations defined by the U.S. Army Corps of Engineers where dredging was conducted, whereas dredging occurrences are unique instances when dredging was conducted and may include successive dredging at the same location.

[135] The cost per cubic yard at the Ohio River (open channel) is $0.37.

[136] The second most expensive dredging job was $55.30 per cubic yard also in St. Louis.

Table 9-6: Estimated Annual Average Navigational Dredging Quantities and Costs at Affected Reaches Based on Historical Averages

Total Sediment Dredged (Millions Cubic Yards)		Annual Costs (Millions of 2023$)	
Low	High	Low	High
544.8	974.9	$57.3	$130.8

Source: U.S. EPA Analysis, 2024.

The difference between the estimated dredging costs using historical averages and costs resulting from the reduction in sediment deposition under a regulatory option as compared to baseline represents the avoided costs under the regulatory option. Table 9-7 presents estimated changes in navigational dredging costs for the three regulatory options. Annualized benefits range from $3,800 to $4,700 under Option A and from $4,400 to $5,500 under Options B and C.

Table 9-7: Estimated Annualized Changes in Navigational Dredging Costs under the Regulatory Options, Compared to Baseline

Regulatory Option	Total Reduction in Sediment Dredged (Thousands Cubic Yards)		Annualized Avoided Costs (Millions of 2023$, 2% Discount Rate)[a]	
	Low	High	Low	High
Option A	7.1	9.3	<$0.01	$0.01
Option B (Final Rule)	8.3	10.8	<$0.01	$0.01
Option C	8.5	11.0	<$0.01	$0.01

a. Positive values represent cost savings.

Source: U.S. EPA Analysis, 2024.

9.2.2.2 Estimated Changes in Reservoir Dredging Costs

EPA identified 2,009 reservoirs within the affected reaches with changes in sediment loads under at least one of the regulatory options, corresponding to approximately one percent of the reservoirs represented in the SPARROW models (Ator, 2019; Hoos & Roland Ii, 2019; Robertson & Saad, 2019; Wise, 2019; Wise, Anning & Miller, 2019). EPA used USACE district regional estimates of average dredging costs to calculate changes in reservoir dredging costs under the regulatory options. The median cost per cubic yard ranges from $0.37 in the Louisville USACE District (Kentucky) to $52.42 in the Rock Island USACE District (Illinois), with a median value of $8.99 for USACE districts which contain affected reservoirs. Table 9-8 presents low and high estimates of the projected volume of sediment to be dredged during the period of 2025 through 2049 from these reservoirs as well as estimated annualized dredging costs, based on historical averages. The estimated reservoir dredging costs based on historical averages range between $771.4 million and $836.7 million.

Table 9-8: Estimated Annualized Reservoir Dredging Volume and Costs based on Historical Averages

Total Sediment Dredged (Millions Cubic Yards)		Annual Costs (Millions of 2023$)	
Low	High	Low	High
5,675.5	34,052.9	$771.4	$4,836.7

Source: U.S. EPA Analysis, 2024.

The difference between the estimated dredging costs using historical averages and costs resulting from the reduction in sediment deposition under a regulatory option as compared to baseline represents the avoided costs for that regulatory option. Table 9-9 presents avoided costs for reservoir dredging under the regulatory options, including low and high estimates. Annualized benefits are approximately $300 under Option A and range from $300 to $400 under Options B and C.

Table 9-9: Estimated Total Annualized Changes in Reservoir Dredging Volume and Costs under the Regulatory Options, Compared to Baseline

Regulatory Option	Total Reduction in Sediment Dredged (Thousands Cubic Yards)		Annualized Avoided Costs[a] (Millions of 2023$ per Year, 2% Discount Rate)	
	Low	High	Low	High
Option A	1.0	1.1	<$0.01	<$0.01
Option B (Final Rule)	1.2	1.3	<$0.01	<$0.01
Option C	1.2	1.4	<$0.01	<$0.01

a. Positive values represent cost savings.

Source: U.S. EPA Analysis, 2024.

9.3 Limitation and Uncertainty

Table 9-10 summarizes key uncertainties and limitations in the analysis of sediment dredging benefits. A more detailed description is provided in Appendix K of the 2015 BCA (U.S. EPA, 2015a). Note that the effect on benefits estimates indicated in the second column of the table refers to the magnitude of the benefits rather than the direction (*i.e.*, a source of uncertainty that tends to underestimate benefits indicates expectation for larger forgone benefits or for larger realized benefits). Uncertainties and limitations associated with SPARROW model estimates of sediment deposition are discussed in the respective regional model reports (Ator, 2019; Hoos & Roland Ii, 2019; Robertson & Saad, 2019; Wise, 2019; Wise, Anning & Miller, 2019).

Table 9-10: Limitations and Uncertainties in Analysis of Changes in Dredging Costs

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
EPA includes only TSS and TN in the estimation of drinking water treatment cost savings.	Underestimate	Drinking water systems may experience cost savings due to TSS, nutrients, halogens, and metals, although EPA lacks statistically reliable treatment cost elasticities for parameters other than TSS and TN.
EPA assumes that only water systems with surface water intakes that are directly affected by steam electric effluents have cost savings, and so water purchasers indirectly affected by the regulation do not accrue cost savings.	Underestimate	Water systems that purchase water from directly-affected systems may realize cost savings in the form of lower water prices. These water systems are excluded from the analysis due to uncertainties surrounding price setting behavior among water retailers.
EPA selects elasticity estimates in Price and Heberling (2018) based on models with complete controls.	Uncertain	Estimated relationships between source water turbidity and TN levels are generally slightly higher when including studies that did not incorporate key controls for confounding variables.

Table 9-10: Limitations and Uncertainties in Analysis of Changes in Dredging Costs

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
EPA imputes costs for all affected systems based on a subset of public systems available in the Community Water System Survey (2006) and uses median values rather than average costs within size category.	Uncertain	The 2006 CWSS was designed to be a representative sample of US drinking water systems, but it is possible that drinking water systems sourcing from surface waters affected by this regulation may have different characteristics and higher or lower drinking water treatment costs, on average. To the extent that systems affected by the regulation differ in their treatment costs from the 2006 CWSS systems, EPA may over or under-estimate true cost savings.
EPA considers drinking water treatment capital costs to be fully realized and not recoverable, so treatment cost savings only vary by ongoing operations & maintenance treatment costs.	Underestimate	Some capital expenditures can be reduced with improvements in source water quality. For example, water systems may be able to switch to less costly treatment processes while still maintaining their water quality objectives. These possible changes in capital expenditures would result in an underestimate of true cost savings.
Disposal costs for coagulated sediment sludge may be significantly higher if the sediment sludge also contains other hazardous chemicals.	Underestimate	To the extent that sediment sludge from drinking water systems affected by steam electric effluents have more toxic chemicals than typical systems, EPA expects that disposal costs for the sludge would be higher.
The analysis of dredging cost savings scales dredging volumes and costs in proportion to the percent change in sediment deposition in navigational waterways and reservoirs.	Uncertain	EPA estimated a linear relationship between changes in sediment deposition and dredging volumes and costs which may not capture non-linear dynamics in the relationships between sediment deposition and dredging volumes and between dredging volumes and costs.
The frequency of navigational dredging is based on the proximity of nearby dredging occurrences.	Uncertain	Because data in the U.S. Army Corps of Engineers Database does not indicate whether different dredging occurrences are part of a single dredging job, EPA determined whether dredging occurrences are part of a single dredging job by comparing their latitudinal and longitudinal coordinates to two decimal places. Changes in the precision of a job's coordinates would affect the number of occurrences that are considered part of the same dredging job. When precision is changed to a single decimal place, the number of occurrences that would be considered part of a single dredging job increases (and vice-versa). A larger (smaller) number of occurrences for a single dredging job would increase (decrease) the frequency of dredging and, as a result, total dredging costs over the period of analysis.
The analysis of navigational waterways includes only jobs reported for 1998 through 2015.	Underestimate	Because some dredging jobs included in the U.S. Army Corps of Engineers Database lack latitude and longitude and the database does not use standardized job names, EPA was only able to map approximately 64 percent of all recorded dredging occurrences. This may lead to potential underestimation of historical costs and changes in dredging costs under the regulatory options.

Table 9-10: Limitations and Uncertainties in Analysis of Changes in Dredging Costs

Uncertainty/Limitation	Effect on Benefits Estimate	Notes
The analysis of reservoir dredging is limited to reservoirs identified on the NHD reach network.	Underestimate	The omission of other reservoirs could understate the magnitude of estimated historical costs and changes in reservoir dredging benefits if there are additional reservoirs located downstream from steam electric power plants.

10 Summary of Estimated Total Monetized Benefits

Table 10-1 summarizes the total annualized monetized benefits. Table 10-2 provides additional details on the time profile of the monetized benefits.

The monetized benefits presented in these two tables do not account for all effects of the regulatory options, including changes in certain cancer and non-cancer health risk (*e.g.*, effects of halogenated disinfection byproducts in drinking water, effects of cadmium on kidney functions and bone density), impacts of pollutant load changes on T&E species habitat, etc. See Chapter 2 for a discussion of categories of benefits EPA did not monetize. Chapter 4 through Chapter 9 provide more detail on the estimation methodologies for each benefit category.

Table 10-1: Summary of Estimated Total Annualized Benefits of the Regulatory Options, Compared to Baseline (Millions of 2023$; 2 Percent Discount)

Benefit Category	Option A	Option B (Final Rule)	Option C
Human Health			
Changes in IQ losses in children from exposure to lead via fish ingestion[a]	<\$0.01	<\$0.01	<\$0.01
Changes in cardiovascular disease mortality from exposure to lead via fish ingestion	\$0.16 – \$0.43	\$0.16 – \$0.43	\$0.16 – \$0.45
Changes in IQ losses in children from exposure to mercury via fish ingestion	\$1.71	\$1.98	\$2.00
Changes in cancer risk from disinfection by-products in drinking water	\$13.37	\$13.37	\$14.27
Ecological Conditions and Recreational Uses Changes			
Use and nonuse values for water quality changes[b]	\$0.79	\$1.24	\$1.68
Market and Productivity Effects[a]			
Changes in drinking water treatment costs	\$0.45 – \$0.54	\$0.46 – \$0.55	\$0.59 – \$0.71
Changes in dredging costs[a]	<\$0.01	<\$0.01	<\$0.01
Air Quality-Related Effects			
Climate change effects from changes in greenhouse gas emissions[c]	\$1,200	\$1,600	\$1,900
Human health effects from changes in NO_X, SO_2, and $PM_{2.5}$ emissions[c,d]	\$1,200	\$1,600	\$2,000
Total[e]	**\$2,417**	**\$3,217**	**\$3,919**
Additional non-monetized benefits	Other avoided adverse health effects (cancer and non-cancer) from reduced exposure to pollutants discharged to receiving waters; improvements in T&E species habitat and potential effects on T&E species populations; changes in property value from water quality improvements; changes in ecosystem effects, visibility impairment, and human health effects from direct exposure to NO_2, SO_2, and hazardous air pollutants.		

a. "<\$0.01" indicates that monetary values are greater than \$0 but less than \$0.01 million.

b. Estimates based on Model 1, which provides EPA's main estimate of non-market benefits. See Chapter 6 for details.

c. Values for air-quality related effects are rounded to two significant figures. EPA estimated the air quality-related benefits for Option B. EPA extrapolated estimates of air quality-related benefits for Options A and C from the estimate for Option B that is based on IPM outputs. For the purpose of scaling the air quality-related benefits, EPA used the subset of social costs associated with the wastestreams modeled in the benefits analyses. See Chapter 8 for details.

d. The values reflect the LT estimates of human health effects from changes in $PM_{2.5}$ and ozone levels. See Chapter 8 for details.

Table 10-1: Summary of Estimated Total Annualized Benefits of the Regulatory Options, Compared to Baseline (Millions of 2023$; 2 Percent Discount)

Benefit Category	Option A	Option B (Final Rule)	Option C

e. Values for individual benefit categories may not sum to the total due to independent rounding.

Source: U.S. EPA Analysis, 2024

Table 10-2: Time Profile of Monetized Benefits (Millions of 2023$)

Year	Option A[1, 2]	Option B (Final Rule)[2]	Option C[1,2]
2025	$3.2	$3.6	$4.5
2026	-$3.3	-$5.1	-$5.9
2027	-$5.9	-$9.5	-$11.4
2028	$4,904.4	$6,404.8	$7,906.1
2029	$4,904.7	$6,505.2	$7,906.5
2030	$2,908.1	$3,808.9	$4,709.9
2031	$3,008.8	$3,909.6	$4,710.6
2032	$5,409.5	$7,010.3	$8,611.3
2033	$5,410.1	$7,110.9	$8,711.9
2034	$5,510.7	$7,211.5	$8,812.6
2035	$5,511.3	$7,212.1	$8,813.1
2036	$5,511.7	$7,212.5	$8,913.6
2037	$5,612.2	$7,313.0	$8,914.1
2038	$1,412.6	$1,843.5	$2,214.5
2039	$1,413.1	$1,854.0	$2,315.0
2040	$1,413.6	$1,854.4	$2,315.5
2041	$1,414.0	$1,864.9	$2,316.0
2042	$584.5	$765.4	$936.5
2043	$594.9	$775.8	$947.0
2044	$595.4	$776.3	$957.5
2045	$605.9	$786.8	$958.0
2046	$606.4	$787.3	$968.6
2047	$616.8	$797.7	$979.0
2048	$397.2	$508.1	$619.5
2049	$397.6	$518.5	$629.9
Annualized Benefits Accounted in 2025-2049, 2%	**$2,410.6**	**$3,211.3**	**$3,912.4**
Annualized Value of Additional Benefits in 2050-2115, 2%[3]	**$6.3**	**$6.3**	**$6.7**
Total Annualized Benefits, 2%	**$2,417**	**$3,218**	**$3,919**

[1] EPA estimated the air quality-related benefits for Option B. EPA extrapolated estimates of air quality-related benefits for Options A and C from the estimate for Option B that is based on IPM outputs. For the purpose of scaling the air quality-related benefits, EPA used the subset of social costs associated with the wastestreams modeled in the benefits analyses.

[2] Values for air-quality related effects included in the total for each year are rounded to two significant figures.

[3] Accounts for avoided bladder cancer benefits in 2050-2115 from reductions in TTHM exposure in 2025-2049

Source: U.S. EPA Analysis, 2024.

11 Summary of Total Social Costs

This chapter discusses EPA's estimates of the costs to society under the regulatory options. Social costs include costs incurred by both private entities and the government (*e.g.*, in implementing the regulation). As described further in Chapter 10 of the RIA (U.S. EPA, 2024e), EPA did not evaluate incremental baseline costs, and associated cost savings to state governments which would no longer have to evaluate and incorporate best professional judgment into NPDES permits under the regulatory options. Consequently, the only category of costs used to calculate social costs are estimated technology implementation costs for steam electric power plants.

11.1 Overview of Costs Analysis Framework

The RIA (Chapter 3) presents EPA's development of costs for the estimated 858 steam electric power plants within the scope of the final rule (U.S. EPA, 2024e). These costs (pre-tax) are used as the basis of the social cost analysis.[137] A subset of these plants (between 141 and 170, depending on the regulatory option) incur non-zero incremental costs under the final rule (Option B), as compared to the baseline. The range corresponds to the lower and upper bound cost scenarios that reflect the uncertainty associated with costs for meeting limits for unmanaged CRL. As described in the RIA, the lower bound scenario reflects the sum of point estimates of costs to meet FGD wastewater, BA transport water, legacy wastewater, and CRL limits, plus the *lower* bound estimate of the cost to meet limits for unmanaged CRL, whereas the upper bound scenario reflects the sum of the point estimates for the four wastestreams plus the *upper* bound estimate of the cost to meet limits for unmanaged CRL.

As described earlier in Chapter 1, EPA estimated that steam electric power plants, in the aggregate, will implement control technologies to meet revised limits for FGD wastewater, BA transport water, and CRL between 2025 and 2029. EPA estimated that plants will implement control technologies to meet legacy wastewater limits in 2044. For the analysis of social costs, EPA estimated a plant- and year-explicit schedule of technology implementation cost outlays over the period of 2025 through 2049.[138] This schedule accounts for retirements and repowerings by zeroing-out O&M costs to operate BA and FGD treatment systems in years following unit retirement or repowering, but continued O&M costs for CRL since treatment of the CRL wastewater is expected to continue even after a unit ceases to generate electricity. After creating a cost-incurrence schedule for each cost component, EPA summed the costs expected to be incurred in each year for each plant, then aggregated these costs to estimate the total costs for each year in the analysis period. Specifically, EPA assumed that capital costs for compliance technology equipment, installation, site preparation, construction, and other upfront, non-annually recurring outlays associated with compliance with the regulatory options are incurred in the modeled compliance year for each plant. Annual fixed O&M costs, including regular annual monitoring, and annual variable O&M costs (*e.g.*, operating labor, maintenance labor and materials, electricity required to operate wastewater treatment systems, chemicals, combustion residual

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[137] As discussed in Section 3.1.1 of the RIA (U.S. Environmental Protection Agency. (2024e). *Regulatory Impact Analysis for Supplemental Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category*. (821-R-24-007).), EPA did not select the lowest-cost technology for five plants to meet zero-discharge limits for CRL. This resulted in the estimated total compliance costs for Option B and Option C being overstated by approximately $6 million (1.5 percent of total costs) on an after-tax basis.

[138] The period of analysis extends through 2049 to capture a substantive portion of the life of the wastewater treatment technology at any steam electric power plant (20 or more years), and the last year of technology implementation (2029).

waste transport and disposal operation and maintenance) are incurred each year. Other non-annual recurring costs are incurred at specified intervals of 5, 6, or 10 years. See Section 3.1.2 in the RIA for details.

Following the approach used for the analyses of the 2015 and 2020 rules, and 2023 proposal (U.S. EPA, 2015a, 2020b, 2023k), after technology implementation costs were assigned to the year of occurrence, the Agency adjusted these costs for change between 2023 (the year when costs were estimated) and the year(s) of their incurrence as follows:

- All technology costs, except planning, were adjusted to their incurrence year(s) using the Construction Cost Index (CCI) from McGraw Hill Construction and the Gross Domestic Product (GDP) deflator index published by the U.S. Bureau of Economic Analysis (BEA).
- Planning costs were adjusted to their incurrence year(s) using the Employment Cost Index (ECI) Bureau of Labor Statistics (BLS) and GDP deflator.

The CCI and ECI adjustment factors were developed only through the year 2031; after these years, EPA assumed that the real change in prices is zero – that is, costs are expected to change in line with general inflation. EPA judges this to be a reasonable approach, given that capital expenditures will occur by 2029 and the uncertainty of long-term future price projections.

After developing the year-explicit schedule of total costs and adjusting them for predicted real change to the year of their incurrence, EPA calculated the present value of these cost outlays as of the anticipated rule promulgation year by discounting the cost in each year back to 2024 using a 2 percent discount rates, following OMB regulatory analysis guidance in Circular A-4 (OMB, 2023). EPA calculated the constant annual equivalent value (annualized value), again using the 2 percent discount rate, over a 25-year social cost analysis period. EPA assumed no re-installation of wastewater treatment technology during the period covered by the social cost analysis, *i.e.*, upfront capital costs are incurred only once.

To assess the economic costs of the regulatory options to society, EPA relied first on the estimated costs to steam electric power plants for the labor, equipment, material, and other economic resources needed to comply with the regulatory options (see U.S. EPA, 2024e for details). In this analysis, the market prices for labor, equipment, material, and other compliance resources represent the opportunity costs to society for use of those resources in regulatory compliance. EPA assumed in its social cost analysis that the regulatory options do not affect the aggregate quantity of electricity that will be sold to consumers and, thus, that the rule's social cost will include no changes in consumer and producer surplus *from changes in electricity sales* by the electricity industry in aggregate. Given the small impact of the regulatory options on electricity production cost for the total industry (see RIA Chapter 5, U.S. EPA, 2024e) and relatively inelastic electricity demand with respect to price, at least in the short term (Burke & Abayasekara, 2018; Bernstein and Griffin (2005)), this approach is reasonable for the social cost analysis (for more details on the impacts of the regulatory options on electricity production cost, see RIA Chapter 5). The social cost analysis considers costs on an as-incurred, year-by-year basis — that is, this analysis associates each cost component to the year(s) in which they are assumed to occur relative to the assumed rule promulgation and technology implementation years.[139]

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[139] The specific assumptions of when each cost component is incurred can be found in Chapter 3 of the RIA (U.S. Environmental Protection Agency. (2024a). *Benefit and Cost Analysis for Supplemental Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category*. (821-R-24-006).).

Finally, as discussed in Chapter 10 of the RIA (U.S. EPA, 2024e; see Section 10.7: Paperwork Reduction Act of 1995), the regulatory options will not result in additional administrative costs for plants to implement, and state and federal NPDES permitting authorities to administer, the rule. The social cost analysis therefore focuses on the resource cost of compliance as the only direct cost incurred by society as a result of the final rule.

11.2 Key Findings for Regulatory Options

Table 11-1 presents annualized incremental costs for the analyzed regulatory options, as compared to the baseline.

Table 11-1: Summary of Estimated Incremental Annualized Costs for Regulatory Options (Millions of 2023$, 2 Percent Discount Rate)

Regulatory Option	Annualized Costs	
	Lower Bound	Upper Bound
Option A	$433.2	$960.9
Option B (Final Rule)	$536.2	$1,063.9
Option C	$622.4	$1,150.1

Source: U.S. EPA Analysis, 2024.

Table 11-2 and Table 11-3 provide additional detail on the social cost calculations for the lower bound and upper bound cost scenarios, respectively. The tables compile, for each regulatory option, the assumed time profiles of technology implementation costs incurred, relative to the baseline, as well as the annualized costs. The maximum technology implementation outlays differ across the options but are incurred over the years 2025 through 2029, *i.e.*, during the estimated window (defined as Period 1 in Section 3.2.1) when steam electric power plants are expected to implement wastewater treatment technologies for FGD wastewater, BA transport water, and CRL. Outlays increase in 2044 due to the implementation of treatment to meet legacy wastewater limits as plants are assumed to start dewatering ponds in that year.

Table 11-2: Time Profile of Costs to Society (Millions of 2023$) – Lower Bound

Year	Option A	Option B (Final Rule)	Option C
2025	$1,096.8	$1,240.0	$1,349.2
2026	$613.0	$748.9	$1,009.8
2027	$1,010.1	$1,123.4	$1,328.2
2028	$1,152.8	$1,448.5	$1,679.5
2029	$718.9	$852.0	$1,027.6
2030	$285.3	$345.3	$399.1
2031	$293.2	$353.2	$406.4
2032	$293.2	$352.6	$405.8
2033	$292.2	$352.2	$405.9
2034	$294.4	$353.0	$405.9
2035	$293.0	$352.4	$405.9
2036	$286.3	$347.2	$401.9
2037	$290.4	$350.4	$403.5
2038	$289.8	$349.2	$402.4
2039	$288.7	$348.7	$402.3
2040	$290.9	$349.5	$402.4
2041	$289.4	$348.9	$402.4
2042	$286.2	$347.1	$401.8
2043	$289.7	$349.7	$402.8

Table 11-2: Time Profile of Costs to Society (Millions of 2023$) – Lower Bound

Year	Option A	Option B (Final Rule)	Option C
2044	$289.8	$803.7	$856.9
2045	$288.7	$376.6	$430.3
2046	$290.9	$377.5	$430.3
2047	$290.1	$377.5	$431.0
2048	$286.3	$375.2	$429.8
2049	$289.7	$377.6	$430.8
Annualized Costs, 2%	**$433.2**	**$536.2**	**$622.4**

Source: U.S. EPA Analysis, 2024.

Table 11-3: Time Profile of Costs to Society (Millions of 2023$) – Upper Bound

Year	Option A	Option B (Final Rule)	Option C
2025	$1,853.6	$1,996.8	$2,106.0
2026	$1,011.7	$1,147.5	$1,408.5
2027	$1,772.3	$1,885.6	$2,090.4
2028	$2,967.8	$3,263.6	$3,494.5
2029	$1,649.2	$1,782.3	$1,957.9
2030	$692.3	$752.3	$806.1
2031	$709.9	$769.8	$823.0
2032	$708.5	$768.0	$821.2
2033	$707.6	$767.5	$821.2
2034	$710.1	$768.7	$821.5
2035	$709.0	$768.5	$822.0
2036	$699.7	$760.6	$815.3
2037	$707.0	$767.0	$820.1
2038	$705.1	$764.6	$817.7
2039	$704.1	$764.0	$817.7
2040	$706.6	$765.2	$818.0
2041	$705.5	$765.0	$818.5
2042	$699.6	$760.5	$815.2
2043	$706.4	$766.3	$819.5
2044	$705.1	$1,219.1	$1,272.2
2045	$704.1	$792.0	$845.6
2046	$706.6	$793.1	$846.0
2047	$706.2	$793.6	$847.1
2048	$699.7	$788.6	$843.2
2049	$706.4	$794.2	$847.4
Annualized Costs, 2%	**$960.9**	**$1,063.9**	**$1,150.1**

Source: U.S. EPA Analysis, 2024.

12 Benefits and Social Costs

This chapter compares total monetized benefits and costs for the regulatory options. Benefits and costs are compared on two bases: (1) incrementally for each of the options analyzed as compared to the baseline and (2) incrementally across options. The comparison of benefits and costs also satisfies the requirements of E.O. 12866: Regulatory Planning and Review (58 FR 51735, October 4, 1993), as amended by E.O. 13563: Improving Regulation and Regulatory Review (76 FR 3821, January 21, 2011) and E.O. 14094: Modernizing Regulatory Review (88 FR 21879, April 11, 2023). See Chapter 9 in the RIA for details (U.S. EPA, 2024e).

12.1 Comparison of Benefits and Costs by Option

Chapters 10 and 11 present estimates of the benefits and costs, respectively, for the regulatory options as compared to the baseline. Table 12-1 presents EPA's estimates of benefits and costs of the regulatory options, annualized over 25 years. The table provides an approximate comparison of total monetized benefits and total costs for the final rule due to differences in wastestreams included in the two analyses. Thus, the benefits analysis omits loading reductions associated with meeting limits for unmanaged CRL and legacy wastewater, even though the costs for meeting these limits are included in the total costs. EPA expects that including these wastestreams in the analysis of benefits would increase the monetized benefits.

Table 12-1: Total Estimated Annualized Benefits and Costs by Regulatory Option and Discount Rate, Compared to Baseline (Millions of 2023$, 2 Percent Discount Rate)

Regulatory Option	Total Monetized Benefits[a,b]	Total Costs[a]	
		Lower Bound	Upper Bound
Option A	$2,417	$433.2	$960.9
Option B (Final Rule)	$3,217	$536.2	$1,063.9
Option C	$3,919	$622.4	$1,150.1

a. EPA's benefits analysis did not account for the effects of loading reductions associated with limits for unmanaged CRL and legacy wastewater, whereas the total costs account for outlays for meeting these limits. See Chapter 11 for details on the lower and upper bound cost scenarios.

b. EPA estimated the air quality-related benefits for the final rule (Option B) only. EPA extrapolated estimates of air quality-related benefits for Options A and C from the estimate for Option B that is based on IPM outputs. See Chapter 8 for details.

Source: U.S. EPA Analysis, 2024.

12.2 Analysis of Incremental Benefits and Costs

In addition to comparing estimated benefits and costs for each regulatory option relative to the baseline, as presented in the preceding section, EPA also estimated the benefits and costs of the options on an incremental basis. The comparison in the preceding section addresses the simple quantitative relationship between estimated benefits and costs for each option and determines whether costs or benefits are greater for a given option and by how much. In contrast, incremental analysis looks at the differential relationship of benefits and costs across options and poses a different question: as increasingly more costly options are considered, by what amount do benefits, costs, and net benefits (*i.e.*, benefits minus costs) change from option to option? Incremental net benefit analysis provides insight into the net gain to society from imposing increasingly more costly requirements.

EPA conducted the incremental net benefit analysis by calculating the change in net benefits, from option to option, in moving from the least stringent option to successively more stringent options, where stringency is determined based on total pollutant loads. As described in Chapter 1, the regulatory options differ in the technology basis for different wastestreams. Thus, the difference in benefits and costs across the options derives from the characteristics of the wastestreams controlled by an option, the relative effectiveness of the control technology in reducing pollutant loads, the timing of control technology implementation, and the distribution and characteristics of steam electric power plants and of the receiving reaches. As was the case for the comparison in Table 12-1, the calculation of net benefits is also an approximation due to the differences in wastestreams included in the analysis of the benefits versus the costs.

As reported in Table 12-2, all options have positive net annual monetized benefits, meaning benefits exceed costs. This is true despite the omission of additional loading reductions from unmanaged CRL and legacy wastewater from the monetized benefits analysis. Net annual monetized benefit estimates range from $2,153 million under Option A to $2,681 million under Option C. Incremental net annual monetized benefit values are also positive across all options, which means that the increase in benefits under the more stringent options is larger than the increase in costs. The incremental net annual monetized benefits of moving from Option A to the final rule (Option B) is $698 million, whereas the incremental net benefits of moving the final rule (Option B) to Option C is $615 million.

Table 12-2: Analysis of Estimated Incremental Net Benefit of the Regulatory Options, Compared to Baseline and to Other Regulatory Options (Millions of 2023$, 2 Percent Discount Rate)

Regulatory Option	Net Annualized Monetized Benefits[a,b]		Incremental Net Annualized Monetized Benefits[c]	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Option A	$1,983	$1,456	NA	NA
Option B (Final Rule)	$2,681	$2,153	$698	$698
Option C	$3,296	$2,769	$615	$615

NA: Not applicable for Option A

a. Net benefits are calculated by subtracting total annualized costs from total annual monetized benefits, where both costs and benefits are measured relative to the baseline.

b. EPA estimated the air quality-related benefits for the final rule (Option B) only. EPA extrapolated estimates of air quality-related benefits for Options A and C from the estimate for Option B that is based on IPM outputs. See Chapter 8 for details.

c. Incremental net benefits are equal to the difference between net benefits of an option and net benefits of the previous, less stringent option.

Source: U.S. EPA Analysis, 2024.

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A Changes to Benefits Methodology since 2020 Final Rule Analysis

The table below summarizes the principal methodological changes EPA made to analyses of the benefits of the final rule regulatory options, as compared to the analyses of the 2020 final rule (U.S. EPA, 2020b) and 2023 proposal (U.S. EPA, 2023c).

Table A-1: Changes to Benefits Analysis Since 2020 Final Rule

Benefits Category and Analysis Component	Analysis Component [2020 final rule analysis value]	Changes to Analysis for Proposed Rule, relative to 2020 Final Rule	Changes to Analysis for 2024 Final Rule, relative to 2023 Proposed Rule
General inputs and pollutant loads			
Universe of plants, EGUs, and receiving reaches	Analysis includes loadings for all coal-fired units operating as of 2020. The analysis also reflects other updates to the steam electric industry profile through the end of 2019, including the timing of projected retirements and refueling projects and existing treatment technologies.	Analysis includes updates to the steam electric industry profile through the end of 2021, including the timing of projected retirements and refueling projects and existing treatment technologies. See TDD for details (U.S. EPA, 2023o).	Analysis includes further updates to the steam electric industry profile through August 25, 2023, including the timing of projected retirements and refueling projects and existing treatment technologies. See TDD for details (U.S. EPA, 2024f).
General pollutant loadings and concentrations	Affected reaches based on immediate receiving reaches and flow paths in medium-resolution NHD.	Updated immediate receiving reaches (and associated downstream reaches) for selected plants. Discharges include CRL discharge outfalls.	Updated immediate receiving reaches (and associated downstream reaches) for selected plants. Discharges include legacy wastewater discharge outfalls.
	SPARROW modeling of nutrient and sediment concentrations in receiving and downstream reaches based on the most recent five regional SPARROW models that use the medium-resolution NHD stream network.	No change.	No change.

Table A-1: Changes to Benefits Analysis Since 2020 Final Rule

Benefits Category and Analysis Component	Analysis Component [2020 final rule analysis value]	Changes to Analysis for Proposed Rule, relative to 2020 Final Rule	Changes to Analysis for 2024 Final Rule, relative to 2023 Proposed Rule
	Uses the annual average loadings for two distinct periods during the analysis: 2021-2028 and 2029-2047, with pre-technology implementation loads set equal to current loads and post-retirement or repowering loads set to zero.	The two analysis periods are 2025-2029 and 2030-2049.	No change.
Water quality index	Expresses overall water quality changes using a seven-parameter index that includes subindex curve parameters for nutrients and sediment based on the regional SPARROW models.	No change.	EPA used updated subindex curves for TN, TP, and TSS derived using NARS water quality assessment data and defined at the level of the associated NARS ecoregions.
Population and socioeconomic characteristics	Based on 2017 ACS data.	Based on 2019 ACS data.	Based on 2021 ACS data.
Human health benefits from changes in exposure to halogenated disinfection byproducts in drinking water			
Public water systems affected by bromide discharges	Modeled changes in bromide concentrations in source water of public water systems.	Modeled changes in bromide concentrations in source water of public water systems and total trihalomethane concentrations in drinking water.	No change from 2023 proposal.
SDWIS database with PWS network and population served information	SDWIS 2020Q1 data	SDWIS 2021Q1 data	SDWIS 2022Q4 data

Table A-1: Changes to Benefits Analysis Since 2020 Final Rule

Benefits Category and Analysis Component	Analysis Component [2020 final rule analysis value]	Changes to Analysis for Proposed Rule, relative to 2020 Final Rule	Changes to Analysis for 2024 Final Rule, relative to 2023 Proposed Rule
Lifetime changes in incidence of bladder cancer	Qualitative discussion. EPA received public comments that further evaluation of certain DBPs should be completed and that the analysis at proposal should be subjected to peer review. EPA acknowledges that further study in this area should be conducted, including peer review of the model used at proposal. EPA will continue to evaluate the scientific data on the health impacts of DBPs.	Applied lifetime risk model to estimate changes in bladder cancer incidence in population served by public water systems. The modeling approach is generally the same EPA used for the 2019 proposed rule analysis. It is also consistent with that in a study by Weisman et al. (2022) which also applied the dose-response information from Regli et al. (2015) with more recent DBP data to estimate the potential number of bladder cancer cases associated with chlorination DBPs in drinking water. Weisman et al. (2022) found that the weight of evidence supporting causality further increased since Regli et al., 2015.	No change.
Monetization of changes in incidence of bladder cancer	Because EPA did not calculate changes in incidence of bladder cancer, the Agency was unable to monetize this effect.	Mortality valued using VSL (U.S. EPA, 2010, updated 2014). Morbidity valued based on COI (Greco et al., 2019).	Mortality valued using VSL (U.S. EPA, 2010, updated 2014). Morbidity valued based on WTP from Bosworth, Cameron and DeShazo (2009).

Table A-1: Changes to Benefits Analysis Since 2020 Final Rule

Benefits Category and Analysis Component	Analysis Component [2020 final rule analysis value]	Changes to Analysis for Proposed Rule, relative to 2020 Final Rule	Changes to Analysis for 2024 Final Rule, relative to 2023 Proposed Rule
Non-market benefits from water quality improvements			
WTP for water quality improvements	Benefits valued using a MRM	EPA added 10 new studies to the 2015 meta-data, revised existing observations as needed to improve consistency within the dataset, and re-estimated the MRM (see ICF, 2022b for details). Similar to the 2015 MRM, the model includes spatial characteristics of the affected water resources: size of the market, waterbody characteristics (length and flow), availability of substitute sites, and land use type in the adjacent counties. Variables characterizing the availability of substitute sites, size of the market, and land-use were revised based on changes in the universe of receiving reaches and CBGs included in the analysis.	No change, except from updates to the model scope and variables to reflect changes in the universe of receiving reaches and CBGs.
Effects on T&E species	Categorical analysis based on designated critical habitat overlap/proximity to reaches with estimated changes in NRWQC exceedances.	EPA updated the list of species included in the analysis based on the 2020 ECOS online database (U.S. FWS, 2020d). EPA also relied on the habitat range of T&E species in determining whether reaches downstream from steam electric power plant outfalls intersect species habitat (U.S. FWS, 2020b), rather than "critical habitat" as the term is defined in the ESA. EPA included all species categorized as having higher vulnerability to water pollution in its analysis (see Chapter 7 and Appendix I for details). The only exception is species endemic to springs and headwaters.	EPA updated the list of species based on critical habitats as of January 4, 2024, as well as the scope of the analysis to reflect additional receiving waters. At this time, EPA also adjusted analysis to remove species delisted by the USFWS in 2023 due to extinction (U.S. Fish & Wildlife Service, 2023).

Table A-1: Changes to Benefits Analysis Since 2020 Final Rule

Benefits Category and Analysis Component	Analysis Component [2020 final rule analysis value]	Changes to Analysis for Proposed Rule, relative to 2020 Final Rule	Changes to Analysis for 2024 Final Rule, relative to 2023 Proposed Rule
Air quality-related effects			
Emissions changes	Emissions from changes in electricity generation profile from 2020 IPM runs. Energy use-associated emissions were updated to reflect emission factors estimated using the 2020 IPM runs.	Emissions from changes in electricity generation profile from 2022 IPM runs. Energy use-associated emissions were updated to reflect emission factors estimated using the 2022 IPM runs.	Emissions from changes in electricity generation profile from 2024 IPM runs. Energy use-associated emissions were updated to reflect emission factors estimated using the 2024 IPM runs.
Air quality changes	Used the ACE modeling methodology to estimate changes in air pollutant concentrations.	Updated methodology to reflect the most recent air quality surfaces.	Updated methodology to reflect the most recent air quality surfaces. See Appendix J for details.
Monetization of health effects	Used BenMAP-CE model to estimate associated human health benefits.	No change.	No change.
Monetization of changes in GHG emissions	Used E.O. 13783 domestic-only SC-GHG values at 3 and 7 percent discounts in main analysis. Presented results based on global SC-GHG values under 2.5, 3, and 7 percent discount rates in sensitivity analysis.	Used IWG (2021) recommended interim global SC-GHG values at 2.5, 3 (average and 95%), and 5 percent discount rates.	Used EPA (2023l) updated global SC-GHG values at 1.5 percent, 2.0 percent, and 2.5 percent near-term Ramsey discount rates. Presented results based on IWG (2021) interim SC-GHG values in Appendix.

B Estimated Costs and Benefits Using Discount Rates from the Proposal

This appendix provides costs and benefits of the final rule using the discount rates used in the proposal BCA to facilitate comparison with the benefits analysis presented at proposal (see 2023 BCA; U.S. EPA, 2023c). As is the case throughout the document, monetary values in this appendix are presented in 2023 dollars (as compared to 2021 dollars for values in the 2023 BCA (U.S. EPA, 2023c)).

B.1 Benefits

Table B-1: Estimated Bromide-related Bladder Cancer Mortality and Morbidity Monetized Benefits

Regulatory Option	Changes in cancer cases from changes in TTHM exposure 2025-2049[a]		Benefits (million 2023$, discounted to 2024)					
	Total bladder cancer cases avoided	Total cancer deaths avoided	Annualized[b] benefits from avoided mortality		Annualized[b] benefits from avoided morbidity		Total annualized[b] benefits	
			3%	7%	3%	7%	3%	7%
Option A	98	28	$9.5	$5.8	$1.7	$1.1	$11.3	$7.0
Option B (Final Rule)	98	28	$9.5	$5.8	$1.7	$1.1	$11.3	$7.0
Option C	104	29	$10.2	$6.3	$1.9	$1.2	$12.1	$7.5

[a] The analysis accounts for the persisting health effects (up until 2125) from changes in TTHM exposure during the period of analysis (2025-2049).

[b] Benefits are annualized over 25 years.

Source: U.S. EPA Analysis, 2024

Table B-2: Estimated Benefits from Avoided IQ Losses for Children Exposed to Lead under the Regulatory Options, Compared to Baseline

Regulatory Option	Average Annual Number of Children 0 to 7 in Scope of the Analysis[b]	Total Avoided IQ Point Losses, 2025 to 2049 in All Children 0 to 7 in Scope of the Analysis[c]	Annualized Value of Avoided IQ Point Losses[a] (Millions 2023$)	
			3% Discount Rate	7% Discount Rate
Option A	1,555,558	0.93	<$0.01	<$0.01
Option B (Final Rule)	1,555,558	0.93	<$0.01	<$0.01
Option C	1,555,558	0.93	<$0.01	<$0.01

a. Based on estimate that the loss of one IQ point results in the loss of 2.63 percent of lifetime earnings, following updated Salkever (1995) values from U.S. EPA (2019d).

b. The number of children in scope of the analysis is based on reaches analyzed across the regulatory options. Some of the children included in this count see no changes in exposure under some options.

c. EPA notes that the IQ point losses are very small. EPA further notes that the IEUBK model does not analyze blood lead level changes beyond two decimal points.

Source: U.S. EPA Analysis, 2024

Table B-3: Estimated Benefits from Avoided IQ Losses for Infants from Mercury Exposure under the Regulatory Options, Compared to Baseline

Regulatory Option	Number of Infants in Scope of the Analysis per Year[b]	Total Avoided IQ Point Losses, 2025 to 2049 in All Infants in Scope of the Analysis	Annualized Value of Avoided IQ Point Losses[a] (Millions 2023$)	
			3% Discount Rate	7% Discount Rate
Option A	201,850	1,190	$1.02	$0.18
Option B (Final Rule)	201,850	1,377	$1.18	$0.21
Option C	201,850	1,393	$1.19	$0.21

a. Based on the estimate that the loss of one IQ point results in the loss of 2.63 percent of lifetime earnings discounted to birth, following updated Salkever (1995) values from U.S. EPA (2019f).

b. The number of infants in scope of the analysis is based on reaches analyzed across the regulatory options. Some of the children included in this count see no changes in exposure under some options.

Source: U.S. EPA Analysis, 2024

Table B-4: Estimated Benefits from Avoided CVD Deaths for Adults (aged 40-80) under the Regulatory Options, Compared to Baseline

Regulatory Option	Number of Adults in Scope of the Analysis per Year[a]	Total CVD Deaths Avoided, 2025 to 2049 in All Adults in Scope of the Analysis[b]		Annualized Value of Avoided CVD Deaths[c] (Millions 2023$)			
				3% Discount Rate		7% Discount Rate	
		Low	High	Low	High	Low	High
Option A	19,571,228	0.42	1.13	$0.16	$0.42	$0.14	$0.37
Option B (Final Rule)	19,571,228	0.42	1.13	$0.16	$0.42	$0.14	$0.37
Option C	19,571,228	0.45	1.20	$0.16	$0.43	$0.14	$0.38

a. The number of adults in scope of the analysis is based on reaches analyzed across the regulatory options. Some of the adults included in this count see no changes in exposure under some options. Benefits accrue to the subset of adults that experience changes in exposure under one or more options (576,537 adults in 2025). Under the assumption that fishers would share their catch with members of their household, EPA included household members in this subset.

b. Assumes that the distribution for the individuals experiencing CVD premature mortality that is caused by lead is the same as the distribution of CVD premature mortality irrespective of the cause.

Source: U.S. EPA Analysis, 2024

Table B-5: Estimated Household and Total Annualized Willingness-to-Pay for Water Quality Improvements under the Regulatory Options, Compared to Baseline (Main Estimates)

Regulatory Option	Number of Affected Households (Millions)[a]	Average Annual WTP Per Household (2023$)[b]	Total Annualized WTP (Millions 2023$)[b]	
			3% Discount Rate	7% Discount Rate
Option A	58.7	$0.01	$0.77	$0.70
Option B (Final Rule)	58.9	$0.02	$1.21	$1.10
Option C	59.6	$0.03	$1.64	$1.50

a. The number of affected households varies across options because of differences in the number of reaches that have non-zero changes in water quality.

b. Estimates based on Model 1, which provides EPA's main estimate of non-market benefits.

Source: U.S. EPA Analysis, 2024

Table B-6: Estimated Household and Total Annualized Willingness-to-Pay for Water Quality Changes under the Regulatory Options, Compared to Baseline (Sensitivity Analysis)

Regulatory Option	Number of Affected Households (Millions)[a]	Average Annual WTP Per Household (2023$)[b]		Total Annualized WTP (Millions 2023$)[b]			
				3% Discount Rate[a,b]		7% Discount Rate[a]	
		Low	High	Low	High	Low	High
Option A	58.7	$0.01	$0.03	$0.84	$1.71	$0.74	$1.52
Option B (Final Rule)	58.9	$0.02	$0.05	$1.27	$2.60	$1.12	$2.30
Option C	59.6	$0.03	$0.07	$1.73	$3.55	$1.55	$3.17

a. The number of affected households varies across options because of differences in the number of reaches that have non-zero changes in water quality.

b. Estimates based on Model 2, which provides a range of estimates that account for uncertainty in the WTP estimates as a sensitivity analysis. For the ∆WQI variable setting in Model 2-based sensitivity analysis, EPA used values of 20 units to develop low estimates and 7 units to develop high estimates (see Appendix H for details).

Source: U.S. EPA Analysis, 2024

Table B-7: Estimated Annualized Climate Benefits from Changes in CO_2 and CH_4 Emissions under the Final Rule during the Period of 2025-2049 by Categories of Air Emissions and Interim SC-GHG Estimates, Compared to Baseline (Millions of 2023$)

Regulatory Option	Category of Air Emissions	Annualized Climate Benefits[a,b]			
		5.0% Average	3.0% Average	2.5% Average	3.0% 95th Percentile
Option B (Final Rule)	Electricity generation	$142.8	$435.9	$620.8	$1,323.6
	Trucking	-$0.0	-$0.1	-$0.1	-$0.2
	Energy use	-$2.6	-$8.2	-$11.8	-$25.1
	Total	**$140.2**	**$427.6**	**$608.9**	**$1,298.4**

a. Values rounded to two significant figures. Negative values indicate forgone benefits whereas positive values indicate positive benefits.

b. Climate benefits estimated using interim SC-GHG (IWG, 2021).

Source: U.S. EPA Analysis, 2024

Table B-8: Estimated Discounted Economic Value of Avoided Ozone and $PM_{2.5}$-Attributable Premature Mortality and Illness for Option B (95 Percent Confidence Interval; millions of 2023$)

Year	3% Discount Rate[a]			7% Discount Rate[a]		
2028	$1,000	*and*	$2,500	$890	*and*	$2,200
	($170 to $2500)		($300 to $6,500)	($120 to $2,200)		($240 to $5,800)
2030	$380	*and*	$1,200	$320	*and*	$1,000
	($77 to $890)		($150 to $3,000)	($51 to $770)		($110 to $2,700)
2035	$1,600	*and*	$3,700	$1,400	*and*	$3,300
	($240 to $4,000)		($430 to $9,800)	($180 to $3,500)		($350 to $8,800)
2040	$480	*and*	$1,200	$410	*and*	$1,100
	($78 to $1,200)		($140 to $3,200)	($57 to $1,000)		($120 to $2,900)
2045	$150	*and*	$370	$130	*and*	$330
	($24 to $360)		($44 to $970)	($17 to $320)		($36 to $870)
2050	$130	*and*	$300	$120	*and*	$260
	($19 to $330)		($34 to $790)	($15 to $290)		($28 to $700)

[a] Values rounded to two significant figures. The two benefits estimates are separated by the word "and" to signify that they are two separate estimates. The estimates do not represent lower- and upper-bound estimates and should not be summed.

Source: U.S. EPA Analysis, 2024

Table B-9: Estimated Annualized Changes in Navigational Dredging Costs under the Regulatory Options, Compared to Baseline

Regulatory Option	Total Reduction in Sediment Dredged (Thousands Cubic Yards)		3% Discount Rate (Millions of 2023$ per Year)[a]		7% Discount Rate (Millions of 2023$ per Year)[a]	
	Low	High	Low	High	Low	High
Option A	7.1	9.3	<$0.01	$0.01	<$0.01	<$0.01
Option B (Final Rule)	8.3	10.8	<$0.01	$0.01	<$0.01	$0.01
Option C	8.5	11.0	<$0.01	$0.01	<$0.01	$0.01

a. Positive values represent cost savings.

Source: U.S. EPA Analysis, 2024.

Table B-10: Estimated Total Annualized Changes in Reservoir Dredging Volume and Costs under the Regulatory Options, Compared to Baseline

	Total Reduction in Sediment Dredged (Thousands Cubic Yards)		Costs at 3% Discount Rate[a] (Millions of 2023$ per Year)		Costs at 7% Discount Rate[a] (Millions of 2023$ per Year)	
Regulatory Option	Low	High	Low	High	Low	High
Option A	1.0	1.1	<$0.01	<$0.01	<$0.01	<$0.01
Option B (Final Rule)	1.2	1.3	<$0.01	<$0.01	<$0.01	<$0.01
Option C	1.2	1.4	<$0.01	<$0.01	<$0.01	<$0.01

a. Positive values represent cost savings.

Source: U.S. EPA Analysis, 2024.

Table B-10: Summary of Estimated Total Annualized Benefits of the Regulatory Options, Compared to Baseline, at 3 Percent (Millions of 2023$)

Benefit Category	Option A	Option B (Final Rule)	Option C
Human Health			
Changes in IQ losses in children from exposure to lead[a]	<$0.01	<$0.01	<$0.01
Changes in cardiovascular disease premature mortality from exposure to lead	$0.16 - $0.42	$0.16 - $0.42	$0.16 - $0.43
Changes in IQ losses in children from exposure to mercury	$1.05	$1.21	$1.23
Changes in cancer risk from disinfection by-products in drinking water	$11.28	$11.28	$12.06
Ecological Conditions and Recreational Uses Changes			
Use and nonuse values for water quality changes[b]	$0.77	$1.21	$1.64
Market and Productivity Effects[a]			
Changes in drinking water treatment costs			
Changes in dredging costs[a]	<$0.01	<$0.01	<$0.01
Air Quality-Related Effects[c]			
Climate change effects from changes in greenhouse gas emissions[c,d]	$330	$430	$520
Human health effects from changes in NO_X, SO_2, and $PM_{2.5}$ emissions[c]	$1,200	$1,600	$2,000
Total[e]	**$1,544**	**$2,044**	**$2,536**

a. "<$0.01" indicates that monetary values are greater than $0 but less than $0.01 million.

b. Estimates based on Model 1, which provides EPA's main estimate of non-market benefits. See Chapter 6 for details.

Table B-10: Summary of Estimated Total Annualized Benefits of the Regulatory Options, Compared to Baseline, at 3 Percent (Millions of 2023$)

Benefit Category	Option A	Option B (Final Rule)	Option C

c. Values for air-quality related effects are rounded to two significant figures. EPA estimated the air quality-related benefits for the final rule (Option B). EPA extrapolated estimates of air quality-related benefits for Options A and C from the estimate for Option B that is based on IPM outputs. See Chapter 8 for details.

d. Climate change benefits are based on interim SC-GHG values for the 3 percent discount rate (IWG, 2021), discounted and annualized using a 3 percent discount.

e. Values for individual benefit categories may not sum to the total due to independent rounding.

Source: U.S. EPA Analysis, 2024

Table B-11: Summary of Estimated Total Annualized Benefits of the Regulatory Options, Compared to Baseline, at 7 Percent (Millions of 2023$)

Benefit Category	Option A	Option B (Final Rule)	Option C
Human Health			
Changes in IQ losses in children from exposure to lead[a]	<$0.01	<$0.01	<$0.01
Changes in cardiovascular disease premature mortality from exposure to lead	$0.14 - $0.37	$0.14 - $0.37	$0.14 - $0.38
Changes in IQ losses in children from exposure to mercury	$0.19	$0.22	$0.22
Changes in cancer risk from disinfection by-products in drinking water	$6.99	$6.99	$7.53
Ecological Conditions and Recreational Uses Changes			
Use and nonuse values for water quality changes[b]	$0.70	$1.10	$1.50
Market and Productivity Effects[a]			
Changes in drinking water treatment costs			
Changes in dredging costs[a]	<$0.01	<$0.01	<$0.01
Air Quality-Related Effects[c]			
Climate change effects from changes in greenhouse gas emissions[c,d]	$330	$430	$520
Human health effects from changes in NO_X, SO_2, and $PM_{2.5}$ emissions[c,e]	$1,100	$1,400	$1,700
Total[f]	**$1,438**	**$1,839**	**$2,230**

a. "<$0.01" indicates that monetary values are greater than $0 but less than $0.01 million.

b. Estimates based on Model 1, which provides EPA's main estimate of non-market benefits. See Chapter 6 for details.

c. Values for air-quality related effects are rounded to two significant figures. EPA estimated the air quality-related benefits for the final rule (Option B). EPA extrapolated estimates of air quality-related benefits for Options A and C from the estimate for Option B that is based on IPM outputs. See Chapter 8 for details.

d. Climate change benefits are based on interim SC-GHG values for the 3 percent discount rate (IWG, 2021), discounted and annualized using a 3 percent discount.

e. The values reflect the LT estimates of human health effects from changes in $PM_{2.5}$ and ozone levels. See Chapter 8 for details.

f. Values for individual benefit categories may not sum to the total due to independent rounding.

Source: U.S. EPA Analysis, 2024

B.2 Social Costs

Table B-12: Summary of Estimated Incremental Annualized Costs for Regulatory Options (Millions of 2023$)

Regulatory Option	Annualized Costs			
	3% Discount Rate		7% Discount Rate	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Option A	$444.2	$974.7	$478.7	$1,028.7
Option B (Final Rule)	$544.8	$1,077.2	$580.1	$1,130.1
Option C	$633.0	$1,165.4	$676.5	$1,226.5

Source: U.S. EPA Analysis, 2024.

B.3 Social Benefits and Costs

Table B-14: Total Estimated Annualized Benefits and Costs by Regulatory Option and Discount Rate, Compared to Baseline (Millions of 2023$)

Regulatory Option	3% Discount			7% Discount		
	Total Monetized Benefits[a,b]	Total Costs		Total Monetized Benefits[a,b]	Total Costs	
		Lower Bound	Upper Bound		Lower Bound	Upper Bound
Option A	$1,544	$444.2	$974.7	$1,244	$478.7	$1,028.7
Option B (Final Rule)	$2,044	$544.8	$1,077.2	$1,653	$580.1	$1,130.1
Option C	$2,536	$633.0	$1,165.4	$2,056	$676.5	$1,226.5

a. EPA estimated the air quality-related benefits for the final rule (Option B) only. EPA extrapolated estimates of air quality-related benefits for Options A and C from the estimate for Option B that is based on IPM outputs. See Chapter 8 for details.

b. Climate change benefits are based on interim SC-GHG values for the 3 percent discount rate (IWG, 2021), discounted and annualized using a 3 percent discount.

Source: U.S. EPA Analysis, 2024.

C WQI Calculation and Regional Subindices

C.1 WQI Calculation

The first step in the implementation of the WQI involves obtaining water quality levels for each parameter, and for each waterbody, under both the baseline conditions and each regulatory option. Some parameter levels are modeled values (TN, TP, TSS, arsenic, cadmium, chromium, copper, lead, mercury, nickel, selenium, and zinc) and vary from the baseline depending on the regulatory option, while others are field measurements (FC, BOD, and DO) and are left unchanged between the baseline and regulatory options.

The second step involves transforming the parameter measurements into subindex values that express water quality conditions on a common scale of 10 to 100. EPA used the subindex transformation curves developed by Dunnette (1979) and Cude (2001) for the Oregon WQI for BOD, DO, and FC. For TSS, TN, and TP concentrations, EPA adapted the approach developed by Cude (2001) to account for the wide range of natural or background nutrient and sediment concentrations that result from variability in geologic and other region-specific conditions, and to reflect the national context of the analysis. TSS, TN, and TP subindex curves were developed for each of the nine ecoregions used for the 2013-2014 and 2018-2019 National Rivers and Stream Assessment (NRSA) (U.S. EPA, 2020e, 2023j). For each of the nine ecoregions, EPA derived the transformation curves by assigning a score of 100 to the 10th percentile of the observations within each ecoregion (*i.e.*, using the 10th percentile as a proxy for “reference” concentrations), and a score of 70 to the median concentration. An exponential equation was then fitted to the two concentration points following the approach used in Cude (2001).

For this analysis, EPA also used a toxics-specific subindex curve based on the number of NRWQC exceedances for toxics in each waterbody. National freshwater chronic NRWQC values are available for arsenic, cadmium, chromium, copper, lead, mercury, nickel, selenium, and zinc. See the EA for details on the NRWQC (U.S. EPA, 2020g; U.S. EPA, 2024b). To develop this subindex curve, EPA used an approach developed by the Canadian Council of Ministers of the Environment (CCME, 2001). The CCME water quality index is based on three attributes of water quality that relate to water quality objectives: scope (number of monitored parameters that exceed water quality standard or toxicological benchmark); frequency (number of individual measurements that do not meet objectives, relative to the total number of measurements for the time period of interest) and amplitude (*i.e.*, amount by which measured values exceed the standards or benchmarks). Following the CCME approach, EPA’s toxics subindex considers the number of parameters with exceedances of the relevant water quality criterion. With regards to frequency, EPA modeled long-term annual average concentrations in ambient water, and therefore any exceedance of an NRWQC may indicate that ambient concentrations exceed NRWQC most of the time (assumed to be 100 percent of the time). EPA did not consider amplitude, because if the annual average concentration exceeds the chronic NRWQC then the water is impaired for that constituent and the level of exceedance is of secondary concern. Using this approach, the subindex curve for toxics assigns the lowest subindex score of 0 to waters where exceedances are observed for all nine of the toxics analyzed, and a maximum score of 100 to waters where there are no exceedances. Intermediate values are distributed evenly between 0 and 100.

Table C-1 presents parameter-specific functions used for transforming water quality data into water quality subindices for freshwater waterbodies for the six pollutants with individual subindices. Table C-2 presents the subindex values for toxics. The equation parameters for each of the nine ecoregion-specific TSS, TN, and TP subindex curves are provided in the next section. The curves include threshold values below or above which the subindex score does not change in response to changes in parameter levels. For example, improving DO levels from 10.5 mg/L to 12 mg/L or from 2 mg/L to 3.3 mg/L would result in no change in the DO subindex score.

Table C-1: Freshwater Water Quality Subindices

Parameter	Concentrations	Concentration Unit	Subindex
Dissolved Oxygen (DO)			
DO saturation ≤100%			
DO	$DO \leq 3.3$	mg/L	10
DO	$3.3 < DO < 10.5$	mg/L	$-80.29+31.88\times DO-1.401\times DO^2$
DO	$DO \geq 10.5$	mg/L	100
100% < DO saturation ≤ 275%			
DO	NA	mg/L	$100 \times \exp((DOsat - 100) \times -1.197\times10^{-2})$
275% < DO saturation			
DO	NA	mg/L	10
Fecal Coliform (FC)			
FC	$FC > 1{,}600$	cfu/100 mL	10
FC	$50 < FC \leq 1{,}600$	cfu/100 mL	$98 \times \exp((FC - 50) \times -9.9178\times10^{-4})$
FC	$FC \leq 50$	cfu/100 mL	98
Total Nitrogen (TN)[a]			
TN	$TN > TN_{10}$	mg/L	10
TN	$TN_{100} < TN \leq TN_{10}$	mg/L	a × exp(TN×b); where a and b are ecoregion-specific values
TN	$TN \leq TN_{100}$	mg/L	100
Total Phosphorus (TP)[b]			
TP	$TP > TP_{10}$	mg/L	10
TP	$TP_{100} < TP \leq TP_{10}$	mg/L	a × exp(TP×b); where a and b are ecoregion-specific values
TP	$TP \leq TP_{100}$	mg/L	100
Suspended Solids[c]			
TSS	TSS > TSS 10	mg/L	10
TSS	TSS 100 < TSS ≤ TSS 10	mg/L	a × exp(TSS×b); where a and b are ecoregion-specific values
TSS	TSS ≤ TSS 00	mg/L	100
Biochemical Oxygen Demand, 5-day (BOD)			
BOD	$BOD > 8$	mg/L	10
BOD	$BOD \leq 8$	mg/L	$100 \times \exp(BOD \times -0.1993)$

a. TN10 and TN100 are ecoregion-specific TN concentration values that correspond to subindex scores of 10 and 100, respectively. Use of 10 and 100 for the lower and upper bounds of the WQI subindex score follow the approach in Cude (2001)

b. TP10 and TP100 are ecoregion-specific TP concentration values that correspond to subindex scores of 10 and 100, respectively. Use of 10 and 100 for the lower and upper bounds of the WQI subindex score follow the approach in Cude (2001)

c. TSS10 and TSS100 are ecoregion-specific SSC concentration values that correspond to subindex scores of 10 and 100, respectively. Use of 10 and 100 for the lower and upper bounds of the WQI subindex score follow the approach in Cude (2001)

Source: EPA Analysis, 2024, based on methodology in Cude (2001).

Table C-2: Freshwater Water Quality Subindex for Toxics

Number of Toxics with NRWQC Exceedances	Subindex
0	100.0
1	88.9
2	77.8
3	66.7
4	55.6
5	44.4
6	33.3
7	22.2
8	11.1
9	0.0

The final step in implementing the WQI involves combining the individual parameter subindices into a single WQI value that reflects the overall water quality across the parameters. EPA calculated the overall WQI for a given reach using a geometric mean function and assigned all WQ parameters an equal weight of 0.143 (1/7th of the overall score). Unweighted scores for individual metrics of a WQI have previously been used in Cude (2001), CCME, 2001, and Carruthers and Wazniak (2003).

Equation C-1 presents EPA's calculation of the overall WQI score.

Equation C-1.

$$WQI_r = \prod_{i=1}^{n} Q_i^{Wi}$$

WQI_r = the multiplicative water quality index (from 0 to 100) for reach *r*

Q_i = the water quality subindex measure for parameter *i*

W_i = the weight of the *i*-th parameter (0.143)

n = the number of parameters (*i.e.*, seven)

C.2 Regional Subindices

The following tables provide the ecoregion-specific parameters used in estimating the TSS, TN, or TP water quality subindex, as follows:

- If [WQ Parameter] ≤ WQ Parameter 100	Subindex = 100
- If WQ Parameter 100 < [WQ Parameter] ≤ WQ Parameter 10	Subindex = a exp(b [WQ Parameter])
- If [WQ Parameter] > WQ Parameter 10	Subindex = 10

Where [WQ Parameter] is the measured concentration of either TSS, TN, or TP and WQ Parameter $_{10}$, WQ Parameter $_{100}$, a, and b are specified in Table C-3 for TSS, Table C-4 for TN, and Table C-5 for TP.

Table C-3: TSS Subindex Curve Parameters, by Ecoregion

Ecoregion	a	b	TSS_{100}	TSS_{10}
Coastal Plains	109.34	-0.015	5.86	156.84
Northern Appalachians	108.11	-0.061	1.29	39.27
Northern Plains	102.07	-0.001	18.10	2,049.20
Southern Appalachians	114.22	-0.012	10.88	199.43
Southern Plains	102.19	-0.001	15.53	1,667.06
Temperate Plains	114.02	-0.003	46.30	858.85
Upper Midwest	101.24	-0.021	0.59	111.70
Western Mountains	108.48	-0.018	4.51	131.95
Xeric	101.72	-0.003	6.53	887.38

Source: U.S. EPA Analysis, 2024

Table C-4: TN Subindex Curve Parameters, by Ecoregion

Ecoregion	a	b	TN_{100}	TN_{10}
Coastal Plains	148.67	-0.85	0.47	3.17
Northern Appalachians	128.25	-1.08	0.23	2.36
Northern Plains	124.98	-0.40	0.56	6.37
Southern Appalachians	178.79	-0.95	0.61	3.04
Southern Plains	113.00	-0.22	0.55	10.95
Temperate Plains	123.62	-0.13	1.57	18.65
Upper Midwest	119.92	-0.40	0.45	6.20
Western Mountains	121.28	-1.99	0.10	1.25
Xeric	130.03	-1.06	0.25	2.43

Source: U.S. EPA Analysis, 2024

Table C-5: TP Subindex Curve Parameters, by Ecoregion

Ecoregion	a	b	TP_{100}	TP_{10}
Coastal Plains	116.13	-5.33	0.03	0.46
Northern Appalachians	104.31	-5.75	0.01	0.41
Northern Plains	117.76	-13.58	0.01	0.18
Southern Appalachians	115.90	-1.02	0.15	2.41
Southern Plains	114.66	-4.37	0.03	0.56
Temperate Plains	103.46	-0.66	0.05	3.56
Upper Midwest	140.90	-1.58	0.22	1.67
Western Mountains	107.15	-3.89	0.02	0.61
Xeric	108.89	-9.72	0.01	0.25

Source: U.S. EPA Analysis, 2024

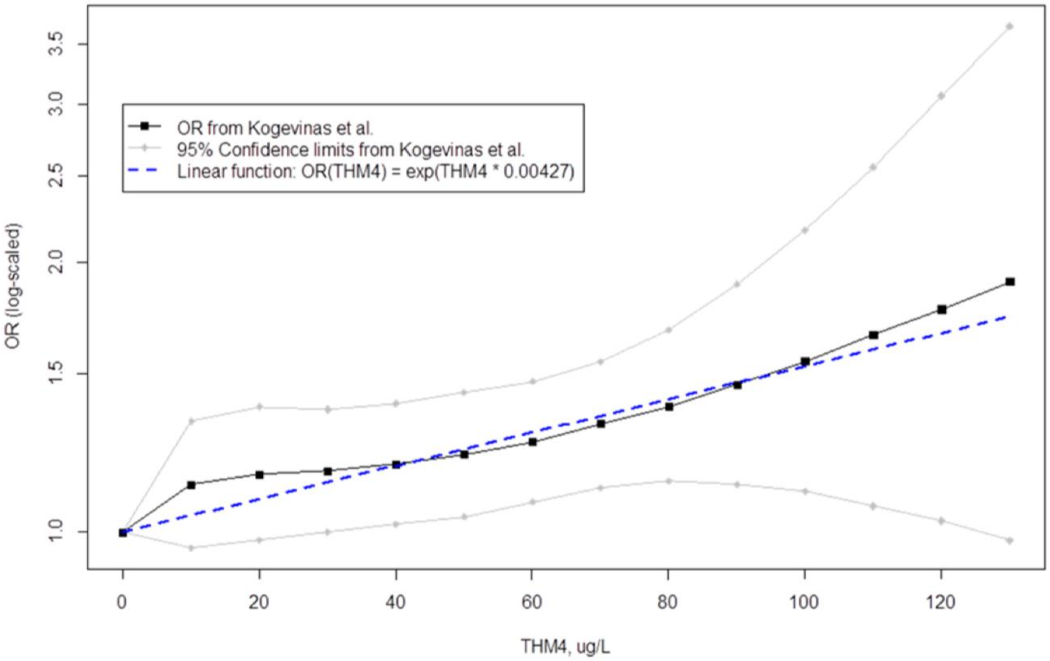
D Additional Details on Modeling Change in Bladder Cancer Incidence from Change in TTHM Exposure

D.1 Details on Life Table Approach

D.1.1 Health Impact Function

Figure D-1 shows the dependence between lifetime odds of bladder cancer and drinking water TTHM concentration as reported by Villanueva et al. (2004). These data were used by Regli et al. (2015) to estimate the log-linear relationship in Equation 4-1, which is also displayed in Figure D-1. As described in Chapter 4, Regli et al. (2015) showed that, while the original analysis deviated from linearity, particularly at low doses, the overall pooled exposure-response relationship for TTHM could be well-approximated by a linear slope factor that predicted an incremental lifetime cancer risk of 1 in ten thousand exposed individuals (10^{-4}) per 1 µg/L increase in TTHM.[140]

Figure D-1: Estimated Relationships between Lifetime Bladder Cancer Risk and TTHM Concentrations in Drinking Water



Source: Regli et al. (2015)

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[140] Regli, S., Chen, J., Messner, M., Elovitz, M. S., Letkiewicz, F. J., Pegram, R. A., Pepping, T. J., . . . Wright, J. M. (2015). Estimating potential increased bladder cancer risk due to increased bromide concentrations in sources of disinfected drinking waters. *Environmental Science & Technology, 49*(22), 13094-13102. addressed some of the limitations noted in the Hrudey, S. E., Backer, L. C., Humpage, A. R., Krasner, S. W., Michaud, D. S., Moore, L. E., Singer, P. C., . . . Stanford, B. D. (2015). Evaluating evidence for association of human bladder cancer with drinking-water chlorination disinfection by-products. *Journal of Toxicology and Environmental Health, Part B, 18*(5), 213-241. analysis. They suggested that the seeming discrepancy between the slope factor derived from the pooled epidemiological data and that from animal studies was due primarily to (1) potentially high human exposures to DBPs by the inhalation route, and (2) that trihalomethanes were acting as proxies for other carcinogenic DBPs.

EPA used the Regli et al. (2015) relationship between the lifetime odds of bladder cancer and lifetime TTHM exposure from drinking water to derive a set of age-specific health impact functions. A person's lifetime TTHM exposure from drinking water by age a—denoted by x_a—is defined as:

Equation D-1.
$$\boldsymbol{x_a = \frac{1}{a}\sum_{i=0}^{a-1} TTHM_i\,, x_0 = 0}.$$

See Table D-1 at the end of this section for definitions of all variables used in the equations in this appendix.

Assuming a baseline exposure of z_a and a regulatory option exposure of x_a (*i.e.*, exposure following implementation of a regulatory option), the relative risk (RR) of bladder cancer by age a under the option exposure relative to the baseline exposure can be expressed as:

Equation D-2
$$RR(x_a, z_a) = \max\left[1 - PAF, \left(\frac{O(x_a)}{O(z_a)}\right)^{-1} \cdot \left(LR_a \cdot \frac{O(x_a)}{O(z_a)} - LR_a + 1\right)\right]$$

where LR_a is the lifetime risk of bladder cancer within age interval $[0, a]$ (Fay et al. 2003) under baseline conditions and PAF is the environmental exposure-related population attributable fraction of bladder cancer incidence set at 0.0394. As such, this equation implies that EPA caps the magnitude of TTHM-related cumulative bladder cancer risk reduction at the PAF of 3.94 percent to ensure plausibility of the estimated bladder cancer benefits size. EPA developed this PAF estimate based on a review of literature on environmental contaminant-attributable risk estimates for cancers (ICF, 2022a).

Combining Equation D-1 and Equation D-2 shows that the relative risk of bladder cancer by age a based on Regli et al. (2015) depends only on the lifetime risk and on the magnitude of change in TTHM concentration from baseline concentration, $\Delta x_a = x_a - z_a$, but not on the baseline TTHM level:

Equation D-3.
$$\begin{aligned} RR_{\text{Regli et al.}}(x_a, z_a) &= \max\left[1 - PAF, \left(\frac{O(0)\cdot e^{0.00427\cdot x_a}}{O(0)\cdot e^{0.00427\cdot z_a}}\right)^{-1} \cdot \left(LR_a \cdot \frac{O(0)\cdot e^{0.00427\cdot x_a}}{O(0)\cdot e^{0.00427\cdot z_a}} - LR_a + 1\right)\right] \\ &= \max\left[1 - PAF, e^{-0.00427\cdot(x_a - z_a)} \cdot \left(LR_a \cdot e^{0.00427\cdot(x_a - z_a)} - LR_a + 1\right)\right] \\ &= \max\left[1 - PAF, e^{-0.00427\cdot\Delta x_a} \cdot \left(LR_a \cdot e^{0.00427\cdot\Delta x_a} - LR_a + 1\right)\right]. \end{aligned}$$

At the average baseline TTHM concentration level of 38.05 μg/L reported in Regli et al. (2015), the slope of the Regli et al. (2015) relationship appears to be a good approximation of the slope of the piece-wise linear relationship implied by the Villanueva et al. (2004) data. For baseline TTHM levels in the 20 μg/L to 60 μg/L range, the Regli et al. (2015) slope is steeper than the slopes of the piece-wise linear relationship whereas for baseline TTHM levels above 60 μg/L the Regli et al. (2015) slope is flatter. While this potentially has implications for the magnitude of the health effects EPA modeled,[141] the relationship based on Villanueva et

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[141] If the piece-wise linear relationship based on Villanueva, C. M., Cantor, K. P., Cordier, S., Jaakkola, J. J. K., King, W. D., Lynch, C. F., Porru, S., . . . Kogevinas, M. (2004). Disinfection byproducts and bladder cancer: a pooled analysis. *Epidemiology*, 357-367. reported data had been used as the basis for health impact function, there would have been larger effect estimates for some individuals and smaller effect estimates for others relative to the estimates obtained using the Regli, S., Chen, J., Messner, M., Elovitz, M. S., Letkiewicz, F. J., Pegram, R. A., Pepping, T. J., . . . Wright, J. M. (2015). Estimating potential increased bladder cancer risk due to increased bromide concentrations in sources of disinfected drinking waters. *Environmental Science & Technology*, *49*(22), 13094-13102. linear approximation.

al. (2004) requires detailed information on the baseline TTHM exposure for the population of interest which is not available.

D.1.2 Health Risk Model

To estimate the health effects of changes in TTHM exposure, the health risk model tracks evolution of two populations over time — the bladder cancer-free population and the bladder cancer population. These two populations are modeled for both the baseline annual TTHM exposure scenario and for the regulatory options TTHM exposure scenarios. Populations in the scenarios are demographically identical but they differ in the TTHM levels to which they are exposed. The population affected by change in bromide discharges associated with a regulatory option is assumed to be exposed to baseline TTHM levels prior to the regulatory option implementation year (in this case 2024) and to alternative TTHM levels that reflect the impact of technology implementation under each regulatory option starting in 2025.

To capture these effects while being consistent with the remainder of the cost-benefit framework, EPA modeled changes in health outcomes resulting from changes in exposure between 2025 and 2049. For these exposures, EPA modeled effects out to 2124 to capture the resultant lagged changes in lifetime bladder cancer risk, but did not attribute changes in bromide loadings and TTHM exposures to the regulatory options beyond 2049.[142]

EPA tracks mortality and bladder cancer experience for a set of model populations defined by sex, location, and age attained by 2025, which is denoted by $A = 0,1,2,3, \dots 100$. Each model population is followed from birth (corresponding to calendar year $2025 - A$) to age 100, using a one-year time step. Below, we first describe the process for quantifying the evolution of model population A under the baseline TTHM exposure assumptions. We then describe the process for quantifying the evolution of the population under the regulatory option TTHM exposures. Finally, we describe the process for estimating the total calendar year y-specific health benefits which aggregate estimates over all model populations ($A = 0,1,2,3, \dots 100$).

<u>Evolution of Model Population *A* under Baseline TTHM Exposure</u>

Given a model population A, for each current age a and calendar year y, the following baseline exposure $z_{a,y} = \frac{1}{a}\sum_{i=0}^{a-1} \text{Baseline TTHM}_{i,y-a+i}$ dependent quantities are computed:

- $l_{C=0,a,y}(z_{a,y})$: The number of bladder cancer-free living individuals at the beginning of age a, in year y;
- $d_{C=0,a,y}(z_{a,y})$: The number of deaths among bladder cancer-free individuals aged a during the year y;
- $l_{C=1,a,y}(z_{a,y})$: The number of new bladder cancer cases among individuals aged a during the year y.

To compute each quantity above, EPA makes an assumption about the priority of events that terminate a person's existence in the pool of bladder cancer-free living individuals. These events are general population

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[142] This approach is equivalent to assuming that TTHM levels revert back to baseline conditions at the end of the regulatory option costing period.

deaths that occur with probability[143] $q_{C=0,a}$ and new bladder cancer diagnoses that occur with probability γ_a, which is approximated by age-specific annual bladder cancer incidence rate $IR_a \cdot 10^{-5}$. In the model, EPA assumes that the new cancer diagnoses occur after general population deaths and uses the following recurrent equations for ages $a > 0$:[144]

Equation D-4.

$$l_{C=0,a,y}(z_{a,y}) = l_{C=0,a-1,y-1}(z_{a-1,y-1}) - d_{C=0,a-1,y-1}(z_{a-1,y-1}) - l_{C=1,a-1,y-1}(z_{a-1,y-1})$$

Equation D-5. $$d_{C=0,a,y}(z_{a,y}) = q_{C=0,a} \cdot l_{C=0,a,y}(z_{a,y})$$

Equation D-6. $$l_{C=1,a,y}(z_{a,y}) = \gamma_a \cdot \left(l_{C=0,a,y}(z_{a,y}) - d_{C=0,a,y}(z_{a,y})\right)$$

To initiate each set of recurrent equations, EPA estimates the number of cancer-free individuals at age $a = 0$, denoted by $l_{C=0,0,y-A}(z_{0,y-A})$, that is consistent with the number of affected persons of age A in 2025, denoted by P. To this end, Equation D-4, Equation D-5, and Equation D-6 are solved to find $l_{C=0,0,y-A}(z_{0,y-A})$ such that $l_{C=0,A,2025}(z_{A,2025}) = P$.

Consistent with available bladder cancer survival statistics, EPA models mortality experience in the bladder cancer populations $l_{C=1,a,y}(z_{a,y})$ as dependent on the age-at-onset a, disease duration k, and cancer stage s (for bladder cancer there are four defined stages: localized, regional, distant, unstaged). Given each age-specific share of new cancer cases $l_{C=1,a,y}(z_{a,y})$ and age-specific share of new stage s cancers $\delta_{S=s,a}$, EPA calculates the number of new stage s cancers occurring at age a in year y:

Equation D-7. $$\tilde{l}_{S=s,a,y,0}(z_{a,y}) = \delta_{S=s,a} \cdot l_{C=1,a,y}(z_{a,y})$$

For a model population aged A years in 2025 and cancer stage s, EPA separately tracks $100 - A + 1$ new stage-specific bladder cancer populations from age-at-onset a to age 100.[145] Next, a set of cancer duration k-dependent annual death probabilities is derived for each population from available data on relative survival rates[146] $r_{S=s,a,k}$ and general population annual death probabilities $q_{C=0,a+k}$ as follows:

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[143] The model does not index the general population death rates using the calendar year, because the model relies on the most recent static life tables.

[144] EPA notes that this is a conservative assumption that results in a lower bound estimate of the policy impact (with respect to this particular uncertainty factor). An upper bound estimate of the policy impact can be obtained by assuming that new bladder diagnoses occur before general population deaths. In a limited sensitivity analysis, EPA found that estimates generated using this alternative assumption were approximately 5 percent larger than the estimates reported here.

[145] In total, there are $4 \cdot (100 - A + 1)$ new cancer populations being tracked for each model population.

[146] Note that $r_{S=s,a,k}$ is a multiplier that modifies the general probability of survival to age k to reflect the fact that the population under consideration has developed cancer k years ago.

Equation D-8. $$\tilde{q}_{S=s,a,k} = 1 - \frac{r_{S=s,a,k+1}}{r_{S=s,a,k}}\left(1 - q_{C=0,a+k}\right).$$

In estimating additional deaths in the cancer population in the year of diagnosis (*i.e.*, when $k = 0$), EPA accounts only for cancer population deaths that are in excess of the general population deaths. As such, the estimate of additional cancer population deaths is computed as follows:

Equation D-9. $$\tilde{d}_{S=s,a,y,0}\left(z_{a,y}\right) = \left(\tilde{q}_{S=s,a,0} - q_{C=0,a}\right) \cdot \tilde{l}_{S=s,a,y,0}\left(z_{a,y}\right),$$

In years that follow the initial diagnosis year (*i.e.*, $k > 0$), EPA uses the following recurrent equations to estimate the number of people living with bladder cancer and the annual number of deaths in the bladder cancer population:

Equation D-10. $$\tilde{l}_{S=s,a,y,k}\left(z_{a,y-k}\right) = \tilde{l}_{S=s,a,y,k-1}\left(z_{a,y-k}\right) - \tilde{d}_{S=s,a,y,k-1}\left(z_{a,y-k}\right),$$

Equation D-11. $$\tilde{d}_{S=s,a,y,k}\left(z_{a,y-k}\right) = \tilde{q}_{S=s,a,k} \cdot \tilde{l}_{S=s,a,y,k}\left(z_{a,y-k}\right).$$

Because EPA is interested in bladder cancer-related deaths rather than all deaths in the bladder cancer population, EPA also tracks the number of excess bladder cancer population deaths (*i.e.*, the number of deaths in the bladder cancer population over and above the number of deaths expected in the general population of the same age). The excess deaths are computed as:

Equation D-12. $$\tilde{e}_{S=s,a,y,k}\left(z_{a,y-k}\right) = \tilde{q}_{S=s,a,k} \cdot \tilde{l}_{S=s,a,y,k}\left(z_{a,y-k}\right) - q_{C=0,a+k} \cdot \tilde{l}_{S=s,a,y,k}\left(z_{a,y-k}\right)$$

Evolution of Model Population A under the Regulatory Option TTHM Exposure

Under the baseline conditions when the change in TTHM is zero (*i.e.*, before 2025), EPA approximates the annual bladder cancer probability γ_a by age-specific annual bladder cancer incidence rate $IR_a \cdot 10^{-5}$. As described in Section 4, current empirical evidence links TTHM exposure to the lifetime bladder cancer risk, rather than annual bladder cancer probability. EPA computes the TTHM-dependent annual new bladder cancer cases under the regulatory option conditions, $l_{C=1,a,y}\left(x_{a,y}\right)$, in three steps. First, EPA recursively estimates $LR_{a,y}\left(z_{a,y}\right)$, the lifetime risk of bladder cancer within age interval $[0, a]$ under the baseline conditions:

Equation D-13. $$LR_{a,y}\left(z_{a,y}\right) = \frac{1}{l_{C=0,0,y-A}\left(z_{0,y-A}\right)} \cdot \sum_{j=0}^{a-1} l_{C=1,j}\left(z_{j,y-A+j}\right),\ a > 0 \text{ and } LR_{0,y-A}\left(z_{0,y-A}\right) = 0$$

Second, the result of Equation D-13 is combined with the relative risk estimate $RR\left(x_{a,y}, z_{a,y}\right)$, based on Regli et al. (2015):

Equation D-14. $$LR_{a,y}\left(x_{a,y}\right) = RR\left(x_{a,y}, z_{a,y}\right)LR_{a,y}\left(z_{a,y}\right)$$

This results in a series of lifetime bladder cancer risk estimates under the option conditions. Third, EPA computes a series of new annual bladder cancer case estimates under the option conditions as follows:

Equation D-15.
$$l_{C=1,a,y}\left(x_{a,y}\right) = \left(LR_{a+1,y+1}\left(x_{a+1,y+1}\right) - LR_{a,y}\left(x_{a,y}\right)\right) \cdot l_{C=0,0,y-A}\left(z_{0,y-A}\right)$$

Health Effects and Benefits Attributable to Regulatory Options

To characterize the overall impact of the regulatory option in a given year y, for each model population defined by age a in 2025, sex, and location, EPA calculates three quantities: the incremental number of new stage s bladder cancer cases ($NC_{A,y,s}$), the incremental number of individuals living with stage s bladder cancer ($LC_{A,y,s}$), and the incremental number of excess deaths in the bladder cancer population ($ED_{A,y}$). The formal definitions of each of these quantities are given below:

Equation D-16.
$$NC_{A,y,s} = [0 \leq y - 2025 + A \leq 100] \cdot \left(\tilde{l}_{S=s,y-2025+A,y,0}\left(z_{y-2025+A,y}\right) - \tilde{l}_{S=s,y-2024+A,0}\left(x_{y-2025+A,y}\right)\right)$$

Equation D-17.
$$LC_{A,y,s} = \sum_{k=1}^{100} [0 \leq y - 2025 + A + k \leq 100] \cdot \left(\tilde{l}_{S=s,y-2025+A-k,y,k}\left(z_{y-2025+A-k,y-k}\right) - \tilde{l}_{S=s,y-2025+A-k,y,k}\left(x_{y-2025+A-k,y-k}\right)\right)$$

Equation D-18.
$$ED_{A,y} = \sum_{k=0}^{100} [0 \leq y - 2025 + A + k \leq 100] \sum_{s \in S} \left(\tilde{e}_{S=s,y-2025+A-k,y,k}\left(z_{y-2025+A-k,y-k}\right) - \tilde{e}_{S=s,y-2025+A-k,y,k}\left(x_{y-2025+A-k,y-k}\right)\right)$$

These calculations are carried out to 2125, when those aged 0 years in 2025 attain the age of 100.

Table D-1: Health Risk Model Variable Definitions

Variable	Definition
$O(x)$	The odds of lifetime bladder cancer incident for an individual exposed to a lifetime average TTHM concentration in residential water supply of x (ug/L)
a	Current age or age at cancer diagnosis
x_a	A person's lifetime option TTHM exposure by age a
z_a	A person's lifetime baseline TTHM exposure by age a
LR_a	Lifetime risk of bladder cancer within age interval $[0, a)$ under the baseline conditions
IR_a	Age-specific baseline annual bladder cancer incidence rate
$RR(x_a, z_a)$	Relative risk of bladder cancer by age a given baseline exposure z_a and option exposure x_a
PAF	Population attributable fraction of bladder cancer incidence
A	Age in 2025 (years)
y	Calendar year
$x_{a,y}$	A person's lifetime option TTHM exposure by age a given that this age occurs in year y
$z_{a,y}$	A person's lifetime baseline TTHM exposure by age a given that this age occurs in year y
$l_{C=0,a,y}\left(z_{a,y}\right)$	The baseline number of bladder cancer-free living individuals at the beginning of age a given that this age occurs in year y

Table D-1: Health Risk Model Variable Definitions

Variable	Definition
$d_{C=0,a,y}(z_{a,y})$	The baseline number of deaths among bladder cancer-free individuals at age a given that this age occurs in year y
$l_{C=1,a,y}(z_{a,y})$	The baseline number of new bladder cancer cases at age a given that this age occurs in year y
$q_{C=0,a}$	Probability of a general population death at age a
γ_a	Baseline probability of a new bladder cancer diagnosis at age a given
k	Bladder cancer duration in years
s	Cancer stage (localized, regional, distant, unstaged)
$\delta_{S=s,a}$	Age-specific share of new stage s bladder cancers
$\tilde{l}_{S=s,a,y,0}(z_{a,y})$	The baseline number of new stage s cancers occurring at age a given that this age occurs in year y
$r_{S=s,a,k}$	Relative survival rate k years after stage s bladder cancer occurrence at age a
$\tilde{q}_{S=s,a,k}$	Stage-specific probability of death in the bladder cancer population whose bladder cancer was diagnosed at age a and they lived k years after the diagnosis. Current age of these individuals is $a + k$.
$\tilde{d}_{S=s,a,y,0}(z_{a,y})$	The baseline number of deaths in the stage s cancer population in the year of diagnosis (*i.e.*, when $k = 0$), given the current age a and the corresponding year y.
$\tilde{l}_{S=s,a,y,k}(z_{a,y-k})$	The baseline number of living with the stage s cancer in the k-th year after diagnosis in year y, given the cancer diagnosis at age a and the cumulative exposure through to that age and year $y - k$.
$\tilde{d}_{S=s,a,y,k}(z_{a,y-k})$	The baseline number of deaths among those with the stage s cancer in the k-th year after diagnosis in year y, given the cancer diagnosis at age a and the cumulative exposure through to that age and year $y - k$.
$\tilde{e}_{S=s,a,y,k}(z_{a,y-k})$	The baseline number of excess bladder cancer deaths (*i.e.*, the number of deaths in the bladder cancer population over and above the number of deaths expected in the general population of the same age) among those with the stage s cancer in the k-th year after diagnosis in year y, given the cancer diagnosis at age a and the cumulative exposure through to that age and year $y - k$.
$LR_{a,y}(z_{a,y})$	Recursive estimate of the lifetime risk of bladder cancer within age interval [0, a) under the baseline conditions, given that age a occurs in year y
$RR(x_{a,y}, z_{a,y})$	Relative risk of bladder cancer by age a given that this age occurs in year y, baseline exposure $z_{a,y}$ and option exposure $x_{a,y}$
$LR_{a,y}(x_{a,y})$	Recursive estimate of the lifetime risk of bladder cancer within age interval [0, a) under the option conditions, given that age a occurs in year y
$NC_{A,y,s}$	The incremental number of new stage s bladder cancer cases in year y for the model population aged A in 2025.
$LC_{A,y,s}$	The incremental number of individuals living with stage s bladder cancer in year y for the model population aged A in 2025.
$ED_{A,y}$	The incremental number of excess in stage s bladder cancer population in year y for the model population aged A in 2025.

D.1.3 Detailed Input Data

As noted in Section 4, EPA relied on the federal government data sources including EPA SDWIS, ACS 2021 (U.S. Census Bureau, 2021), the Surveillance, Epidemiology, and End Results (SEER) program database (National Cancer Institute), and the Center for Disease Control (CDC) National Center for Health Statistics to characterize sex- and age group-specific general population mortality rates and bladder cancer incidence rates used in model simulations. All of these data are compiled by the relevant federal agencies and thus meet federal government data quality standards. These data sources are appropriate for this analysis based on the standards underlying their collection and publication, and their applicability to analyzing health effects of exposure to TTHM via drinking water. Table 4-7 in Section 4 summarizes the sex- and age group-specific share of general population mortality rates and bladder cancer incidence. Table D-2 below summarizes sex-and age group-specific distribution of bladder cancer cases over four analyzed stages as well as onset-specific relative survival probability for each stage.

Table D-2: Summary of Baseline Bladder Cancer Incidence Data Used in the Model

Age	Females					Males				
	Incidence per 100K	Percent of Incidence in Stage				Incidence per 100K	Percent of Incidence in Stage			
		Localized	Regional	Distant	Unstaged		Localized	Regional	Distant	Unstaged
<1	-	77	4.5	14	4.5	-	66	23	11	0
1-4	-	77	4.5	14	4.5	-	66	23	11	0
5-9	-	77	4.5	14	4.5	-	66	23	11	0
10-14	-	77	4.5	14	4.5	-	66	23	11	0
15-19	-	82	8.2	5.1	4.9	0.11	90	4.8	3.1	2.5
20-24	0.17	82	8.2	5.1	4.9	0.3	90	4.8	3.1	2.5
25-29	0.26	82	8.2	5.1	4.9	0.51	90	4.8	3.1	2.5
30-34	0.5	82	8.2	5.1	4.9	1.1	90	4.8	3.1	2.5
35-39	0.89	82	8.2	5.1	4.9	2.1	90	4.8	3.1	2.5
40-44	1.5	83	8.6	6.1	2.7	4.2	85	7.4	4.9	2.5
45-49	2.9	83	8.6	6.1	2.7	8.8	85	7.4	4.9	2.5
50-54	6.6	83	8.6	6.1	2.7	19	85	7.4	4.9	2.5
55-59	11	83	8.6	6.1	2.7	38	85	7.4	4.9	2.5
60-64	18	83	8.6	6.1	2.7	67	85	7.4	4.9	2.5
65-69	29	84	7.9	5.6	2.8	114	86	6.7	4.3	2.9
70-74	43	84	7.9	5.6	2.8	176	86	6.7	4.3	2.9
75-79	58	80	7.1	5.8	6.8	245	85	6.2	4.1	5.2
80-84	71	80	7.1	5.8	6.8	315	85	6.2	4.1	5.2
85+	76	80	7.1	5.8	6.8	357	85	6.2	4.1	5.2

Table D-3: Summary of Relative and Absolute Bladder Cancer Survival Used in the Model

Age at Diagnosis	Follow-Up Time	Females								Males							
		Relative Survival by Stage (Percent)				Absolute Survival (Average) by Stage (Percent)				Relative Survival by Stage (Percent)				Absolute Survival (Average) by Stage (Percent)			
		Localized	Regional	Distant	Unstaged	Localized	Regional	Distant	Unstaged	Localized	Regional	Distant	Unstaged	Localized	Regional	Distant	Unstaged
Ages 15-39	1 year	98	79	20	90	97	79	20	90	99	85	46	100	97	83	45	98
Ages 15-39	2 years	97	58	4	83	96	57	4	83	99	67	23	97	96	65	22	95
Ages 15-39	3 years	96	47	0	80	95	46	0	79	98	60	14	95	96	58	13	92
Ages 15-39	4 years	95	39	0	80	94	39	0	79	97	58	11	91	95	56	11	89
Ages 15-39	5 years	95	32	0	80	93	32	0	79	96	56	11	91	94	54	11	89
Ages 15-39	6 years	94	28	0	80	93	27	0	79	96	56	9	91	93	54	9	89
Ages 15-39	7 years	94	28	0	80	92	27	0	79	96	56	7	91	93	54	7	88
Ages 15-39	8 years	93	28	0	80	92	27	0	78	95	56	7	91	92	54	7	88
Ages 15-39	9 years	93	28	0	80	91	27	0	78	94	52	5	91	91	51	4	88
Ages 15-39	10 years	93	28	0	80	91	27	0	78	93	52	5	85	90	50	4	82
Ages 40-64	1 year	97	73	34	84	92	69	32	80	98	78	36	85	90	72	33	78
Ages 40-64	2 years	95	53	15	81	90	50	14	76	96	57	16	79	87	52	15	72
Ages 40-64	3 years	94	45	9	77	88	42	9	72	94	48	11	75	85	43	10	67
Ages 40-64	4 years	93	40	7	76	87	37	7	70	93	43	9	73	83	38	8	65
Ages 40-64	5 years	92	37	5	74	85	34	5	69	91	40	8	71	81	35	7	63
Ages 40-64	6 years	91	36	5	74	84	33	5	68	90	38	7	68	79	33	7	60
Ages 40-64	7 years	90	34	4	73	82	31	4	66	89	37	7	66	77	32	6	57
Ages 40-64	8 years	89	32	4	71	80	29	4	64	88	36	7	64	75	30	6	54
Ages 40-64	9 years	88	31	4	70	79	28	3	63	87	35	7	61	73	29	6	51
Ages 40-64	10 years	87	31	4	70	77	27	3	62	86	34	7	61	71	28	6	51
Ages 65-74	1 year	95	67	25	72	88	62	24	66	97	74	32	81	86	66	29	72
Ages 65-74	2 years	92	48	11	67	83	44	10	61	94	55	16	75	82	48	13	65
Ages 65-74	3 years	90	38	8	63	80	34	7	57	92	47	11	72	77	39	9	60
Ages 65-74	4 years	88	34	6	60	77	30	5	52	89	42	8	69	73	34	6	56
Ages 65-74	5 years	86	31	5	58	73	26	5	50	88	39	6	66	70	31	5	52
Ages 65-74	6 years	85	28	5	56	71	23	4	47	86	36	6	64	66	27	4	49

Table D-3: Summary of Relative and Absolute Bladder Cancer Survival Used in the Model

		Females								Males							
		Relative Survival by Stage (Percent)				Absolute Survival (Average) by Stage (Percent)				Relative Survival by Stage (Percent)				Absolute Survival (Average) by Stage (Percent)			
Age at Diagnosis	**Follow-Up Time**	**Localized**	**Regional**	**Distant**	**Unstaged**	**Localized**	**Regional**	**Distant**	**Unstaged**	**Localized**	**Regional**	**Distant**	**Unstaged**	**Localized**	**Regional**	**Distant**	**Unstaged**
Ages 65-74	7 years	84	27	4	54	68	22	3	44	84	34	5	61	62	25	4	45
Ages 65-74	8 years	82	25	4	52	64	20	3	41	82	32	5	57	58	23	4	40
Ages 65-74	9 years	81	25	3	51	61	19	2	39	80	30	4	56	54	20	3	38
Ages 65-74	10 years	79	25	3	51	58	18	2	37	79	29	4	56	50	19	3	36
Ages 75+	1 year	86	48	17	39	44	25	9	20	92	60	22	59	45	30	11	29
Ages 75+	2 years	81	36	8	32	40	18	4	16	87	44	10	51	42	21	5	24
Ages 75+	3 years	77	30	6	27	38	15	3	13	84	38	7	45	38	17	3	21
Ages 75+	4 years	76	28	5	24	36	13	2	11	81	35	5	40	35	15	2	17
Ages 75+	5 years	73	26	4	22	33	12	2	10	79	33	5	37	33	14	2	15
Ages 75+	6 years	71	24	4	22	31	11	2	9	76	32	4	34	30	13	2	13
Ages 75+	7 years	69	22	3	20	29	9	1	8	74	29	3	31	27	11	1	11
Ages 75+	8 years	68	21	3	18	27	8	1	7	72	28	3	29	25	10	1	10
Ages 75+	9 years	66	21	2	18	25	8	1	7	70	28	3	26	22	9	1	8
Ages 75+	10 years	65	18	2	18	23	6	1	6	68	28	3	23	20	8	1	7

Table D-4: Summary of All-Cause and Bladder Cancer Mortality Data Used in the Model

Age	Females			Males		
	Rate per 100K		Percent Bladder Cancer	Rate per 100K		Percent Bladder Cancer
	All-Cause	Bladder Cancer		All-Cause	Bladder Cancer	
<1	579	-	0	702	-	0
1-4	25	-	0	31	-	0
5-9	12	-	0	14	-	0
10-14	13	-	0	19	-	0
15-19	33	-	0	78	-	0
20-24	47	-	0	136	0.009	0.01
25-29	60	0.019	0.03	148	0.016	0.01
30-34	80	0.037	0.05	165	0.055	0.03
35-39	113	0.111	0.10	204	0.142	0.07
40-44	168	0.230	0.14	281	0.380	0.14
45-49	254	0.471	0.19	419	1.05	0.25
50-54	378	0.893	0.24	631	2.39	0.38
55-59	558	1.64	0.29	933	5.13	0.55
60-64	833	2.88	0.35	1,361	9.72	0.71
65-69	1,256	4.88	0.39	1,963	16.9	0.86
70-74	1,997	8.62	0.43	2,977	28.8	0.97
75-79	3,271	14.1	0.43	4,704	48.8	1.04
80-84	5,550	22.8	0.41	7,623	81.8	1.07
85+	13,559	40.6	0.30	15,543	151	0.97

D.2 Detailed Results from Analysis

The health impact model assumes that the regulatory changes begin in 2025 and end by 2049 and thus TTHM changes are in effect during this period. After 2049, TTHM levels return to baseline levels, *i.e.*, ΔTTHM is zero. Due to the lasting effects of changes in TTHM exposure, the benefits of the policies after 2049 were included in the final calculations for each option. Table D-5 summarizes the health impact and valuation results in millions of 2023 dollars for each regulatory option, as shown graphically and discussed in Section 4.4.

Table D-5: Number of Adverse Health Effects Avoided Over Time Starting from 2025

Option	**Evaluation period**											**Total[d]**
	2025-2029	**2030-2039**	**2040-2049**	**2050-2059**	**2060-2069**	**2070-2079**	**2080-2089**	**2090-2099**	**2100-2109**	**2110-2119**	**2120-2125**	
	Cancer morbidity cases avoided[a,c]											
Options A & B	3	17	25	12	12	12	10	6	2	0	0	98
Option C	4	18	26	13	13	12	10	7	2	0	0	104
	Excess cancer deaths avoided[b,c]											
Options A & B	1	4	6	4	3	3	3	2	1	0	0	28
Option C	1	4	6	4	4	4	3	2	1	0	0	29
	Value of morbidity avoided (million 2023 dollars, 2% discount rate)[c]											
Options A & B	$1.94	$9.48	$12.32	$5.15	$4.29	$3.38	$2.32	$1.24	$0.35	-$0.05	-$0.02	$40.39
Option C	$2.44	$9.95	$12.89	$5.51	$4.58	$3.61	$2.47	$1.33	$0.38	-$0.05	-$0.03	$43.07
	Value of mortality avoided (million 2023 dollars, 2% discount rate)[c]											
Options A & B	$7.52	$45.60	$64.14	$34.90	$25.20	$20.52	$14.97	$9.26	$3.59	$0.19	-$0.05	$225.84
Option C	$9.44	$48.58	$67.19	$37.12	$26.96	$21.92	$15.97	$9.88	$3.83	$0.21	-$0.05	$241.02

Notes:

a. Number of TTHM-attributable bladder cancer cases that are expected to be avoided under the policy in the calendar time period.

b. Number of excess deaths among the TTHM-attributable bladder cancer cases that are expected to be avoided under the policy in the calendar time period.

c. Number of attributable cases and deaths are rounded to the nearest digit. Values of avoided morbidity and mortality are rounded to the nearest cent. Negative values represent increases in the number of cases/deaths and morbidity/mortality costs.

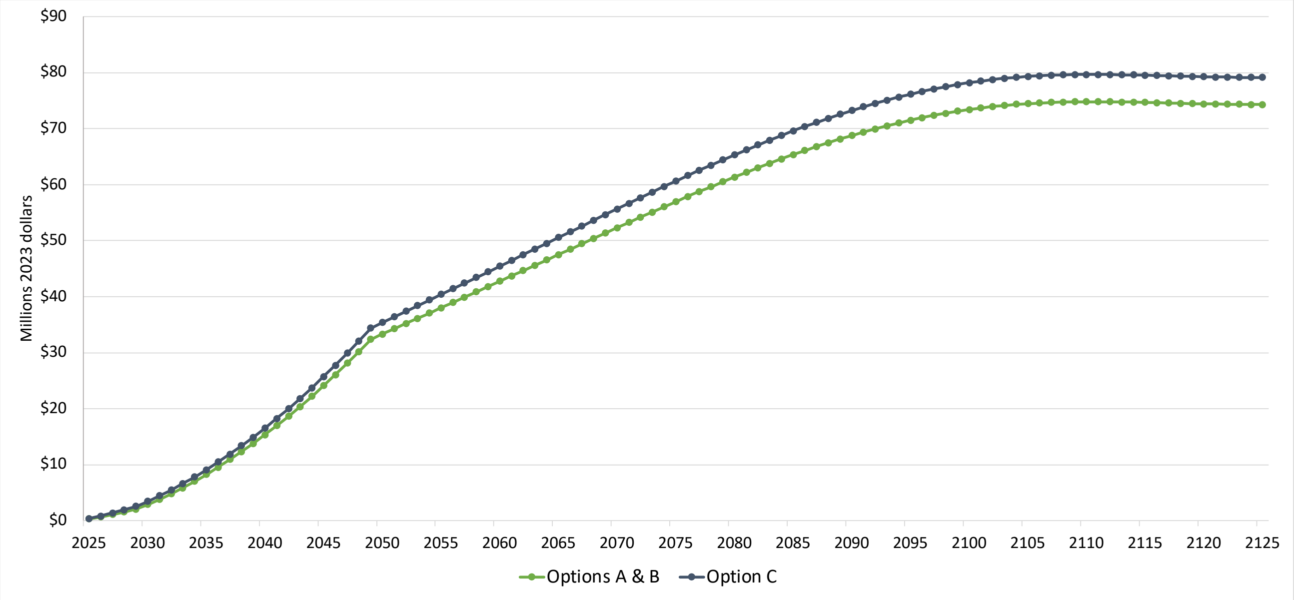
d. Total TTHM-attributable adverse health effects that are expected to be avoided between 2025 and 2125 as a result of the regulatory option changes in 2025-2049.

Source: U.S. EPA Analysis, 2024

D.3 Temporal Distribution of Benefits

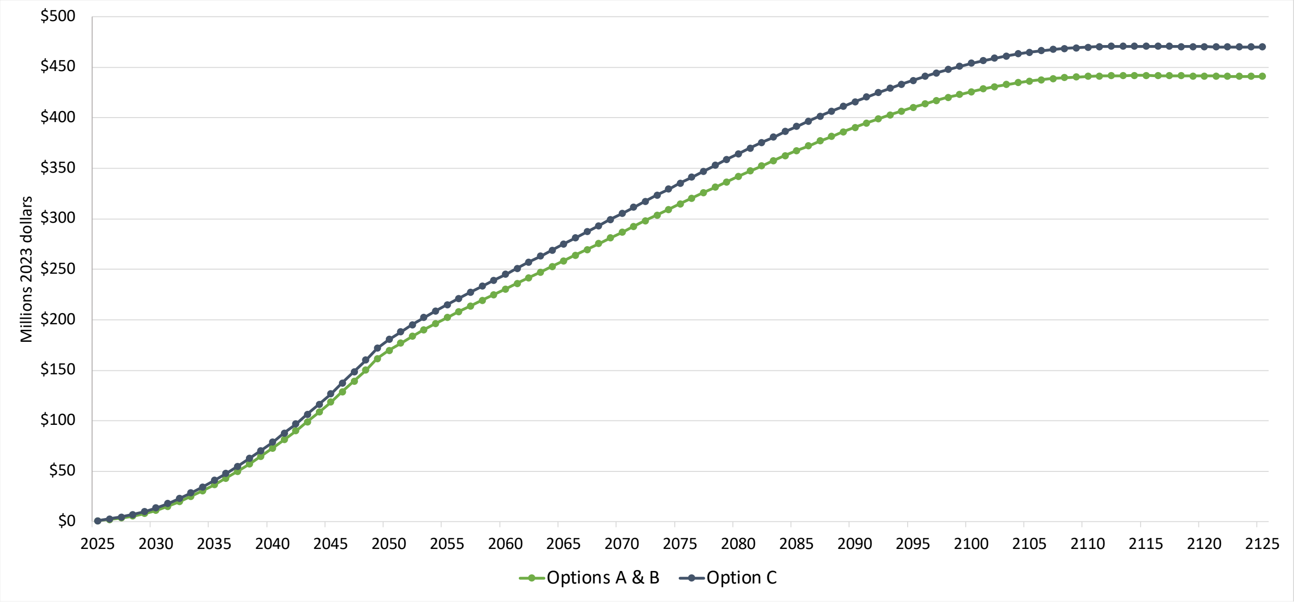
Figure D-2 and Figure D-3 illustrate patterns of changes in benefits for the three regulatory options for the 100-year simulation period of 2025 through 2125 based on the cumulative annual value of morbidity avoided and the cumulative annual value of mortality, respectively (values are undiscounted). These figures show the gradual increase in benefits for Options A, B, and C between 2025 and 2049, which continues but at a reduced rate after 2049 until levelling off around 2111. As discussed in Section 4.4, benefits decrease during the final decades for Options A, B, and C. The benefits associated with Options A and B are smaller than those of Option C.

Figure D-2: Cumulative Annual Value of Cancer Morbidity Avoided, 2025-2125 (Million 2023$ undiscounted).



Source: U.S. EPA Analysis, 2024.

Figure D-3: Cumulative Annual Value of Mortality Avoided, 2025-2125 (Million 2023$ undiscounted).



Source: U.S. EPA Analysis, 2024.

E Derivation of Ambient Water and Fish Tissue Concentrations in Downstream Reaches

This appendix describes the methodology EPA used to estimate water and fish tissue concentrations under the baseline and each of the regulatory options. The concentrations are used as inputs to estimate the water quality changes and human health benefits of the regulatory options. Specifically, EPA used ambient water toxics concentrations to derive fish tissue concentrations used to analyze human health effects from consuming self-caught fish (see Chapter 5) and to analyze non-use benefits of water quality changes (see Chapter 6). Nutrient and suspended solids concentrations are used to support analysis of non-use benefits from water quality changes (see Chapter 6).

The overall modeling methodology builds on data and methods described in the EA and TDD for the regulatory options (U.S. EPA, 2024b; 2024f). The following sections discuss calculations of the toxics concentrations in ambient water and fish tissue and nutrient and sediment concentrations in ambient water.

E.1 Toxics

E.1.1 Estimating Water Concentrations in each Reach

EPA first estimated the baseline and regulatory option toxics concentrations in reaches receiving steam electric power plant discharges and downstream reaches.

The D-FATE model (see Chapter 3) was used to estimate water concentrations. The model tracks the fate and transport of discharged pollutants through a reach network defined based on the medium resolution NHD.[147] The hydrography network represented in the D-FATE model consists of 11,607 reaches within 300 km of a steam electric power plant, 11,080 of which are estimated to be potentially fishable.[148]

The analysis involved the following key steps for the baseline and each of the regulatory options:

- **Summing plant-level loadings to the receiving reach**. EPA summed the estimated plant-level annual average loads for each unique reach receiving plant discharges from steam electric power plants in the baseline and under the regulatory options. For a description of the approach EPA used to identify the receiving waterbodies, see U.S. EPA, 2023g.

- **Performing dilution and transport calculations**. The D-FATE model calculates the concentration of the pollutant in a given reach based on the total mass transported to the reach from upstream sources and the EROM flows for each reach from NHDPlus v2. In the model, a plant is assumed to

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[147] The USGS's National Hydrology Dataset (NHD) defines a reach as a continuous piece of surface water with similar hydrologic characteristics. In the NHD each reach is assigned a reach code; a reach may be composed of a single feature, like a lake or isolated stream, but reaches may also be composed of several contiguous features. Each reach code occurs only once throughout the nation and once assigned a reach code is permanently associated with its reach. If the reach is deleted, its reach code is retired.

[148] Reaches represented in the D-FATE model are those estimated to be potentially fishable based on type and physical characteristics. Because the D-FATE model calculates the movement of a chemical release downstream using flow data, reaches must have at least one downstream or upstream connecting reach and have a non-negative flow and velocity. The D-FATE model does not calculate concentrations for certain types of reaches, such as coastlines, treatment reservoirs, and bays; the downstream path of any chemical is assumed to stop if one of these types of reach is encountered.

release its annual load at a constant rate throughout the year. Each source-pollutant release is tracked throughout the NHD reach network until the terminal reach.[149]

- **Specifying concentrations in the water quality model**. The D-FATE model includes background data on estimated annual average pollutant concentrations to surface waters from facilities that reported to the TRI in 2019. EPA added background concentrations where available to concentration estimates from steam electric power plant dischargers.

EPA used the approach above to estimate annual average concentrations of ten toxics: arsenic, cadmium, hexavalent chromium, copper, lead, mercury, nickel, selenium, thallium, and zinc.

E.1.2 Estimating Fish Tissue Concentrations in each Reach

To support analysis of the human health benefits associated with water quality improvements (see Chapter 5), EPA estimated concentrations of arsenic, lead, and mercury in fish tissue based on the D-FATE model outputs discussed above.

The methodology follows the same general approach described in the EA for estimating fish tissue concentrations for receiving reaches (U.S. EPA, 2024b), but applies the calculations to the larger set of reaches modeled using D-FATE, which include not only the receiving reaches analyzed in the EA, but also downstream reaches. Further, the calculations use D-FATE-estimated concentrations as inputs, which account not only for the steam electric power plant discharges, but also other major dischargers that report to TRI.

The analysis involved the following key steps for the baseline and each of the regulatory options:

7. **Obtaining the relationship between water concentrations and fish tissue concentrations**. EPA used the results of the Immediate Receiving Water (IRW) model (see EA, U.S. EPA, 2023g) to parameterize the linear relationship between water concentrations in receiving reaches and composite fish tissue concentrations (representative of trophic levels 3 and 4 fish consumed) in these same reaches for each of the three toxics.

8. **Calculating fish tissue data for affected reaches**. For reaches for which the D-FATE model provides non-zero water concentrations (*i.e.*, reaches affected by steam electric power plants or other TRI dischargers), EPA used the relationship obtained in Step 1 to calculate a preliminary fish tissue concentration for each pollutant.

The analysis provides background toxic-specific composite fish fillet concentrations for each reach modeled in the D-FATE model (Table E-1).

Table E-1: Background Fish Tissue Concentrations, based on 10th Percentile

Parameter	Pollutant Concentration (mg/kg)
As	0.039
Hg	0.058
Pb	0.039

Source: U.S. EPA Analysis, 2024

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[149] For some analyses, EPA limits the scope of reaches to 300 km (186 miles) downstream from steam electric power plant outfalls.

E.2 Nutrients and Suspended Sediment

EPA used the USGS's regional SPARROW models to estimate nutrient and sediment concentrations in receiving and downstream reaches. The regional models used for this analysis are the five regional models developed for the Pacific, Southwest, Midwest, Southeast, and Northeast regions for flow, total nitrogen (TN), total phosphorus (TP), and suspended sediment (Ator, 2019; Hoos & Roland Ii, 2019; Robertson & Saad, 2019; Wise, 2019; Wise, Anning & Miller, 2019). EPA adjusted the models to include a variable for steam electric discharges using the following steps:

- **Specifying a source load parameter for steam electric discharges.** The regional SPARROW models do not include an explicit explanatory variable for point sources related to industrial dischargers (non publicly owned treatment works). EPA recalibrated the regional models by adding a variable for steam electric loadings, initially setting all loadings for this parameter equal to zero, assigning this new variable a calibration coefficient value of 1, and specifying zero land-to-water delivery effects associated with this new variable.

- **Appending steam electric TN, TP, and TSS loadings to regional input data.** Once the regional SPARROW models were recalibrated to include the steam electric loadings variable, EPA added the steam electric TN, TP, and TSS[150] loadings to the model input data and ran each regional model for each pollutant to obtain catchment-level TN, TP, and SSC predictions.

For Periods 1 and 2, the SPARROW models output predicted annual average baseline and regulatory option concentrations in each reach. EPA compared the baseline predictions to the predictions obtained for each of the regulatory options to estimate changes in concentrations.

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[150] TSS loadings are converted to SSC values at this step by using location-specific relationships built into the SPARROW regional models.

F Georeferencing Surface Water Intakes to the Medium-resolution Reach Network

For the 2024 final rule analysis, EPA used the following steps to assign PWS surface water intakes to waters represented in the medium-resolution NHD Plus version 2 dataset and identify those intakes potentially affected by steam electric power plant discharges.

1. Identify the downstream flowpath via NHD Plus Version 2 Flowlines for all steam electric dischargers.
2. Identify intakes within a 5-kilometer buffer of the downstream flowpath. This distance is used to limit the set of points to be visually reviewed in the next step and provides an upper bound of the distance between an intake and its potential associated receiving water.
3. Visually review the location of each intake within the five-kilometer buffer to determine whether the intake is on a waterbody downstream of steam electric power plant discharges. The visual assessment accounts for hydrographic connectivity and flow direction.

EPA then paired the intakes that were confirmed to be impacted to the closest NHD COMID based on a simple cartesian distance.

G Sensitivity Analysis for IQ Point-based Human Health Effects

EPA monetized the value of an IQ point based on the methodology from Salkever (1995) but with more recent data from the 1997 National Longitudinal Survey of Youth (U.S. EPA, 2019d). As a sensitivity analysis of the benefits of changes in lead and mercury exposure, EPA used alternative, more conservative estimates provided in Lin, Lutter and Ruhm (2018), which indicate that a one-point IQ reduction reduces expected lifetime earnings by 1.39 percent, as compared to 2.63 percent based on Salkever (1995). As noted in Sections 5.3 and 5.4, values of an IQ point used in the analysis of health effects in children from lead exposure are discounted to the third year of life to represent the midpoint of the exposed children population, and values of an IQ point used in the analysis of health effects associated with in-utero exposure to mercury are discounted to birth. Table G-1 summarizes the estimated values of an IQ point based on Lin, Lutter and Ruhm (2018), using 2 percent, 3 percent, and 7 percent discount rates.

Table G-1: Value of an IQ Point (2023$) based on Expected Reductions in Lifetime Earnings

Discount Rate	Value of an IQ Point[a] (2023$)
Value of an IQ point Discounted to Age 3 (Lead)	
2 Percent	$21,653
3 percent	$13,718
7 percent	$2,885
Value of an IQ point Discounted to Birth (Mercury)	
2 Percent	$20,404
3 percent	$12,554
7 percent	$2,355

a. Values are adjusted for the cost of education.

Source: U.S. EPA, 2019d and 2019e analysis of data from Lin, Lutter and Ruhm (2018); 2 percent estimates calculated for U.S. EPA (2023f)

G.1 Health Effects in Children from Changes in Lead Exposure

Table G-2 shows the benefits associated with avoided IQ losses from lead exposure via fish consumption. The total net change in avoided IQ point losses over the entire population of children with reductions in lead exposure is approximately one point. Annualized benefits of avoided IQ losses from reductions in lead exposure, based on the Lin, Lutter and Ruhm (2018) IQ point value, range from approximately $100 (7 percent discount rate) to $800 (2 percent discount rate).

Table G-2: Estimated Benefits of Avoided IQ Losses for Children Exposed to Lead under the Regulatory Options, Compared to Baseline

Regulatory Option	Average Annual Number of Children 0 to 7 in Scope of the Analysis[b]	Total Avoided IQ Point Losses, 2025 to 2049, in All Children 0 to 7 in Scope of the Analysis	Annualized Value of Changes in IQ Point Losses[a] (Thousands of 2023$)		
			2% Discount Rate	3% Discount Rate	7% Discount Rate
Option A	1,555,558	0.93	$0.8	$0.5	$0.1
Option B (Final Rule)	1,555,558	0.93	$0.8	$0.5	$0.1
Option C	1,555,558	0.93	$0.8	$0.5	$0.1

Table G-2: Estimated Benefits of Avoided IQ Losses for Children Exposed to Lead under the Regulatory Options, Compared to Baseline

Regulatory Option	Average Annual Number of Children 0 to 7 in Scope of the Analysis[b]	Total Avoided IQ Point Losses, 2025 to 2049, in All Children 0 to 7 in Scope of the Analysis	Annualized Value of Changes in IQ Point Losses[a] (Thousands of 2023$)		
			2% Discount Rate	3% Discount Rate	7% Discount Rate

a. Based on estimates that the loss of one IQ point results in the loss of 1.39 percent of lifetime earnings (following Lin, Lutter and Ruhm (2018) values from U.S. EPA, 2019d).

b. The number of affected children is based on reaches analyzed across the regulatory options. Some of the children included in this count see no changes in exposure under some options.

Source: U.S. EPA Analysis, 2024

G.2 Heath Effects in Children from Changes in Mercury Exposure

Table G-3 shows the estimated changes in avoided IQ point losses for infants exposed to mercury in-utero and the corresponding monetary benefits, using 2 percent, 3 percent, and 7 percent discount rates. The final rule (Option B) results in 1,377 avoided IQ point losses over the entire in-scope population of infants with changes in mercury exposure. Annualized benefits of avoided IQ losses from reductions in mercury exposure, based on the Lin, Lutter and Ruhm (2018) IQ point value, range from $0.1 million (7 percent discount rate) to $1.1 million (2 percent discount rate) under the final rule (Option B).

Table G-3: Estimated Benefits of Avoided IQ Losses for Infants from Mercury Exposure under the Regulatory Options, Compared to Baseline

Regulatory Option	Average Annual Number of Infants in Scope of the Analysis[b]	Total Avoided IQ Point Losses, 2025 to 2049, in All Infants in Scope of the Analysis	Annualized Value of Changes in IQ Point Losses[a] (Millions 2023$)		
			2% Discount Rate	3% Discount Rate	7% Discount Rate
Option A	201,850	1,190	$0.9	$0.6	$0.1
Option B (Final Rule)	201,850	1,377	$1.1	$0.6	$0.1
Option C	201,850	1,393	$1.1	$0.7	$0.1

a. Based on estimates that the loss of one IQ point results in the loss of 1.39 percent of lifetime earnings (following Lin, Lutter and Ruhm (2018) values from U.S. EPA, 2019d and 2019e).

b. The number of affected children is based on reaches analyzed across the regulatory options. Some of the children included in this count see no changes in exposure under some options.

Source: U.S. EPA Analysis, 2024

H Methodology for Estimating WTP for Water Quality Changes

To estimate the nonmarket benefits of the water quality changes resulting from the regulatory options, EPA used updated results from a meta-analysis of stated preference studies described in detail in Appendix H in the 2015 BCA (U.S. EPA, 2015a). To update results of the 2015 meta-analysis, EPA first conducted a literature review and identified 10 new studies to augment the existing meta-data. EPA also performed quality assurance on the meta-data, identifying revisions that improved accuracy and consistency within the meta-data, and added or removed observations from existing studies, as appropriate. EPA then re-estimated the MRM and made additional improvements to the model by introducing explanatory variables to account for different survey methodologies, WTP estimation methodologies, payment mechanisms, and water quality metrics used in some of the added studies. A memorandum titled "Revisions to the Water Quality Meta-Data and Meta-Regression Models after the 2020 Steam Electric Analysis through December 2021" (ICF, 2022b) details changes to the meta-data and MRMs following the 2020 Steam Electric ELG analysis (U.S. EPA, 2020f), summarizes how the studies and observations included in the meta-data have changed from 2015 to 2020 to present, and compares the latest MRM results with those from 2015 (U.S. EPA, 2015a) and 2020 (U.S. EPA, 2020f).

Table H-1 summarizes studies in the revised meta-data, including number of observations from each study, state-level study location, waterbody type, geographic scope, and household WTP summary statistics. In total, the revised meta-data includes 189 observations from 59 stated preference studies that estimated per household WTP (use plus nonuse) for water quality changes in U.S. waterbodies. The studies address various waterbody types including, rivers, lakes, salt ponds/marshes, and estuaries. The ten studies added to the meta-data since 2015 are shaded in Table H-1.

Table H-1: Primary Studies Included in the Meta-data

Study	Obs. In Meta-data	State(s)	Waterbody Type(s)	Geographic Scope	WTP Per Household (2019$)		
					Mean	Min	Max
Aiken (1985)	1	CO	river/ stream and lake	Entire state	$238.19	$238.19	$238.19
Anderson and Edwards (1986)	1	RI	salt pond /marsh	Coastal salt ponds (South Kingstown, Charlestown, and Narragansett)	$222.82	$222.82	$222.82
Banzhaf et al. (2006)	2	NY	lake	Adirondack Park, New York State	$70.86	$66.69	$75.03
Banzhaf et al. (2016)	1	VA, WV, TN, NC, GA	river/ stream	Southern Appalachian Mountains region	$18.67	$18.67	$18.67
Bockstael, McConnell and Strand (1989)	2	MD, DC, VA	estuary	Chesapeake Bay (Baltimore-Washington Metropolitan Area)	$137.31	$93.30	$181.32
Borisova et al. (2008)	2	VA/WV	river/ stream	Opequon Creek watershed	$42.54	$22.25	$62.83
Cameron and Huppert (1989)	1	CA	estuary	San Francisco Bay	$61.07	$61.07	$61.07
Carson et al. (1994)	2	CA	estuary	Southern California Bight	$73.24	$50.81	$95.67

Table H-1: Primary Studies Included in the Meta-data

Study	Obs. In Meta-data	State(s)	Waterbody Type(s)	Geographic Scope	WTP Per Household (2019$)		
					Mean	Min	Max
Choi and Ready (2019)	6	PA	river/ stream	Three creek watersheds: Spring, Mahantango, and Conewago	$4.56	$1.73	$10.40
Clonts and Malone (1990)	2	AL	river/ stream	15 free-flowing rivers, AL	$112.28	$96.56	$128.00
Collins and Rosenberger (2007)	1	WV	river/ stream	Cheat River Watershed	$22.43	$22.43	$22.43
Collins, Rosenberger and Fletcher (2009)	1	WV	river/ stream	Deckers Creek Watershed	$229.82	$229.82	$229.82
Corrigan (2008)	1	IA	lake	Clear Lake	$152.03	$152.03	$152.03
Croke, Fabian and Brenniman (1986-1987)	6	IL	river/ stream	Chicago metropolitan area river system	$90.25	$75.60	$107.18
De Zoysa (1995)	1	OH	river/ stream	Maumee River Basin	$86.53	$86.53	$86.53
Desvousges, Smith and Fisher (1987)	12	PA	river/ stream	Monongahela River basin (PA portion)	$72.98	$24.46	$169.24
Downstream Strategies LLC (2008)	2	PA	river/ stream	West Branch Susquehanna River watershed	$15.70	$13.19	$18.21
Farber and Griner (2000)	6	PA	river/ stream	Loyalhanna Creek and Conemaugh River basins (western PA)	$93.91	$20.45	$183.21
Hayes, Tyrell and Anderson (1992)	2	RI	estuary	Upper Narragansett Bay	$490.05	$481.71	$498.38
Herriges and Shogren (1996)	1	IA	lake	Storm Lake watershed	$76.09	$76.09	$76.09
Hite (2002)	2	MS	river/ stream	Entire state	$74.09	$71.81	$76.36
Holland and Johnston (2017)	6	ME	river/ stream	Merriland, Branch Brook and Little River Watershed	$13.90	$8.16	$21.27
Huang, Haab. T.C. and Whitehead (1997)	2	NC	estuary	Albemarle and Pamlico Sounds	$318.92	$314.43	$323.40
Interis and Petrolia (2016)	10	AL/LA	estuary	Mobile Bay, AL; Barataria-Terrebonne estuary, LA	$87.91	$45.00	$140.47
Irvin, Haab and Hitzhusen (2007)	4	OH	river/ stream and lake	Entire state	$26.72	$24.22	$28.64

Table H-1: Primary Studies Included in the Meta-data

Study	Obs. In Meta-data	State(s)	Waterbody Type(s)	Geographic Scope	WTP Per Household (2019$)		
					Mean	Min	Max
Johnston and Ramachandran (2014)	3	RI	river/ stream	Pawtuxet watershed	$14.11	$7.05	$21.16
Johnston, Swallow and Bauer (2002)	1	RI	river/ stream	Wood-Pawcatuck watershed	$48.08	$48.08	$48.08
R. J. Johnston et al. (2017)	3	RI	river/ stream	Pawtuxet watershed	$4.79	$2.40	$7.19
Kaoru (1993)	1	MA	salt pond /marsh	Martha's Vineyard	$269.56	$269.56	$269.56
Lant and Roberts (1990)	3	IA/IL	river/ stream	Des Moines, Skunk, English, Cedar, Wapsipinicon, Turkey; Illinois: Rock, Edwards, La Moine, Sangamon, Iroquois, and Vermillion River basins	$177.47	$152.94	$190.26
Lant and Tobin (1989)	9	IA/IL	river/ stream	Edwards River, Wapsipinicon River, and South Skunk drainage basins	$68.59	$50.04	$83.40
Lichtkoppler and Blaine (1999)	1	OH	river/ stream and lake	Ashtabula River and Ashtabula Harbor	$51.69	$51.69	$51.69
Lindsey (1994)	8	MD	estuary	Chesapeake Bay	$82.37	$41.18	$126.02
Lipton (2004)	1	MD	estuary	Chesapeake Bay Watershed	$78.88	$78.88	$78.88
Londoño Cadavid and Ando (2013)	2	IL	river/ stream	Cities of Champaign and Urbana	$47.70	$44.30	$51.10
Loomis (1996)	1	WA	river/ stream	Elwha River	$114.75	$114.75	$114.75
Lyke (1993)	2	WI	river/ stream and lake	Wisconsin Great Lakes	$97.10	$73.68	$120.52
Mathews, Homans and Easter (1999)	1	MN	river/ stream	Minnesota River	$22.36	$22.36	$22.36
Moore et al. (2018)	2	MD, VA, DC, DE, NY, PA, WV, CT, FL, GA, ME, MA, NH, NJ, NC, RI, SC, VT	lake	Chesapeake Bay Watershed	$131.21	$77.75	$184.67
Nelson et al. (2015)	2	UT	river/ stream and lake	Entire state	$259.70	$167.07	$352.33

Table H-1: Primary Studies Included in the Meta-data

Study	Obs. In Meta-data	State(s)	Waterbody Type(s)	Geographic Scope	WTP Per Household (2019$)		
					Mean	Min	Max
Opaluch et al. (1998)	1	NY	estuary	Peconic Estuary System	$170.73	$170.73	$170.73
Roberts and Leitch (1997)	1	MN/SD	lake	Mud Lake	$10.30	$10.30	$10.30
Rowe et al. (1985)	1	CO	river/ stream	Eagle River	$165.95	$165.95	$165.95
Sanders, Walsh and Loomis (1990)	4	CO	river/ stream	Cache la Poudre, Colorado, Conejos, Dollores, Elk, Encampment, Green, Gunnison, Los Pinos, Piedra, and Yampa rivers	$198.13	$99.89	$258.99
Schulze et al. (1995)	4	MT	river/ stream	Clark Fork River Basin	$75.19	$56.62	$95.54
Shrestha and Alavalapati (2004)	2	FL	river/ stream and lake	Lake Okeechobee watershed	$192.92	$170.12	$215.72
Stumborg, Baerenklau and Bishop (2001)	2	WI	lake	Lake Mendota Watershed	$103.94	$82.28	$125.59
Sutherland and Walsh (1985)	1	MT	river/ stream and lake	Flathead River drainage system	$180.05	$180.05	$180.05
Takatsuka (2004)	4	TN	river/ stream	Clinch River watershed	$353.72	$224.28	$483.16
Van Houtven et al. (2014)	32	VA, NC, SC, AL, GA, KY, MS, TN	lake	Entire state (separate observations for each state)	$316.16	$260.91	$374.11
Wattage (1993)	2	IA	river/ stream	Bear Creek watershed	$53.68	$49.61	$57.76
Welle (1986)	4	MN	lake	Entire state	$175.44	$135.13	$227.59
Welle and Hodgson (2011)	3	MN	lake	Lake Margaret and Sauk River Chain of Lakes watersheds	$178.91	$13.06	$351.48
Wey (1990)	1	RI	salt pond /marsh	Great Salt Pond (Block Island)	$78.85	$78.85	$78.85
Whitehead (2006)	3	NC	river/ stream	Neuse River watershed	$230.79	$33.93	$450.72
Whitehead and Groothuis (1992)	2	NC	river/ stream	Tar-Pamlico River	$43.08	$39.33	$46.82
Whitehead et al. (1995)	1	NC	estuary	Albermarle-Pamlico estuary system	$115.56	$115.56	$115.56
Whittington (1994)	1	TX	estuary	Galveston Bay estuary	$240.09	$240.09	$240.09
Zhao, Johnston and Schultz (2013)	3	RI	river/ stream and lake	Pawtuxet watershed	$7.19	$3.59	$10.78

Table H-1: Primary Studies Included in the Meta-data

Study	Obs. In Meta-data	State(s)	Waterbody Type(s)	Geographic Scope	WTP Per Household (2019$)		
					Mean	Min	Max

Source: U.S. EPA Analysis, 2024

Similar to the 2015 MRM, the updated MRM satisfies the adding-up condition, a theoretically desirable property.[151] This condition ensures that if the model were used to estimate WTP for the cumulative water quality change resulting from several CWA regulations, the benefits estimates would be equal to the sum of benefits from using the model to estimate WTP for water quality changes separately for each rule (Moeltner, 2019; Newbold et al., 2018).

The meta-analysis is based on 189 observations from 59 stated preference studies, published between 1985 and 2021. The variables in the meta-data fall into four general categories:

- *Study methodology and year variables* characterize such features as the year in which a study was conducted, payment vehicle and elicitation formats, and publication type. These variables are included to explain differences in WTP across studies but are not expected to vary across benefit transfer for different policy applications.
- *Region and surveyed populations variables* characterize such features as the geographical region within the United States in which the study was conducted, the average income of respondent households, and the representation of users and nonusers within the survey sample.
- *Sampled market and affected resource variables* characterize features such as the geospatial scale (or size) of affected waterbodies, the size of the market area over which populations were sampled, as well as land cover and the quantity of substitute waterbodies.
- *Water quality (baseline and change) variables* characterize baseline conditions and the extent of the water quality change. To standardize the results across these studies, EPA expressed water quality (baseline and change) in each study using the 100-point WQI, if they did not already employ the WQI or WQL.

In the latest version of the MRM, EPA built upon published versions of the MRM (R. J. Johnston et al., 2017; Johnston, Besedin & Holland, 2019; U.S. EPA, 2020b; U.S. EPA, 2015a), with revisions to better account for methodological differences in the underlying studies (see ICF (2022b) for detail on changes in the meta-data and the explanatory variables used in the regression equation).

EPA also revised regional indicators to match the U.S. Census regions (U.S. Census Bureau, n.d.). To correct for heteroskedasticity, the model is estimated using weighted least squares with observations weighted by sample size and robust standard errors (Nelson & Kennedy, 2009). Detailed discussion of this approach can be found in Vedogbeton and Johnston (2020). A comprehensive review of these methods is provided by Stanley (2005).

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[151] For a WTP function $WTP(WQI_0, WQI_2, Y_0)$ to satisfy the adding-up property, it must meet the simple condition that $WTP(WQI_0, WQI_1, Y_0) + WTP(WQI_1, WQI_2, Y_0 - WTP(WQI_0, WQI_1, Y_0)) = WTP(WQI_0, WQI_2, Y_0)$ for all possible values of baseline water quality (WQI_0), potential future water quality levels (WQI_1 and WQI_2), and baseline income (Y_0).

Table H-2 provides definitions and presents descriptive statistics for variables included in the MRM, based on the meta-data studies.

Table H-2: Definition and Summary Statistics for Model Variables

Variable	Definition	Units	Mean	St. Dev.
Dependent Variable				
ln_OWTP	Natural log of WTP per unit (one point) of water quality improvement, per household.	Natural log of 2019$	1.873	1.391
OWTP[a]	WTP per unit of water quality improvement, per household.	2019$	15.931	23.595
Study Methodology and Year				
OneShotVal	Binary variable indicating that the study's survey only included one valuation question.	Binary (Value: 0 or 1)	0.534	0.500
tax_only[b]	Binary variable indicating that the payment mechanism used to elicit WTP is increased taxes.	Binary (Value: 0 or 1)	0.397	0.491
user_cost[b]	Binary variable indicating that the payment mechanism used to elicit WTP is increased user costs.	Binary (Value: 0 or 1)	0.021	0.144
volunt[b]	Binary variable indicating that WTP was estimated using a payment vehicle described as voluntary as opposed to, for example, property taxes.	Binary (Value: 0 or 1)	0.058	0.235
RUM	Binary variable indicating that the study used a Random Utility Model to estimate WTP.	Binary (Value: 0 or 1)	0.566	0.497
IBI	Binary variable indicating that the study used the index of biotic integrity as the water quality metric.	Binary (Value: 0 or 1)	0.079	0.271
lnyear	Natural log of the year in which the study was conducted (*i.e.*, data was collected), converted to an index by subtracting 1980.	Natural log of years (year ranges from 1981 to 2017).	2.629	0.979
non_reviewed	Binary variable indicating that the study was not published in a peer-reviewed journal.	Binary (Value: 0 or 1)	0.159	0.366
thesis	Binary variable indicating that the study is a thesis.	Binary (Value: 0 or 1)	0.079	0.271
lump_sum	Binary variable indicating that the study provided WTP as a one-time, lump sum or provided annual WTP values for a payment period of five years or less. This variable enables the policy analyst to estimate annual WTP values by setting *lump_sum*=0.	Binary (Value: 0 or 1)	0.180	0.385
Region and Surveyed Populations				
census_south[c]	Binary variable indicating that the affected waters are located entirely within the South Census region, which includes the following states: DE, MD, DC, WV, VA, NC, SC, GA, FL, KY, TN, MS, AL, AR, LA, OK, and TX.	Binary (Value: 0 or 1)	0.349	0.478
census_midwest[c]	Binary variable indicating that the affected waters are located entirely within the Midwest Census region, which includes the following states: OH, MI, IN, IL, WI, MN, IA, MO, ND, SD, NE, and KS.	Binary (Value: 0 or 1)	0.228	0.420

Table H-2: Definition and Summary Statistics for Model Variables

Variable	Definition	Units	Mean	St. Dev.
census_west[c]	Binary variable indicating that the affected waters are located entirely within the West Census region, which includes the following states: MT, WY, CO, NM, ID, UT, AZ, NV, WA, OR, and CA.	Binary (Value: 0 or 1)	0.090	0.287
nonusers	Binary variable indicating that the survey was implemented over a population of nonusers (default category for this variable is a survey of any population that includes both users and nonusers).	Binary (Value: 0 or 1)	0.058	0.235
lnincome	Natural log of the median income (in 2019$) for the sample area of each study based on historical U.S. Census data. It was designed to provide a consistent income variable given differences in reporting of respondent income across studies in the meta-data (*i.e.*, mean vs. median). Also, some studies do not report respondent income. This variable was estimated for all studies in the meta-data regardless of whether the study reported summary statistics for respondent income.	Natural log of income (2019$)	10.946	0.160
Sampled Market and Affected Resource				
swim_use	Binary variable indicating that the affected use(s) stated in the survey instrument include swimming.	Binary (Value: 0 or 1)	0.222	0.417
gamefish	Binary variable indicating that the affected use stated in the survey instrument is game fishing.	Binary (Value: 0 or 1)	0.190	0.394
ln_ar_agr[d]	Natural log of the proportion of the affected resource area that is agricultural based on National Land Cover Database, reflecting the nature of development in the area surrounding the resource. The affected resource area is defined as all counties that intersect the affected resource(s).	Natural log of proportion (Proportion Range: 0 to 1; km^2/km^2)	-1.648	0.912
ln_ar_ratio	The ratio of the sampled area, in km^2, relative to the affected resource area. When not explicitly reported in the study, the affected resource area is measured as the total area of counties that intersect the affected resource(s), to create the variable *ar_total_area*. From here, *ln_ar_ratio* = log(*sa_area* / *ar_total_area*), where *sa_area* is the size of the sampled area in km^2.	Natural log of ratio (km^2/km^2)	-0.594	2.408
sub_proportion[e]	The water bodies affected by the water quality change, as a proportion of all water bodies of the same hydrological type in the sampled area. The affected resource appears in both the numerator and denominator when calculating *sub_proportion*. The value can range from 0 to 1.	Proportion (Range: 0 to 1; km/km)	0.351	0.401

Table H-2: Definition and Summary Statistics for Model Variables

Variable	Definition	Units	Mean	St. Dev.
	Water Quality Baseline and Change			
ln_Q	Natural log of the mid-point of the baseline and policy water quality: Q = *(1/2)(WQI-BL + WQI-PC).*	Natural log of WQI units	3.944	0.295
lnquality_ch	Natural log of the change in mean water quality (*quality_ch*), specified on the WQI.	Natural log of WQI units	2.552	0.801

a. Provided for informational purposes. Model uses the natural log version of the *OWTP* variable as the dependent variable.

b. The payment types omitted from the payment type binary variables are: (1) increased prices, (2) increased prices and/or taxes, (3) multiple methods, (4) earmarked fund, and (5) not specified/unknown.

c. The regions omitted from the regional binary variables are the Northeast Census region (ME, NH, VT, MA, RI, CT, NY, PA, and NJ) and the Chesapeake Bay (studies focused on the Chesapeake Bay or Chesapeake Bay Watershed since the Chesapeake Bay Watershed spans two Census regions).

d. In addition to the *ln_ar_agr* variable, EPA tested a variable for the proportion of the affected resource area that is developed, but it did not improve model fit.

e. The *sub_proportion* estimation method differs by waterbody type. For rivers, the calculation is the length of the affected river reaches as a proportion of all reaches of the same order. For lakes and ponds, the calculation is the area of the affected waterbody as a proportion of all water bodies of the same National Hydrography Dataset classification. For bays and estuaries, the calculation is the shoreline length of the waterbody as a proportion of all analogous (*e.g.*, coastal) shoreline lengths. To account for observations where multiple waterbody types are affected, the variable *sub_proportion* is defined as the maximum of separate substitute proportions for rivers, lakes, and estuaries/bays.

Source: U.S. EPA Analysis, 2024.

Using the updated meta-data, EPA developed MRMs that predict how WTP for a one-point improvement on the WQI (hereafter, one-point WTP) depends on a variety of methodological, population, resource, and water quality change characteristics. The estimated MRMs predict the one-point WTP values that would be generated by a stated preference survey with a particular set of characteristics chosen to represent the water quality changes and other specifics of the regulatory options where possible, and best practices in economic literature (*e.g.*, excluding outlier responses from estimating WTP). As with the 2015 meta-analysis, EPA developed two MRMs (U.S. EPA, 2015a). Model 1 is used to provide EPA’s main estimate of non-market benefits. Model 2 provides alternative estimates by including an additional variable (*lnquality_ch*), which accounts for the magnitude of WQI changes (*e.g.*, low or high) and the associated effect on estimated WTP values. The two models differ only in how they account for the magnitude of the water quality changes presented to respondents in the original stated preference studies:

- Model 1 assumes that individuals’ one-point WTP depends on the average level of water quality between the baseline and regulatory options. It does not depend on the magnitude of the water quality change specified in the surveys of studies included in the underlying meta-data. This restriction means that the meta-model satisfies the adding-up condition, a theoretically desirable property.
- Model 2 allows one-point WTP to depend not only on the average level of water quality but also on the magnitude of the water quality change specified in the surveys of studies included in the underlying meta-data. The model allows for the possibility that the WTP for a one-point improvement on the WQI depends on both the average level of water quality between the baseline and the regulatory options and the total water quality change that respondents were asked to value. Since

environmental quality is considered by economists to be a normal good,[152] one-point WTP is expected to decrease when the total WQI change increases according to the law of diminishing marginal utility. As indicated by a negative sign on the *lnquality_ch* coefficient, the estimated WTP for a one-point improvement on the WQI scale is larger when respondents were asked to value a 10-point improvement compared to a 20-point improvement. EPA used Model 2 to generate alternative estimates of non-market benefits. This model provides a better statistical fit to the meta-data, but it satisfies the adding-up condition only if the same magnitude of the water quality change is considered (*e.g.*, 10 points). To uniquely define the demand curve and satisfy the adding-up condition using this model, EPA treats the water quality change variable as a methodological variable and therefore must make an assumption about the size of the water quality change that would be appropriate to use in a stated preference survey designed to value water quality changes resulting from the regulatory options.

EPA used the two MRMs in a benefit transfer approach that follows standard methods described by Johnston et al. (2005), Shrestha, Rosenberger and Loomis (2007), and Rosenberger and Phipps (2007). Based on benefit transfer literature (*e.g.*, Stapler & Johnston, 2009; Boyle & Wooldridge, 2018), methodological variables are assigned values that either reflect "best practices" associated with reducing measurement errors in primary studies or set to their mean values over the meta-data. The literature also recommends setting variables representing policy outcomes and policy context (*i.e.*, resource and population characteristics) at the levels that might be expected from a regulation. The benefit transfer approach uses CBGs as the geographic unit of analysis.[153] This approach involves estimating benefits in each CBG and year, based on the following general benefit function:

Equation H-1.

$$\ln\left(OWTP_{Y,B}\right) = Intercept + \sum (coefficient_i) \times (independent\ variable\ value_i)$$

Where

$\ln(OWTP_{Y,B})$ = The predicted natural log of one-point household WTP for a given year (Y) and CBG (B).

coefficient = A vector of variable coefficients from the meta-regression.

independent variable values = A vector of independent variable values. Variables include baseline water quality level ($WQI\text{-}BL_{Y,B}$) and expected water quality under the regulatory option ($WQI\text{-}PC_{Y,B}$) for a given year and CBG.

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[152] Environmental quality, including water quality, is a "normal" good because people want more of it as their real incomes increase.

[153] A Census Block Group is a group of Census Blocks (the smallest geographic unit for the Census) in a contiguous area that never crosses a State or county boundary. A block group typically contains a population between 600 and 3,000 individuals. There are 239,780 block groups in the United States based on the 2020 Census. See https://www.census.gov/geographies/reference-files/time-series/geo/tallies.html. http://www.census.gov/geo/maps-data/data/tallies/tractblock.html.

Here, $ln(OWTP_{Y,B})$ is the dependent variable in the meta-analysis—the natural log of an average WTP per one point improvement per household, in a given CBG B for water quality in a given year Y.[154] The baseline water quality level ($WQI\text{-}BL_{Y,B}$) and expected water quality under the regulatory option ($WQI\text{-}PC_{Y,B}$) were based on water quality in waterbodies within a 100-mile buffer of the centroid of each CBG. A buffer of 100 miles is consistent with Viscusi, Huber and Bell (2008) and with the assumption that the majority of recreational trips would occur within a 2-hour drive from home. Because one-point WTP is assumed to depend, according to Equation H-1, on both baseline water quality level ($WQI\text{-}BL_{Y,B}$) and expected water quality under the regulatory option ($WQI\text{-}PC_{Y,B}$), EPA estimated the one-point WTP for water quality changes resulting from the regulatory options at the mid-point of the range over which water quality was changed, $WQI_{Y,B} = (1/2)(WQI\text{-}BL_{Y,B} + WQI\text{-}PC_{Y,B})$.

In this analysis, EPA estimated WTP for the households in each CBG for waters within a 100-mile radius of that CBG's centroid. EPA chose the 100 mile-radius because households are likely to be most familiar with waterbodies and their qualities within the 100-mile distance. However, this assumption may be an underestimate of the distance beyond which households have familiarity with and WTP for waterbodies affected by steam electric power plant discharges and their quality. By focusing on a buffer around the CBG as a unit of analysis, rather than buffers around affected waterbodies, each household is included in the assessment exactly once, eliminating the potential for double-counting of households.[155] Total national WTP is calculated as the sum of estimated CBG-level WTP across all CBGs that have at least one affected waterbody within 100 miles. Using this approach, EPA is unable to analyze the WTP for CBGs with no affected waters within 100 miles. Appendix E in U.S. EPA (2020b) describes the methodology used to identify the relevant populations.

In each CBG and year, predicted WTP per household is tailored by choosing appropriate input values for the meta-analysis parameters describing the resource(s) valued, the extent of resource changes (*i.e.*, $WQI\text{-} PC_{Y,B}$), the scale of resource changes relative to the size of the buffer and relative to available substitutes, the characteristics of surveyed populations (*e.g.*, users, nonusers), and other methodological variables. For example, EPA projected that household income (an independent variable) changes over time, resulting in household WTP values that vary by year.

Table H-3 provides details on how EPA used the meta-analysis to predict household WTP for each CBG and year. The table presents the estimated regression equation intercepts and variable coefficients ($coefficient_i$) for the two models, and the corresponding independent variables names and assigned values. The MRM allows the Agency to forecast WTP based on assigned values for model variables that are chosen to represent a resource change in the context of the regulatory options.

In this instance, EPA assigned six study and methodology variables, (*thesis, volunt, non_reviewed, lump_sum, user_cost, IBI*) a value of zero. Three methodological variables (*OneShotVal*, *tax_only*, *RUM*) were included with an assigned value of 1. For the study year variable *(lnyear),* EPA gave the variable a value of 3.6109 (or the ln(2017-1980)), which is the maximum value in the meta-data. This value assignment reflects a time trend interpretation of the variable. Model 2 includes an additional variable, water quality change (*ln_quality_ch*), which allows the benefit transfer function to reflect differences in one-point WTP based on the magnitude of

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[154] To satisfy the adding-up condition, as noted above, EPA normalized WTP values reported in the studies included in the meta-data so that the dependent variable is WTP for a one-point improvement on the WQI.

[155] Population double-counting issues can arise when using "distance to waterbody" to assess simultaneous improvements to many waterbodies.

changes presented to survey respondents when eliciting WTP values. To ensure that the benefit transfer function satisfies the adding-up condition, the *ln_quality_ch* variable was treated as a demand curve shifter, similar to the methodological control variables, and held fixed for the benefit calculations. To estimate low and high sensitivity analysis values of WTP for water quality changes resulting from the regulatory options, EPA estimated one-point WTP using two alternative settings of the *ln_quality_ch* variable: ΔWQI = 7 units and ΔWQI = 20 units. These two values represent the 25th percentile and 75th percentile values of the meta-data.

All but one of the region and surveyed population variables vary based on the characteristics of each CBG. EPA set the variable *nonusers_only* to zero for all CBGs because water quality changes are expected to enhance both use and non-use values of the affected resources and thus benefit both users and nonusers (a nonuser value of 1 implies WTP values that are representative of nonusers only, whereas the default value of 0 indicates that both users and nonusers are included in the surveyed population). For median household income, EPA used CBG-level median household income data from the 2021 American Community Survey (5-year data) and accounted for projected income growth over the analysis period using the methodology described in Section 1.3.6.

The geospatial variables corresponding to the sampled market and scale of the affected resources (*ln_ar_agr*, *ln_ar_ratio*, *sub_proportion*) vary based on attributes of the CBG and attributes of the nearby affected resources. For all options, the affected resource is based on the 9,358 NHD reaches potentially affected by steam electric power generating plant discharges under baseline conditions. The affected resource for each CBG is the portion of the 9,358 reaches that falls within the 100-mile buffer of the CBG. Spatial scale is held fixed across regulatory options. The variable corresponding to the sampled market (*ln_ar_ratio*) is set to the mean value across all COMIDs within the scope of the analysis and thus does not vary across affected CBGs.

Because data on specific recreational uses of the water resources affected by the regulatory options are not available, the recreational use variables (*swim_use*, *gamefish*) are set to zero, which corresponds to "unspecified" or "all" recreational uses in the meta-data.[156] Water quality variables (*Q* and *lnquality_ch*) vary across CBGs and regulatory options based on the magnitude of the reach-length weighted average water quality changes in resources within scope of the analysis within the 100-mile buffer of each CBG.

Table H-3: Independent Variable Assignments for Surface Water Quality Meta-Analysis

Variable	Coefficient		Assigned Value	Explanation
	Model 1	Model 2		
Study Methodology and Year				
intercept	-2.823	-10.020		
OneShotVal	0.247	0.552	1	Binary variable indicating that the study's survey only included one valuation question. Set to one because one valuation scenario follows best practices for generating incentive-compatible WTP estimates (Carson, Groves & List, 2014; Johnston, Boyle, et al., 2017).

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[156] If a particular recreational use was not specified in the survey instrument, EPA assessed that survey respondents were thinking of all relevant uses.

Variable	Coefficient		Assigned Value	Explanation
	Model 1	Model 2		
tax_only	-0.177	-0.478	1	Binary variable indicating that the payment mechanism used to elicit WTP is increased taxes. Set to one because using taxes as the payment mechanism generates incentive-compatible WTP estimates and is inclusive of both users and nonusers.
user_cost	-0.873	-1.199	0	Binary variable indicating that the payment mechanism used to elicit WTP is increased user cost. Set to zero because user cost payment mechanisms are less inclusive of nonusers than tax-based payment mechanisms.
volunt	-1.656	-1.870	0	Binary variable indicating that WTP was estimated using a payment vehicle described as voluntary as opposed to, for example, property taxes. Set to zero because hypothetical voluntary payment mechanisms are not incentive compatible (Johnston, Boyle, et al., 2017).
RUM	0.901	0.680	1	Binary variable indicating that the study used a Random Utility Model to estimate WTP. Set to one because use of a Random Utility Model to estimate WTP is a standard best practice in modern stated preference studies.
IBI	-2.355	-2.185	0	Binary variable indicating that the study used the Index of Biotic Integrity as the water quality metric. Set to zero because the meta-regression uses the WQI as the water quality metric, not the Index of Biotic Integrity.
lnyear	-0.135	-0.362	ln(2017-1980)	Natural log of the year in which the study was conducted (*i.e.*, data were collected), converted to an index by subtracting 1980. Set to the natural log of the maximum value from the meta-data (ln(2017-1980)) to reflect a time trend interpretation of the variable.
non_reviewed	-0.233	-0.247	0	Binary variable indicating that the study was not published in a peer-reviewed journal. Set to zero because studies published in peer-reviewed journals are preferred.
thesis	0.431	0.580	0	Binary variable indicating that the study is a thesis or dissertation. Set to zero because studies published in peer-reviewed journals are preferred.
lump_sum	0.534	0.518	0	Binary variable indicating that the study provided WTP as a one-time, lump sum or provided annual WTP values for a payment period of five years or less. Set to zero to reflect that the majority of studies from the meta-data estimated an annual WTP, and to produce an annual WTP prediction.
Region and Surveyed Population				
census_south	0.693	0.990	Varies	Binary variable indicating that the affected waters are located entirely within the South Census region, which includes the following states: DE, MD, DC, WV, VA, NC, SC, GA, FL, KY, TN, MS, AL, AR, LA, OK, and TX. Set based on the state in which the CBG is located.
census_midwest	0.667	0.945	Varies	Binary variable indicating that the affected waters are located entirely within the Midwest Census region, which includes the following states: OH, MI, IN, IL, WI, MN, IA, MO, ND, SD, NE, and KS. Set based on the state in which the CBG is located.

Table H-3: Independent Variable Assignments for Surface Water Quality Meta-Analysis

Variable	Coefficient		Assigned Value	Explanation
	Model 1	Model 2		
census_west	0.393	0.400	Varies	Binary variable indicating that the affected waters are located entirely within the West Census region, which includes the following states: MT, WY, CO, NM, ID, UT, AZ, NV, WA, OR, and CA. Set based on the state in which the CBG is located.
nonusers	-0.283	-0.380	0	Binary variable indicating that the sampled population included nonusers only; the alternative case includes all households. Set to zero to estimate the total value for water quality changes for all households, including users and nonusers.
lnincome	0.478	1.199	Varies	Natural log of median household income values assigned separately for each CBG. Varies by year based on the estimated income growth in future years.
Sampled Market and Affected Resource				
swim_use	0.300	0.361	0	Binary variables indicating that the affected use(s) stated in the survey instrument include swimming and gamefishing. Set to zero, which corresponds to all recreational uses, since data on specific recreational uses of the reaches affected by steam electric power plant discharges are not available.
gamefish	0.871	0.531	0	
ln_ar_agr	-0.572	-0.654	Varies	Natural log of the proportion of the affected resource area which is agricultural based on the National Land Cover Database, reflecting the nature of development in the area surrounding the resource. Used Census county boundary layers to identify counties that intersect affected resources within the 100-mile buffer of each CBG. For intersecting counties, calculated the fraction of total land area that is agricultural using the National Land Cover Dataset. The *ln_ar_agr* variable was coded in the metadata to reflect the area surrounding the affected resources.
ln_ar_ratio	-0.157	-0.153	3.648	The natural log of the ratio of the sampled area (*sa_area*) relative to the affected resource area (defined as the total area of counties that intersect the affected resource[s]) (*ar_total_area*). In the context of the steam electric scenario, *sa_area* is set based on the total area within the 100-mile buffer from the COMIDs in scope of the analysis, while *ar_total_area* is set based on the area of counties intersecting each affected reach (COMID). *ln_ar_ratio* is set to the mean value from all COMIDs within the scope of the analysis.
sub_proportion	0.993	0.650	Varies	The size of the resources within the scope of the analysis relative to available substitutes. Calculated as the ratio of affected reaches miles to the total number of reach miles within the buffer that are the same or greater than the order(s) of the affected reaches within the buffer. Its value can range from 0 to 1.

Table H-3: Independent Variable Assignments for Surface Water Quality Meta-Analysis

Variable	Coefficient		Assigned Value	Explanation
	Model 1	Model 2		
Water Quality				
ln_Q	-0.666	-0.259	Varies	Because WTP for a one-point improvement on the WQI is assumed to depend on both baseline water quality and expected water quality under the regulatory option, this variable is set to the natural log of the mid-point of the range of water quality changes due to the regulatory options, $WQI_{Y,B} = (1/2)(WQI\text{-}BL_{Y,B} + WQI\text{-}PC_{Y,B})$. Calculated as the length-weighted average WQI score for all potentially affected reaches within the 100-mile buffer of each CBG.
lnquality_ch	NA	-0.683	ln(7) ln(20)	*ln_quality_ch* was set to the natural log of ΔWQI=7 or ΔWQI=20 for high and low estimates of the one-point WTP, respectively. These two values represent the 25th percentile and 75th percentile values of the meta-data.

I Identification of Threatened and Endangered Species Potentially Affected by the Final Rule Regulatory Options

As discussed in Chapter 7, EPA identified a total of 184 T&E species whose habitat range intersects reaches affected by steam electric power plant discharges. These species include amphibians, arachnids, birds, clams, crustaceans, fishes, insects, mammals, reptiles, and snails. Table I-1 summarizes the number of species within each group that have habitat ranges intersecting reaches with NRWQC exceedances for at least one pollutant under the baseline or regulatory options in Period 1 (2025-2029) or Period 2 (2030-2049). As shown in the table, several species of amphibians, birds, clams, fishes, mammals, and reptiles have habitat ranges overlapping reaches with baseline exceedances in Period 1. There are no additional exceedances under any of the regulatory options, but water quality improvements under each regulatory option reduce the number of exceedances from the baseline conditions.

Table I-1: Number of T&E Species with Habitat Range Intersecting Reaches Downstream from Steam Electric Power Plant Outfalls, by Species Group

Species Group	Number of Individual Species with NRWQC Exceedances for at Least One Pollutant in Reaches Intersecting their Habitat Range							
	Period 1				Period 2			
	Baseline	Option A	Option B (Final Rule)	Option C	Baseline	Option A	Option B (Final Rule)	Option C
Amphibians	1	1	0	0	1	1	0	0
Arachnids	0	0	0	0	0	0	0	0
Birds	6	6	6	6	5	5	5	0
Clams	9	9	9	9	9	9	0	0
Crustaceans	0	0	0	0	0	0	0	0
Fishes	4	4	4	4	3	3	3	0
Insects	0	0	0	0	0	0	0	0
Mammals	5	5	5	5	4	4	0	0
Reptiles	5	5	0	0	5	5	0	0
Snails	0	0	0	0	0	0	0	0
Total	**30**	**30**	**24**	**24**	**27**	**27**	**8**	**0**

Source: U.S. EPA Analysis, 2024

Table I-2 provides further details on the 184 T&E species whose habitat range intersects reaches affected by steam electric power plant discharges. The table denotes, for each species, the number of reaches with at least one reported exceedance of a NRWQC in the baseline or regulatory options in Period 1 and Period 2. The table also includes the results of EPA's assessment of species vulnerability to water pollution. As noted in Chapter 7, EPA classified species as follows:

- Higher vulnerability – species living in aquatic habitats for several life history stages and/or species that obtain a majority of their food from aquatic sources.
- Moderate vulnerability – species living in aquatic habitats for one life history stage and/or species that obtain some of their food from aquatic sources.
- Lower vulnerability – species whose habitats overlap bodies of water, but whose life history traits and food sources are terrestrial.

EPA obtained species life history data from a wide variety of sources to assess T&E species vulnerability to water pollution. These sources included: U.S. DOI, 2019; Froese and Pauly, 2019; NatureServe, 2020; NOAA Fisheries, 2020; Southwest Fisheries Science Center (SWFSC), 2019; U.S. FWS, 2019a, 2019b, 2019c, 2019d, 2019e, 2019f, 2019g, 2020a, 2020b, 2020c, 2020e, 2020f, 2020g, 2020h, 2020i, 2020j, 2020k; Upper Colorado River Endangered Fish Recovery Program, 2020.

Section 7.3.2 discusses impacts on selected higher vulnerability species whose habitat ranges intersect reaches with estimated changes in NRWQC exceedance status under the regulatory options.

Table I-2: T&E Species with Habitat Range Intersecting Reaches Downstream from Steam Electric Power Plant Outfalls (Shading Highlights Change from Baseline)

Species Group	Species Count	Species Name	Vulnerability	Number of Intersected Reaches Exceeding NRWQC for at Least One Pollutant							
				Period 1				Period 2			
				Baseline	Option A	Option B (Final Rule)	Option C	Baseline	Option A	Option B (Final Rule)	Option C
Amphibians	9	*Ambystoma bishopi*	Moderate	0	0	0	0	0	0	0	0
		Ambystoma cingulatum	Higher	1	1	0	0	1	1	0	0
		Bufo houstonensis	Moderate	0	0	0	0	0	0	0	0
		Cryptobranchus alleganiensis bishopi	Higher	0	0	0	0	0	0	0	0
		Necturus alabamensis	Higher	0	0	0	0	0	0	0	0
		Phaeognathus hubrichti	Lower	0	0	0	0	0	0	0	0
		Plethodon nettingi	Lower	0	0	0	0	0	0	0	0
		Rana pretiosa	Higher	0	0	0	0	0	0	0	0
		Rana sevosa	Lower	0	0	0	0	0	0	0	0
Arachnids	6	*Cicurina baronia*	Lower	0	0	0	0	0	0	0	0
		Cicurina madla	Lower	0	0	0	0	0	0	0	0
		Cicurina venii	Lower	0	0	0	0	0	0	0	0
		Cicurina vespera	Lower	0	0	0	0	0	0	0	0
		Tayshaneta microps	Lower	0	0	0	0	0	0	0	0
		Texella cokendolpheri	Lower	0	0	0	0	0	0	0	0
Birds	26	*Ammodramus savannarum floridanus*	Lower	0	0	0	0	0	0	0	0
		Aphelocoma coerulescens	Lower	0	0	0	0	0	0	0	0
		Brachyramphus marmoratus	Moderate	0	0	0	0	0	0	0	0
		Calidris canutus rufa	Lower	11	11	0	0	11	11	0	0
		Campephilus principalis	Lower	0	0	0	0	0	0	0	0
		Charadrius melodus	Moderate	3	2	2	2	2	0	0	0
		Coccyzus americanus	Lower	6	3	3	3	3	3	3	0
		Empidonax traillii extimus	Lower	3	0	0	0	0	0	0	0
		Eremophila alpestris strigata	Lower	0	0	0	0	0	0	0	0
		Falco femoralis septentrionalis	Lower	0	0	0	0	0	0	0	0
		Grus americana	Moderate	0	0	0	0	0	0	0	0
		Grus canadensis pulla	Higher	0	0	0	0	0	0	0	0
		Gymnogyps californianus	Lower	0	0	0	0	0	0	0	0
		Laterallus jamaicensis ssp. jamaicensis	Lower	0	0	0	0	0	0	0	0

Table I-2: T&E Species with Habitat Range Intersecting Reaches Downstream from Steam Electric Power Plant Outfalls (Shading Highlights Change from Baseline)

Species Group	Species Count	Species Name	Vulnerability	Number of Intersected Reaches Exceeding NRWQC for at Least One Pollutant							
				Period 1				Period 2			
				Baseline	Option A	Option B (Final Rule)	Option C	Baseline	Option A	Option B (Final Rule)	Option C
		Mycteria americana	Moderate	2	2	1	1	2	2	0	0
		Numenius borealis	Lower	0	0	0	0	0	0	0	0
		Picoides borealis	Lower	1	1	0	0	1	1	0	0
		Polyborus plancus audubonii	Lower	0	0	0	0	0	0	0	0
		Rallus obsoletus yumanensis	Higher	0	0	0	0	0	0	0	0
		Rostrhamus sociabilis plumbeus	Higher	0	0	0	0	0	0	0	0
		Setophaga chrysoparia	Lower	0	0	0	0	0	0	0	0
		Sterna antillarum browni	Higher	0	0	0	0	0	0	0	0
		Sterna dougallii dougallii	Higher	0	0	0	0	0	0	0	0
		Strix occidentalis caurina	Lower	0	0	0	0	0	0	0	0
		Strix occidentalis lucida	Lower	0	0	0	0	0	0	0	0
		Tympanuchus cupido attwateri	Lower	0	0	0	0	0	0	0	0
Clams	56	*Amblema neislerii*	Higher	0	0	0	0	0	0	0	0
		Arcidens wheeleri	Higher	0	0	0	0	0	0	0	0
		Cumberlandia monodonta	Higher	10	10	0	0	10	10	0	0
		Cyprogenia stegaria	Higher	11	11	1	1	11	11	0	0
		Dromus dromas	Higher	0	0	0	0	0	0	0	0
		Elliptio chipolaensis	Higher	0	0	0	0	0	0	0	0
		Elliptio lanceolata	Higher	0	0	0	0	0	0	0	0
		Elliptio spinosa	Higher	0	0	0	0	0	0	0	0
		Elliptoideus sloatianus	Higher	0	0	0	0	0	0	0	0
		Epioblasma brevidens	Higher	0	0	0	0	0	0	0	0
		Epioblasma capsaeformis	Higher	0	0	0	0	0	0	0	0
		Epioblasma obliquata obliquata	Higher	0	0	0	0	0	0	0	0
		Epioblasma rangiana	Higher	0	0	0	0	0	0	0	0
		Epioblasma triquetra	Higher	10	10	0	0	10	10	0	0
		Fusconaia cor	Higher	0	0	0	0	0	0	0	0
		Fusconaia cuneolus	Higher	0	0	0	0	0	0	0	0
		Fusconaia masoni	Higher	0	0	0	0	0	0	0	0
		Hamiota altilis	Higher	0	0	0	0	0	0	0	0
		Hamiota perovalis	Higher	0	0	0	0	0	0	0	0
		Hamiota subangulata	Higher	0	0	0	0	0	0	0	0
		Hemistena lata	Higher	0	0	0	0	0	0	0	0
		Lampsilis abrupta	Higher	12	12	2	2	12	12	0	0
		Lampsilis higginsii	Higher	0	0	0	0	0	0	0	0
		Lampsilis rafinesqueana	Higher	0	0	0	0	0	0	0	0
		Lampsilis virescens	Higher	0	0	0	0	0	0	0	0
		Lasmigona decorata	Higher	0	0	0	0	0	0	0	0
		Leptodea leptodon	Higher	0	0	0	0	0	0	0	0

Table I-2: T&E Species with Habitat Range Intersecting Reaches Downstream from Steam Electric Power Plant Outfalls (Shading Highlights Change from Baseline)

Species Group	Species Count	Species Name	Vulnerability	Number of Intersected Reaches Exceeding NRWQC for at Least One Pollutant							
				Period 1				Period 2			
				Baseline	Option A	Option B (Final Rule)	Option C	Baseline	Option A	Option B (Final Rule)	Option C
		Margaritifera hembeli	Higher	0	0	0	0	0	0	0	0
		Margaritifera marrianae	Higher	0	0	0	0	0	0	0	0
		Medionidus acutissimus	Higher	0	0	0	0	0	0	0	0
		Medionidus parvulus	Higher	0	0	0	0	0	0	0	0
		Medionidus penicillatus	Higher	0	0	0	0	0	0	0	0
		Obovaria retusa	Higher	1	1	1	1	1	1	0	0
		Parvaspina collina	Higher	0	0	0	0	0	0	0	0
		Plethobasus cicatricosus	Higher	0	0	0	0	0	0	0	0
		Plethobasus cooperianus	Higher	1	1	1	1	1	1	0	0
		Plethobasus cyphyus	Higher	11	11	1	1	11	11	0	0
		Pleurobema clava	Higher	1	1	1	1	1	1	0	0
		Pleurobema decisum	Higher	0	0	0	0	0	0	0	0
		Pleurobema furvum	Higher	0	0	0	0	0	0	0	0
		Pleurobema georgianum	Higher	0	0	0	0	0	0	0	0
		Pleurobema hanleyianum	Higher	0	0	0	0	0	0	0	0
		Pleurobema perovatum	Higher	0	0	0	0	0	0	0	0
		Pleurobema plenum	Higher	1	1	1	1	1	1	0	0
		Pleurobema pyriforme	Higher	0	0	0	0	0	0	0	0
		Pleurobema taitianum	Higher	0	0	0	0	0	0	0	0
		Pleuronaia dolabelloides	Higher	0	0	0	0	0	0	0	0
		Potamilus capax	Higher	0	0	0	0	0	0	0	0
		Potamilus inflatus	Higher	0	0	0	0	0	0	0	0
		Ptychobranchus greenii	Higher	0	0	0	0	0	0	0	0
		Ptychobranchus subtentus	Higher	0	0	0	0	0	0	0	0
		Quadrula cylindrica cylindrica	Higher	0	0	0	0	0	0	0	0
		Quadrula fragosa	Higher	0	0	0	0	0	0	0	0
		Theliderma intermedia	Higher	0	0	0	0	0	0	0	0
		Theliderma sparsa	Higher	0	0	0	0	0	0	0	0
		Villosa fabalis	Higher[a]	0	0	0	0	0	0	0	0
Crustaceans	5	*Antrolana lira*	Higher	0	0	0	0	0	0	0	0
		Cambarus aculabrum	Higher	0	0	0	0	0	0	0	0
		Cambarus zophonastes	Higher	0	0	0	0	0	0	0	0
		Orconectes shoupi [b]	Higher	0	0	0	0	0	0	0	0
		Palaemonias alabamae	Higher	0	0	0	0	0	0	0	0
Fishes	28	*Acipenser oxyrinchus (=oxyrhynchus) desotoi*	Higher	0	0	0	0	0	0	0	0
		Amblyopsis rosae	Higher	0	0	0	0	0	0	0	0
		Chrosomus saylori	Higher[a]	0	0	0	0	0	0	0	0
		Cyprinella caerulea	Higher	0	0	0	0	0	0	0	0

Table I-2: T&E Species with Habitat Range Intersecting Reaches Downstream from Steam Electric Power Plant Outfalls (Shading Highlights Change from Baseline)

Species Group	Species Count	Species Name	Vulnerability	Number of Intersected Reaches Exceeding NRWQC for at Least One Pollutant							
				Period 1				Period 2			
				Baseline	Option A	Option B (Final Rule)	Option C	Baseline	Option A	Option B (Final Rule)	Option C
		Elassoma alabamae	Higher[a]	0	0	0	0	0	0	0	0
		Etheostoma boschungi	Higher	0	0	0	0	0	0	0	0
		Etheostoma chienense	Higher	0	0	0	0	0	0	0	0
		Etheostoma etowahae	Higher	0	0	0	0	0	0	0	0
		Etheostoma nianguae	Higher	0	0	0	0	0	0	0	0
		Etheostoma phytophilum	Higher	0	0	0	0	0	0	0	0
		Etheostoma rubrum	Higher	0	0	0	0	0	0	0	0
		Etheostoma scotti	Higher	0	0	0	0	0	0	0	0
		Etheostoma trisella	Higher	0	0	0	0	0	0	0	0
		Gila cypha	Higher	3	3	3	3	3	3	3	0
		Gila elegans	Higher	0	0	0	0	0	0	0	0
		Macrhybopsis tetranema	Higher	0	0	0	0	0	0	0	0
		Notropis cahabae	Higher	0	0	0	0	0	0	0	0
		Notropis topeka (=tristis)	Higher	3	2	2	2	2	0	0	0
		Oncorhynchus apache	Higher	0	0	0	0	0	0	0	0
		Percina aurora	Higher	0	0	0	0	0	0	0	0
		Percina rex	Higher	0	0	0	0	0	0	0	0
		Percina tanasi	Higher	0	0	0	0	0	0	0	0
		Ptychocheilus lucius	Higher	6	3	3	3	3	3	3	0
		Salvelinus confluentus	Higher	0	0	0	0	0	0	0	0
		Scaphirhynchus albus	Higher	0	0	0	0	0	0	0	0
		Scaphirhynchus suttkusi	Higher	0	0	0	0	0	0	0	0
		Speoplatyrhinus poulsoni	Higher[a]	0	0	0	0	0	0	0	0
		Xyrauchen texanus	Higher	3	0	0	0	0	0	0	0
Insects	10	*Batrisodes venyivi*	Lower	0	0	0	0	0	0	0	0
		Bombus affinis	Lower	0	0	0	0	0	0	0	0
		Euphydryas editha taylori	Lower	0	0	0	0	0	0	0	0
		Hesperia dacotae	Lower	0	0	0	0	0	0	0	0
		Lycaeides melissa samuelis	Lower	0	0	0	0	0	0	0	0
		Neonympha mitchellii mitchellii	Lower	0	0	0	0	0	0	0	0
		Nicrophorus americanus	Lower	0	0	0	0	0	0	0	0
		Rhadine exilis	Lower	0	0	0	0	0	0	0	0
		Rhadine infernalis	Lower	0	0	0	0	0	0	0	0
		Somatochlora hineana	Lower	0	0	0	0	0	0	0	0
Mammals	15	*Antilocapra americana sonoriensis*	Lower	0	0	0	0	0	0	0	0
		Canis lupus	Lower	0	0	0	0	0	0	0	0
		Corynorhinus (=Plecotus) townsendii ingens	Lower	0	0	0	0	0	0	0	0

Table I-2: T&E Species with Habitat Range Intersecting Reaches Downstream from Steam Electric Power Plant Outfalls (Shading Highlights Change from Baseline)

Species Group	Species Count	Species Name	Vulnerability	Number of Intersected Reaches Exceeding NRWQC for at Least One Pollutant							
				Period 1				Period 2			
				Baseline	Option A	Option B (Final Rule)	Option C	Baseline	Option A	Option B (Final Rule)	Option C
		Corynorhinus (=Plecotus) townsendii virginianus	Lower	0	0	0	0	0	0	0	0
		Eumops floridanus	Lower	0	0	0	0	0	0	0	0
		Lynx canadensis	Lower	3	0	0	0	0	0	0	0
		Mustela nigripes	Lower	0	0	0	0	0	0	0	0
		Myotis grisescens	Moderate	1	1	1	1	1	1	0	0
		Myotis septentrionalis	Lower	16	15	5	5	15	13	0	0
		Myotis sodalis	Lower	12	12	2	2	12	12	0	0
		Puma (=Felis) concolor (all subsp. except coryi)	Lower	0	0	0	0	0	0	0	0
		Puma (=Felis) concolor coryi	Lower	0	0	0	0	0	0	0	0
		Thomomys mazama pugetensis	Lower	0	0	0	0	0	0	0	0
		Thomomys mazama yelmensis	Lower	0	0	0	0	0	0	0	0
		Trichechus manatus	Higher	1	1	0	0	1	1	0	0
Reptiles	19	*Alligator mississippiensis*	Higher	0	0	0	0	0	0	0	0
		Caretta caretta	Lower	1	1	0	0	1	1	0	0
		Chelonia mydas	Lower	1	1	0	0	1	1	0	0
		Crocodylus acutus	Higher	0	0	0	0	0	0	0	0
		Dermochelys coriacea	Lower	1	1	0	0	1	1	0	0
		Drymarchon couperi	Lower	1	1	0	0	1	1	0	0
		Eretmochelys imbricata	Lower	1	1	0	0	1	1	0	0
		Eumeces egregius lividus	Lower	0	0	0	0	0	0	0	0
		Glyptemys muhlenbergii	Higher	0	0	0	0	0	0	0	0
		Gopherus agassizii	Lower	0	0	0	0	0	0	0	0
		Gopherus polyphemus	Lower	0	0	0	0	0	0	0	0
		Graptemys flavimaculata	Higher	0	0	0	0	0	0	0	0
		Lepidochelys kempii	Lower	0	0	0	0	0	0	0	0
		Neoseps reynoldsi	Lower	0	0	0	0	0	0	0	0
		Pituophis melanoleucus lodingi	Lower	0	0	0	0	0	0	0	0
		Pituophis ruthveni	Lower	0	0	0	0	0	0	0	0
		Pseudemys alabamensis	Higher	0	0	0	0	0	0	0	0
		Sistrurus catenatus	Lower	0	0	0	0	0	0	0	0
		Sternotherus depressus	Higher	0	0	0	0	0	0	0	0
Snails	10	*Athearnia anthonyi*	Higher	0	0	0	0	0	0	0	0
		Campeloma decampi	Higher	0	0	0	0	0	0	0	0
		Elimia crenatella	Higher	0	0	0	0	0	0	0	0
		Leptoxis foremani	Higher	0	0	0	0	0	0	0	0
		Leptoxis taeniata	Higher	0	0	0	0	0	0	0	0
		Lioplax cyclostomaformis	Higher	0	0	0	0	0	0	0	0

Table I-2: T&E Species with Habitat Range Intersecting Reaches Downstream from Steam Electric Power Plant Outfalls (Shading Highlights Change from Baseline)

Species Group	Species Count	Species Name	Vulnerability	Number of Intersected Reaches Exceeding NRWQC for at Least One Pollutant							
				Period 1				Period 2			
				Baseline	Option A	Option B (Final Rule)	Option C	Baseline	Option A	Option B (Final Rule)	Option C
		Marstonia ogmorhaphe	Higher	0	0	0	0	0	0	0	0
		Pleurocera foremani	Higher	0	0	0	0	0	0	0	0
		Triodopsis platysayoides	Lower	0	0	0	0	0	0	0	0
		Tulotoma magnifica	Higher	0	0	0	0	0	0	0	0

[a] Species that could be categorized as highly vulnerable to water quality changes are endemic only to waters (headwater streams and springs) that are not likely to receive discharges from steam electric plants or be affected by upstream discharges. This may be reflected in a lower vulnerability rating for certain species.

[b] U.S. Fish and Wildlife Service proposed delisting this species on September 23, 2020. See notice of proposed rulemaking “Endangered and Threatened Wildlife and Plants: Removal of the Nashville Crayfish from the Federal List of Endangered and Threatened Wildlife.” (85 FR 59732)

Source: U.S. EPA Analysis, 2024

J Methodology for Modeling Air Quality Changes for the Final Rule

As noted in Chapter 8, EPA used photochemical modeling to create air quality surfaces[157] that were then used in air pollution benefits calculations of the final rule. The modeling-based surfaces captured air pollution impacts resulting from changes in electricity generation profiles due to the incremental costs to generate electricity at plants incurring water treatment costs and did not simulate the impact of emissions changes resulting from changes in energy use by steam electric power plants or resulting from changes in trucking of CCR and other waste. This appendix describes the source apportionment modeling and associated methods used to create air quality surfaces for the baseline scenario and a scenario representing water treatment technology implementation-driven EGU profile changes for 7 analytic years: 2028, 2030, 2035, 2040, 2045, and 2050. EPA created air quality surfaces for the following pollutants and metrics: annual average $PM_{2.5}$; April-September average of 8-hr daily maximum (MDA8) ozone (AS-MO3).

New ozone and PM source apportionment modeling outputs were created to support analyses in the RIAs for multiple final EGU rulemaking efforts. The basic methodology for determining air quality changes is the same as that used in the RIAs from multiple previous rules (U.S. EPA, 2019i, 2020a, 2020b, 2021b, 2022c). EPA calculated baseline and Final Rule EGU emissions estimates of NO_x and SO_2 for all seven IPM model years from the Integrated Planning Model (IPM) (Chapter 5 of the RIA; U.S. EPA, 2024e). EPA also used IPM outputs to estimate EGU emissions of $PM_{2.5}$ based on the methodology described in U.S. EPA (2020c). This appendix provides additional details on the source apportionment modeling simulations and on the methods used to translate these emissions scenarios into air quality surfaces.

J.1 Air Quality Modeling Simulations

The air quality modeling utilized a 2016-based modeling platform which included meteorology and base year emissions from 2016 and projected future-year emissions for 2026 for all sectors other than EGUs and 2030 for EGUs. The air quality modeling included photochemical model simulations for a 2016 base year and a future year representing the combined 2026/2030 emissions described above to provide hourly concentrations of ozone and $PM_{2.5}$ component species nationwide. In addition, source apportionment modeling was performed for the future year to quantify the contributions to ozone from NO_X emissions and to $PM_{2.5}$ from NO_X, SO_2 and directly emitted $PM_{2.5}$ emissions from EGUs on a state-by-state and fuel-type basis. As described below, the modeling results for 2016 and the future year, in conjunction with EGU emissions data for the baseline and three illustrative scenarios in 2028, 2030, 2035, 2040, 2045, and 2050 were used to construct the air quality surfaces that reflect the influence of emissions changes between the baseline and the three illustrative scenarios in each year.

The air quality model simulations (*i.e.*, model runs) were performed using the Comprehensive Air Quality Model with Extensions (CAMx) version 7.10[158] (Ramboll Environ, 2020). The nationwide modeling domain (*i.e.*, the geographic area included in the modeling) covers all lower 48 states plus adjacent portions of Canada and Mexico using a horizontal grid resolution of 12 × 12 km shown in Figure J-1. CAMx requires a variety of input files that contain information pertaining to the modeling domain and simulation period. These include gridded, hourly emissions estimates and meteorological data, and initial and boundary concentrations. The meteorological data and the initial and boundary concentrations were identical to those described in U.S. EPA

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[157] “air quality surfaces” refers to continuous gridded spatial fields using a 12-km grid-cell resolution

[158] This CAMx simulation set the Rscale NH_3 dry deposition parameter to 0 which resulted in more realistic model predictions of $PM_{2.5}$ nitrate concentrations than using a default Rscale parameter of 1.

(2023a). Separate emissions inventories were prepared for the 2016 base year and the projected future year. All other inputs (*i.e.*, meteorological fields, initial concentrations, ozone column, photolysis rates, and boundary concentrations) were specified for the 2016 base year model application and remained unchanged for the projection-year model simulation.

2016 base year emissions are described in detail in U.S. EPA (2023q). The types of sources included in the emission inventory include stationary point sources such as EGUs and non-EGUs; non-point emissions sources including those from oil and gas production and distribution, agriculture, residential wood combustion, fugitive dust, and residential and commercial heating and cooking; mobile source emissions from onroad and nonroad vehicles, aircraft, commercial marine vessels, and locomotives; wild, prescribed, and agricultural fires; and biogenic emissions from vegetation and soils. Future year emissions from all sources other than EGUs were based on the 2026 emissions projections described in U.S. EPA (2023q) . The Post-IRA 2022 Reference Case of EPA's Power Sector Platform v6 using Integrated Planning Model (IPM), which includes the Final GNP, was also reflected[159]. The EGU projected inventory represents demand growth, fuel resource availability, generating technology cost and performance, and other economic factors affecting power sector behavior. It also reflects environmental rules and regulations, consent decrees and settlements, plant closures, and newly built units for the calendar year 2030. In this analysis, the projected EGU emissions include provisions of tax incentives impacting electricity supply in the Inflation Reduction Act of 2022 (IRA), Final GNP, 2021 Revised Cross-State Air Pollution Rule Update (RCU), the 2016 Standards of Performance for Greenhouse Gas Emissions from New, Modified, and Reconstructed Stationary Sources, the Mercury and Air Toxics Rule (MATS) finalized in 2011, and other finalized rules. Documentation and results of the Post-IRA 2022 Reference Case, where the Final GNP was also included for EGUs, are available at (https://www.epa.gov/power-sector-modeling/final-pm-naaqs).

Model predictions of ozone and $PM_{2.5}$ concentrations were compared against ambient measurements (U.S. EPA, 2022a; 2022b). Ozone and $PM_{2.5}$ model evaluations showed model performance that was adequate for applying these model simulations for the purpose of creating air quality surfaces to estimate ozone and $PM_{2.5}$ benefits.

Figure J-1: Air Quality Modeling Domain

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[159] https://www.epa.gov/power-sector-modeling/post-ira-2022-reference-case

The contributions to ozone and $PM_{2.5}$ component species (*e.g.*, sulfate, nitrate, ammonium, elemental carbon (EC), organic aerosol (OA), and crustal material[160]) from EGU emissions in individual states and from each EGU-fuel type were modeled using the "source apportionment" tool. In general, source apportionment modeling quantifies the air quality concentrations formed from individual, user-defined groups of emissions sources or "tags". These source tags are tracked through the transport, dispersion, chemical transformation, and deposition processes within the model to obtain hourly gridded[161] contributions from the emissions in each individual tag to hourly modeled concentrations. For this RIA we used the source apportionment contribution data to provide a means to estimate the effect of changes in emissions from each group of emissions sources (*i.e.*, each tag) to changes in ozone and $PM_{2.5}$ concentrations. Specifically, we applied outputs from source apportionment modeling for ozone and $PM_{2.5}$ component species using the future year modeled case to obtain the contributions from EGUs emissions in each state and fuel-type to ozone and $PM_{2.5}$ component species concentrations in each 12 x 12 km model grid cell nationwide. Ozone contributions were modeled using the Anthropogenic Precursor Culpability Assessment (APCA) tool and $PM_{2.5}$ contributions were modeled suing the Particulate Matter Source Apportionment Technology (PSAT) tool.

(Ramboll Environ, 2020). The ozone source apportionment modeling was performed for the period April through September to provide data for developing spatial fields for the April through September maximum daily eight hour (MDA8) (*i.e.*, AS-MO3) average ozone concentration exposure metric. The $PM_{2.5}$ source apportionment modeling was performed for a full-year to provide data for developing annual average $PM_{2.5}$ spatial fields. Table J-1, Table J-2, and Table J-3 provide emissions that were tracked for each source apportionment tag.

Table J-1: Future-year Emissions Allocated to Each Modeled Coal State Source Apportionment Tag

State Tag	Ozone Season NO_X Emissions	Annual NO_X emissions	Annual SO_2 emissions	Annual $PM_{2.5}$ emissions
AL[5]	NA	5,046	1,929	700
AL+ MS[5]	2,541			
AR[4]	NA	304	331	51
AZ	1,005	2,536	4,515	609
CA	222	511	99	27
CO	19	269	287	21
CT	0	0	0	0
DC	0	0	0	0
DE	0	0	0	0
FL	1,110	1,401	7,163	277
GA	1,654	2,534	3,247	159
IA	8,354	18,776	9,656	1,203
ID	0	0	0	0
IL	1,639	3,742	6,773	270
IN	4,886	18,146	26,584	2,252
KS[1]	NA	214	121	NA
KY	3,551	7,333	7,127	560
LA[2,4]	NA	47	NA	NA
MA	0	0	0	0

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[160] Crustal material refers to elements that are commonly found in the earth's crust such as Aluminum, Calcium, Iron, Magnesium, Manganese, Potassium, Silicon, Titanium and the associated oxygen atoms.

[161] Hourly contribution information is provided for each grid cell to provide spatial patterns of the contributions from each tag.

Table J-1: Future-year Emissions Allocated to Each Modeled Coal State Source Apportionment Tag

State Tag	Ozone Season NO_X Emissions	Annual NO_X emissions	Annual SO_2 emissions	Annual $PM_{2.5}$ emissions
MD[3]	NA	139	272	31
MD + PA[3]	708	NA	NA	NA
ME	0	0	0	0
MI	1,532	4,071	12,478	380
MN	724	1,549	3,289	94
MO	2,947	23,480	38,989	853
MS[5]	NA	252	507	23
MT	3,771	8,842	4,056	1,252
NC	266	482	634	35
ND	8,583	19,562	25,398	1,923
NE[1]	NA	17,507	43,858	NA
NE + KS[1]	7,817	NA	NA	374
NH	0	0	0	0
NJ	0	0	0	0
NM	1,442	2,757	6,800	1,739
NV	0	1	1	0
NY	0	0	0	0
OH	3,152	10,485	21,721	901
OK[4]	NA	212	152	21
OR	0	0	0	0
PA[3]	NA	1,530	4,932	167
RI	0	0	0	0
SC	807	1,939	3,429	364
SD	418	1,100	1,022	27
TN	259	259	269	32
TX[2,4]	NA	7,031	NA	NA
TX + LA[2]	NA	NA	11,607	1,578
TX-reg[4]	2,698	NA	NA	NA
UT	2,702	4,236	7,625	232
VA	466	1,124	259	445
VT	0	0	0	0
WA	0	0	0	0
WI	866	2,137	838	90
WV	6,824	16,358	17,631	1,753
WY	6,066	13,222	11,754	1,024

[1] KS and NE emissions grouped into multi-state tag for direct $PM_{2.5}$ and ozone season NO_X

[2] LA and TX emissions grouped into multi-state tag for SO_2 and direct $PM_{2.5}$

[3] MD and PA emissions grouped into multi-state tag for ozone season NO_X

[4] AR, LA,OK and TX emissions grouped into multi-state tag ("TX-reg") for ozone season NO_X

[5] AL and MS emissions group into multi-state tag for ozone season NOx

Table J-2: Future-year Emissions Allocated to Each Modeled Natural Gas EGU State Source Apportionment Tag

State Tag	Ozone Season NO_X Emissions	Annual NO_X emissions	Annual SO_2 emissions	Annual $PM_{2.5}$ emissions
AL	2,833	5,132	0	1,979
AR	1,651	2,957	0	632

Table J-2: Future-year Emissions Allocated to Each Modeled Natural Gas EGU State Source Apportionment Tag

State Tag	Ozone Season NO_X Emissions	Annual NO_X emissions	Annual SO_2 emissions	Annual $PM_{2.5}$ emissions
AZ	1,759	3,146	0	686
CA	1,960	5,773	0	1,964
CO	957	1,825	0	461
CT	461	778	0	160
DC	6	11	0	7
DE	383	502	0	134
FL	7,550	14,372	0	4,996
GA	2,279	4,182	0	1,740
IA	875	1,106	0	327
ID	336	513	0	185
IL	1,624	2,705	0	825
IN	1,180	2,166	0	955
KS	329	621	0	54
KY	980	2,806	0	699
LA	3,771	8,706	0	2,158
MA	482	725	0	244
MD	402	710	0	435
ME	232	273	0	21
MI	6,523	11,372	0	1,508
MN	661	928	0	87
MO	587	875	0	342
MS	1,926	3,860	0	1,140
MT	11	19	0	7
NC	1,803	3,426	0	1,213
ND	25	41	0	3
NE	13	47	0	4
NH	120	136	0	34
NJ	1,024	1,910	0	608
NM	733	1,128	0	131
NV	1,693	2,471	0	648
NY	2,793	5,125	0	1,270
OH	1,838	3,824	0	1,617
OK	1,558	2,448	0	546
OR	5	188	0	87
PA	6,811	12,386	0	3,280
RI	115	153	0	73
SC	1,092	2,090	0	917
SD	93	105	0	11
TN	464	1,107	0	388
TX	7,652	14,715	0	3,567
UT	1,189	1,779	0	514
VA	1,836	3,409	0	1,087
VT	4	8	0	6
WA	485	1,311	0	464
WI	847	1,447	0	369
WV	109	180	0	50
WY	203	206	0	28

Table J-3: Future-year Emissions Allocated to Each Other EGU Source Apportionment Tag

State Tag	Ozone Season NO_X Emissions	Annual NO_X emissions	Annual SO_2 emissions	Annual $PM_{2.5}$ emissions
US[a]	20,611	48,619	9,631	7,915

[a] Only includes US emissions from the contiguous 48 states.

Examples of the magnitude and spatial extent of ozone and $PM_{2.5}$ contributions are provided in Figure J-2 through Figure J-5 for EGUs in California, Georgia, Iowa, and Ohio. These figures show how the magnitude and the spatial patterns of contributions of EGU emissions to ozone and $PM_{2.5}$ component species depend on multiple factors including the magnitude and location of emissions as well as the atmospheric conditions that influence the formation and transport of these pollutants. For instance, NO_X emissions are a precursor to both ozone and $PM_{2.5}$ nitrate. However, ozone and nitrate form under very different types of atmospheric conditions, with ozone formation occurring in locations with ample sunlight and ambient VOC concentrations while nitrate formation requires colder and drier conditions and the presence of gas-phase ammonia. California's complex terrain that tends to trap air and allow pollutant build-up combined with warm sunny summer and cooler dry winters and sources of both ammonia and VOCs make its atmosphere conducive to formation of both ozone and nitrate. While the magnitude of EGU NO_X emissions from gas plus coal EGUs is substantially larger in Iowa than in California (Table J-1 and Table J-2), the emissions from California lead to larger maximum contributions to the formation of those pollutants due to the conducive conditions in that state. Georgia and Ohio both had substantial NO_X emissions. While maximum ozone impacts shown for Georgia and Ohio EGUs are similar order of magnitude to maximum ozone impacts from California EGUs, nitrate impacts are negligible in both Georgia and Ohio due to less conducive atmospheric conditions for nitrate formation in those locations. California EGU SO_2 emissions in the future year source apportionment modeling are several orders of magnitude smaller than SO_2 emissions in Ohio and Georgia (Table J-1) leading to much smaller sulfate contributions from California EGUs than from Ohio and Georgia EGUs. $PM_{2.5}$ organic aerosol EGU contributions in this modeling come from primary $PM_{2.5}$ emissions rather than secondary atmospheric formation. Consequently, the impacts of EGU emissions on this pollutant tend to occur closer to the EGU sources than impacts of secondary pollutants (ozone, nitrate, and sulfate) which have spatial patterns showing a broader regional impact. These patterns demonstrate how the model captures important atmospheric processes which impact pollutant formation and transport from emissions sources. Finally, Figure J-6 and Figure J-7 show EGU ozone and PM2.5 contributions from all contiguous U.S. EGUs split out by fuel type. The spatial differences between coal EGU, natural gas EGU, and other EGU contributions reflect the varying location and magnitude of emissions from each type of EGU.

Figure J-2: Maps of California EGU Tag contributions to a) April-September Seasonal Average MDA8 Ozone (ppb); b) Annual Average $PM_{2.5}$ Nitrate (µg/m^3); c) Annual Average $PM_{2.5}$ sulfate (µg/m^3); d) Annual Average $PM_{2.5}$ Organic Aerosol (µg/m^3)

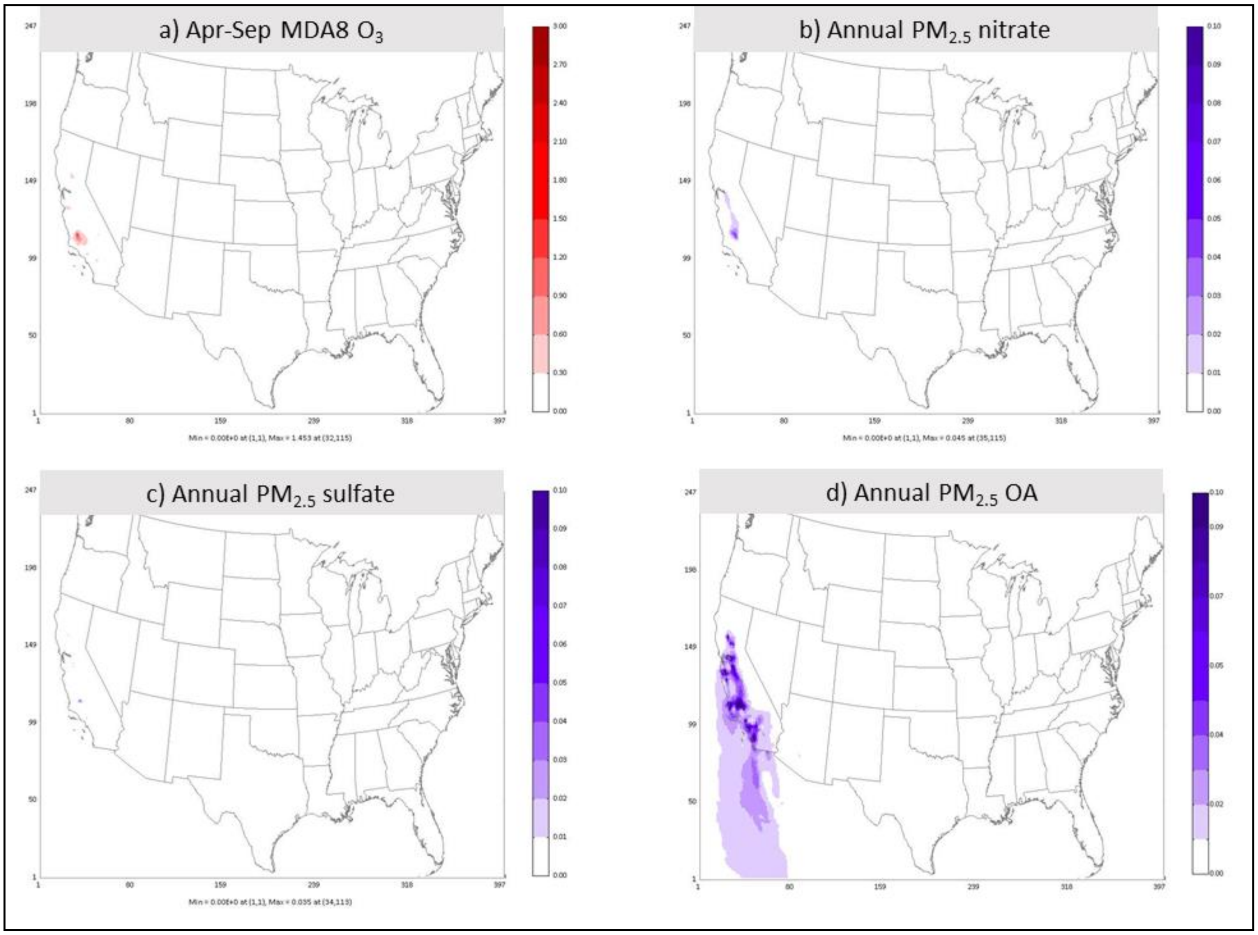


Figure J-3: Maps of Georgia EGU Tag contributions to a) April-September Seasonal Average MDA8 Ozone (ppb); b) Annual Average $PM_{2.5}$ Nitrate (µg/m^3); c) Annual Average $PM_{2.5}$ sulfate (µg/m^3); d) Annual Average $PM_{2.5}$ Organic Aerosol (µg/m^3)

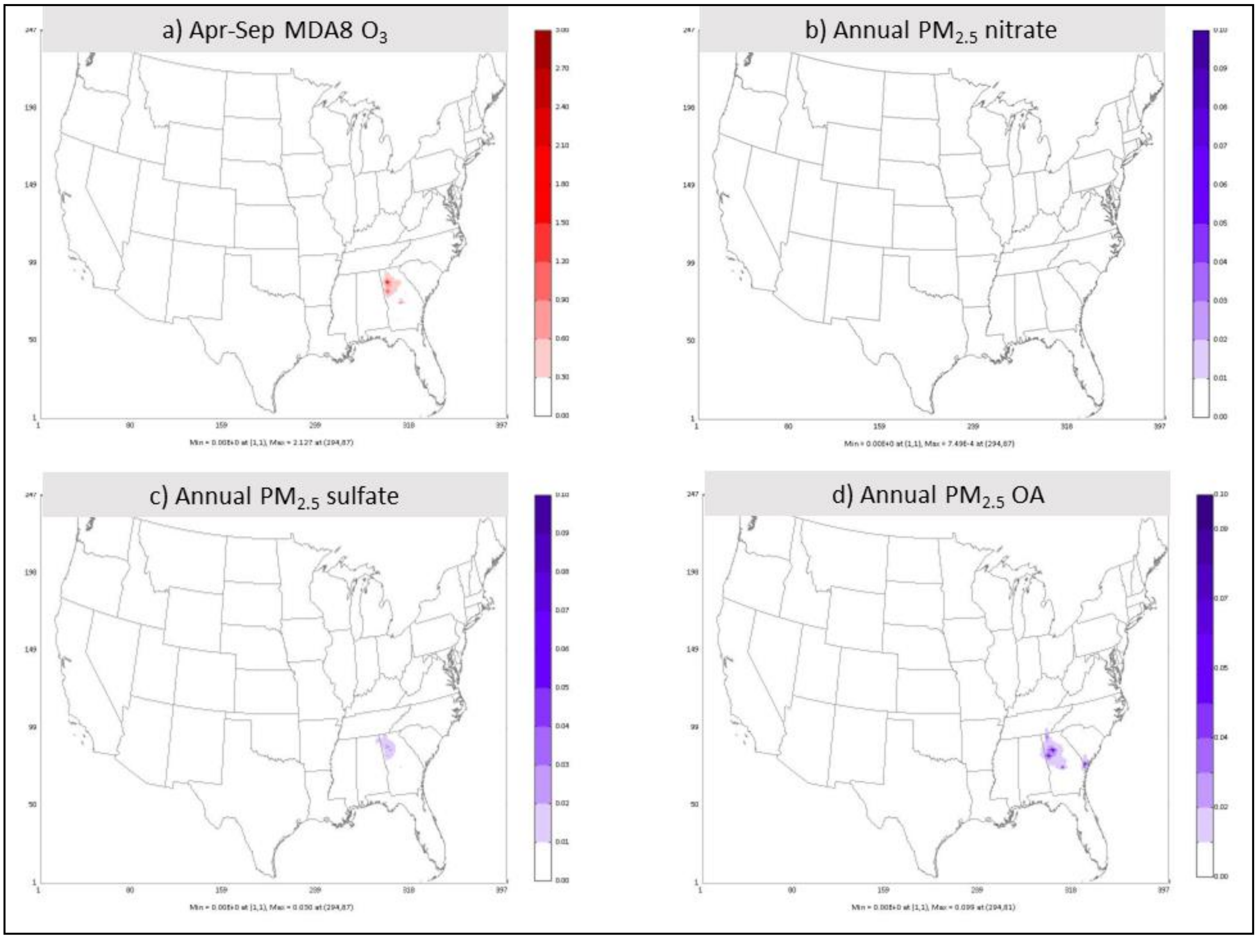


Figure J-4: Maps of Iowa EGU Tag contributions to a) April-September Seasonal Average MDA8 Ozone (ppb); b) Annual Average $PM_{2.5}$ Nitrate (µg/m^3); c) Annual Average $PM_{2.5}$ sulfate (µg/m^3); d) Annual Average $PM_{2.5}$ Organic Aerosol (µg/m^3)

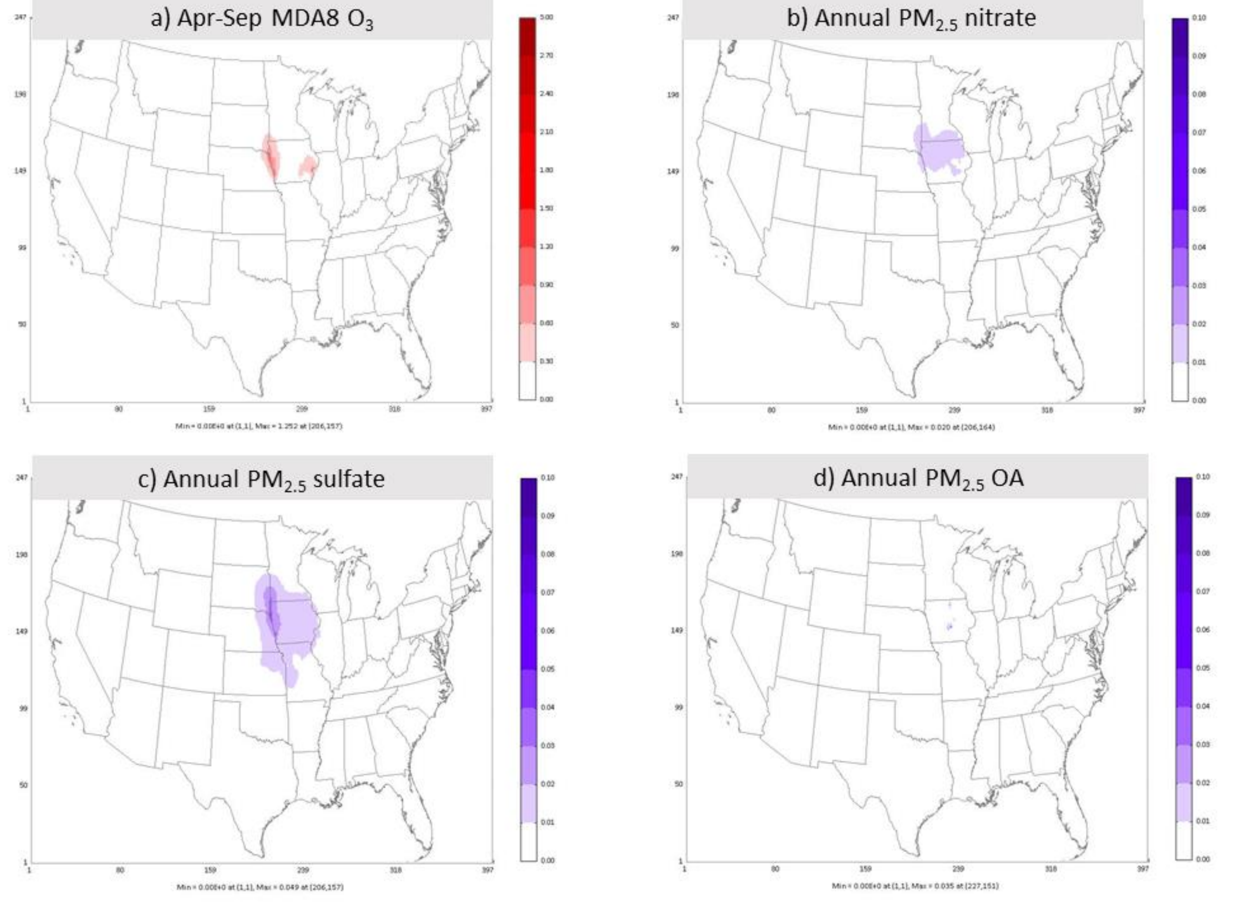


Figure J-5: Maps of Ohio EGU Tag contributions to a) April-September Seasonal Average MDA8 Ozone (ppb); b) Annual Average $PM_{2.5}$ Nitrate (µg/m^3); c) Annual Average $PM_{2.5}$ sulfate (µg/m^3); d) Annual Average $PM_{2.5}$ Organic Aerosol (µg/m^3)

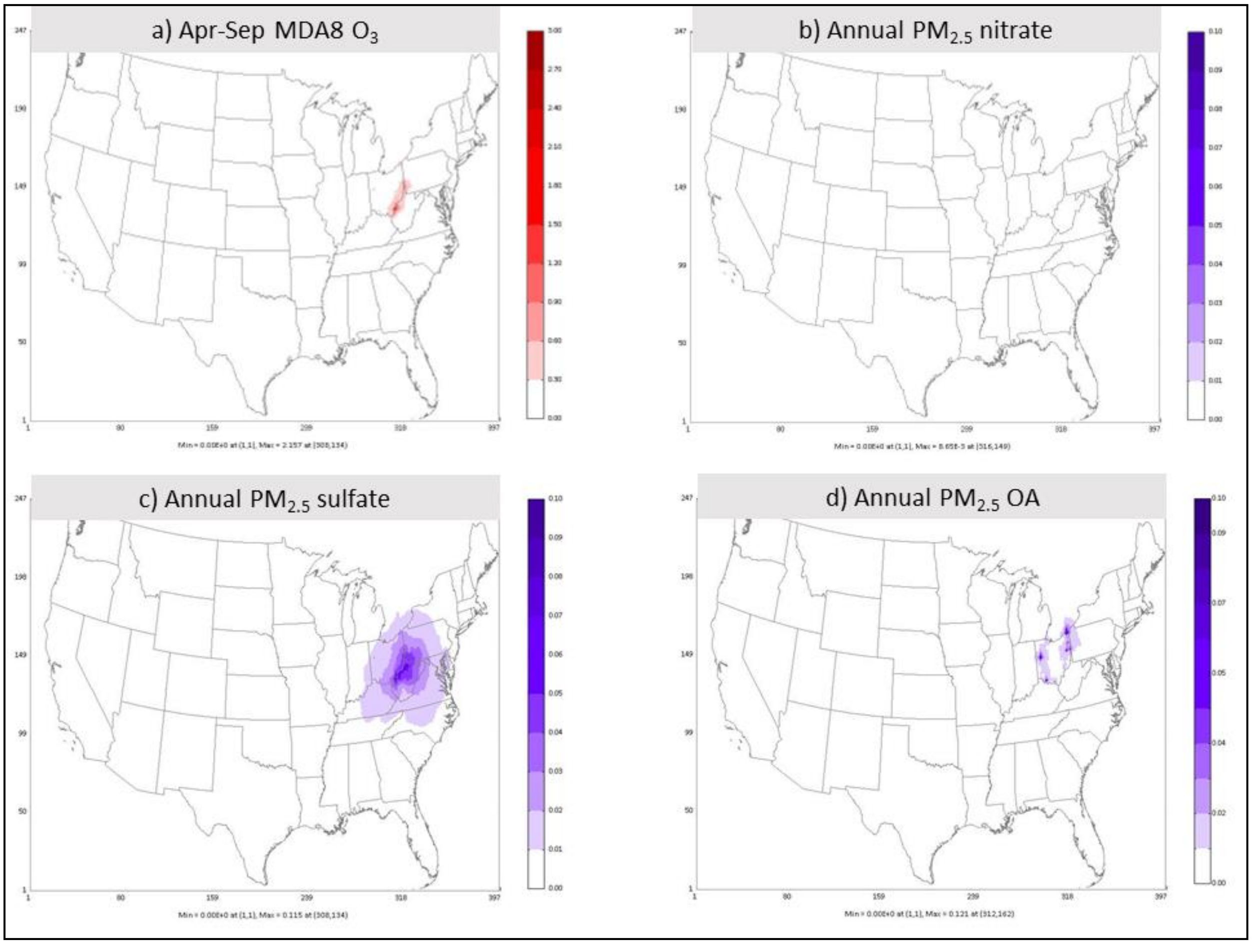


Figure J-6: Maps of National EGU Tag contributions to April-September Seasonal Average MDA8 ozone (ppb) by fuel for a) Coal EGUs; b) Natural Gas EGUs; c) All Other EGUs

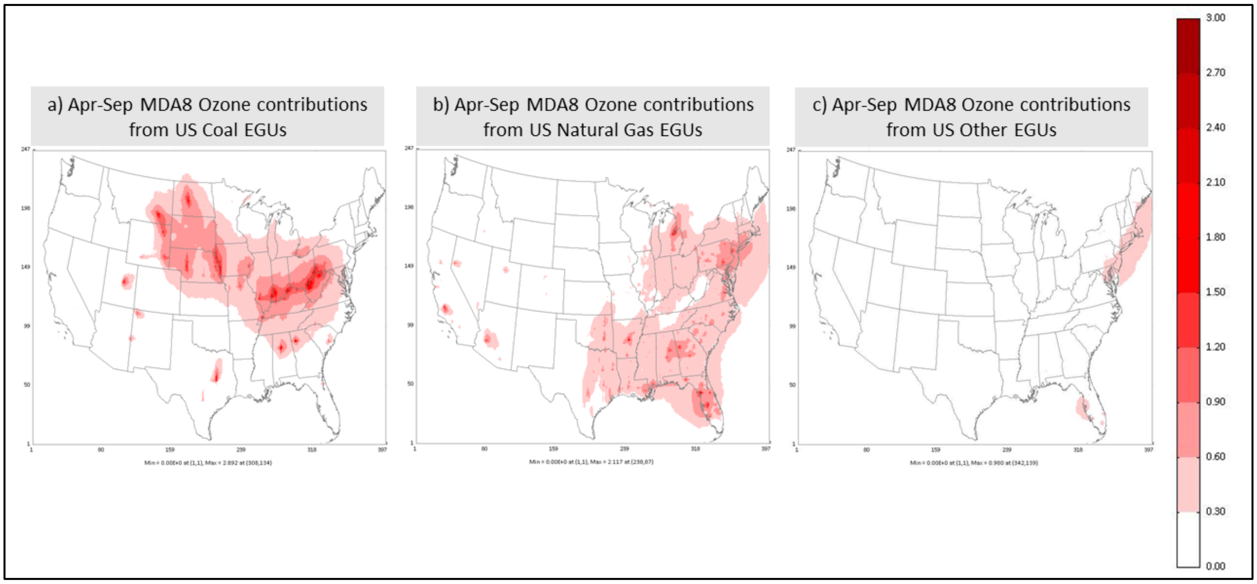
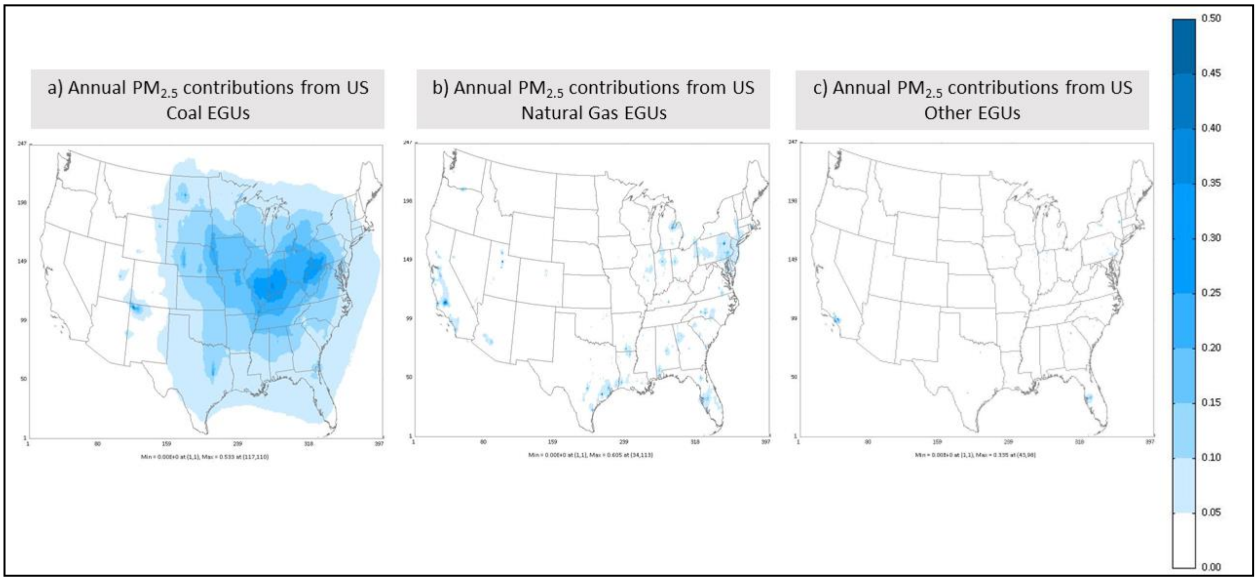


Figure J-7: Maps of National EGU Tag contributions to Annual Average $PM_{2.5}$ (µg/m3) by fuel for a) Coal EGUs; b) Natural Gas EGUs; c) All Other EGUs



J.2 Applying Modeling Outputs to Create Spatial Fields

In this section we describe the method for creating spatial fields of AS-MO3 and annual average $PM_{2.5}$ based on the 2016 and future year modeling. The foundational data include (1) ozone and speciated $PM_{2.5}$ concentrations in each model grid cell from the 2016 and the future year modeling, (2) ozone and speciated PM2.5 contributions in the future year of EGUs emissions from each state in each model grid cell[162], (3) future year emissions from EGUs that were input to the contribution modeling (Table J-1, Table J-2, and Table J-3), and (4) the EGU emissions from IPM for baseline and policy scenarios in year of analysis (2028, 2030, 2035, 2040, 2045, and 2050). The method to create spatial fields applies scaling factors to gridded source apportionment contributions based on emissions changes between future year projections and the baseline and the control cases to the modeled contributions. This method is described in detail below.

Spatial fields of ozone and $PM_{2.5}$ in the future year were created based on "fusing" modeled data with measured concentrations at air quality monitoring locations. To create the spatial fields for each future emissions scenario these fused future year model fields are used in combination with future year source apportionment modeling and the EGU emissions for each scenario and analytic year[163]. Contributions from each state and fuel EGU contribution "tag" were scaled based on the ratio of emissions in the year/scenario being evaluated to the emissions in the modeled future year scenario. Contributions from tags representing sources other than EGUs are held constant at 2026 levels for each of the scenarios and year. For each scenario and year analyzed, the scaled contributions from all sources were summed together to create a gridded surface of total modeled ozone and $PM_{2.5}$. The process is described in a step-by-step manner below starting with the methodology for creating AS-MO3 spatial fields followed by a description of the steps for creating annual $PM_{2.5}$ spatial fields.

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[162] Contributions from EGUs were modeled using projected emissions for the future year modeled scenario. The resulting contributions were used to construct spatial fields in 2028, 2030, 2035, 2040, 2045, and 2050.

[163] *i.e.*, 2028, 2030, 2035, 2040, 2045, and 2050

J.2.1 Ozone

1. Create fused spatial fields of future year AS-MO3 incorporating information from the air quality modeling and from ambient measured monitoring data. The enhanced Voronoi Neighbor Average (eVNA) technique (Gold et al., 1997; US EPA, 2007; Ding et al., 2015) was applied to ozone model predictions in conjunction with measured data to create modeled/measured fused surfaces that leverage measured concentrations at air quality monitor locations and model predictions at locations with no monitoring data.
    - 1.1. The AS-MO3 eVNA spatial fields are created for the 2016 base year with EPA's software package, Software for the Modeled Attainment Test – Community Edition (SMAT-CE) using 3 years of monitoring data (2015-2017) and the 2016 modeled data.
    - 1.2. The model-predicted spatial fields (*i.e.*, not the eVNA fields) of AS-MO3 in 2016 were paired with the corresponding model-predicted spatial fields in the future year to calculate the ratio of AS-MO3 between 2016 and the future year in each model grid cell.
    - 1.3. To create a gridded future year eVNA surfaces, the spatial fields of 2016/future year ratios created in step (1.2) were multiplied by the corresponding eVNA spatial fields for 2016 created in step (1.1) to produce an eVNA AS-MO3 spatial field for the future year using equation 1.

$$eVNA_{g,future} = \left(eVNA_{g,2016}\right) \times \frac{Model_{g,future}}{Model_{g,2016}} \qquad \text{Eq-1}$$

- $eVNA_{g,future}$ is the eVNA concentration of AS-MO3 or $PM_{2.5}$ component species in grid-cell, g, in the future year
- $eVNA_{g,2016}$ is the eVNA concentration of AS-MO3 or $PM_{2.5}$ component species in grid-cell, g, in 2016
- $Model_{g,future}$ is the CAMx modeled concentration of AS-MO3 or $PM_{2.5}$ component species in grid-cell, g, in the future year
- $Model_{g,2016}$ is the CAMx modeled concentration of AS-MO3 or $PM_{2.5}$ component in grid-cell, g, in 2016

2. Create spatial fields of total EGU AS-MO3 contributions for each combination of scenario and analytic year evaluated.
    - 2.1. Use the EGU ozone season NOX emissions for the 2028 baseline and the corresponding future year modeled EGU ozone season emissions (Table J-1, Table J-2, and Table J-3) to calculate the ratio of 2028 baseline emissions to future year modeled emissions for each EGU tag (*i.e.*, an ozone scaling factor calculated for each state-fuel combination)[164]. These scaling factors are provided in Table J-4, Table J-5, and Table J-11.
    - 2.2. Calculate adjusted gridded AS-MO3 EGU contributions that reflect differences in state-fuel EGU NOX emissions between the modeled future year and the 2028 baseline by multiplying the ozone season NOX scaling factors by the corresponding gridded AS-MO3 ozone contributions from each state-fuel EGU tag.
    - 2.3. Add together the adjusted AS-MO3 contributions for each EGU-state tag to produce spatial

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[164] Preliminary testing of this methodology showed unstable results when very small magnitudes of emissions were tagged especially when being scaled by large factors. To mitigate this issue, in cases where state-fuel EGU tags were associated with no or very small emissions, tags were combined into multi-state regions.

fields of adjusted EGU totals for the 2028 baseline.[165]

2.4. Repeat steps 2.1 through 2.3 for the 2028 final rule scenario and for the baseline and final rule scenarios for each additional analytic year. The scaling factors for the baseline scenarios and the final rule scenarios are provided in Table J-4, Table J-5, and Table J-11.

3. Create a gridded spatial field of AS-MO3 associated with IPM emissions for the 2028 baseline by combining the EGU AS-MO3 contributions from steps (2.3) with the corresponding contributions to AS-MO3 from all other sources. Repeat for each of the EGU contributions created in step (2.4) to create separate gridded spatial fields for the rest of the baseline and final rule scenarios for each analytic year.

Steps 2 and 3 in combination can be represented by equation 2:

$$AS\text{-}MO3_{g,i,y} = eVNA_{g,y} \times \left(\frac{C_{g,BC}}{C_{g,Tot}} + \frac{C_{g,int}}{C_{g,Tot}} + \frac{C_{g,bio}}{C_{g,Tot}} + \frac{C_{g,fires}}{C_{g,Tot}} + \frac{C_{g,USanthro}}{C_{g,Tot}} + \sum_{t=1}^{T} \frac{C_{EGUVOC,g,t}}{C_{g,Tot}} + \sum_{t=1}^{T} \frac{C_{EGUNOx,g,t}\, S_{NOx,t,i,y}}{C_{g,Tot}} \right) \quad \text{Eq-2}$$

- $AS\text{-}MO3_{g,i,y}$ is the estimated fused model-obs AS-MO3 for grid-cell, “g”, scenario, “i”[166], and year, “y”[167];
- $eVNA_{g,future}$ is the future year eVNA future year AS-MO3 concentration for grid-cell “g” calculated using Eq-1.
- $C_{g,Tot}$ is the total modeled AS-MO3 for grid-cell “g” from all sources in the future year source apportionment modeling
- $C_{g,BC}$ is the future year AS-MO3 modeled contribution from the modeled boundary inflow;
- $C_{g,int}$ is the future year AS-MO3 modeled contribution from international emissions within the modeling domain;
- $C_{g,bio}$ is the future year AS-MO3 modeled contribution from biogenic emissions;
- $C_{g,fires}$ is the future year AS-MO3 modeled contribution from fires;
- $C_{g,USanthro}$ is the total future year AS-MO3 modeled contribution from U.S. anthropogenic sources other than EGUs;
- $C_{EGUVOC,g,t}$ is the future year AS-MO3 modeled contribution from EGU emissions of VOCs from state, “t”;

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[165] The contributions from the unaltered O3V tags are added to the summed adjusted O3N EGU tags.

[166] Scenario “i" can represent either the baseline or the final rule scenario

[167] Analytic year “y” can represent 2028, 2030, 2035, 2040, 2045 or 2050

- $C_{EGUNOx,g,t}$ is the future year AS-MO3 modeled contribution from EGU emissions of NO_X from tag, "t"; and
- $S_{NOx,t,i,y}$ is the EGU NO_X scaling factor for tag, "t", scenario "i", and year, "y".

J.2.2 $PM_{2.5}$

4. Create fused spatial fields of future year annual $PM_{2.5}$ component species incorporating information from the air quality modeling and from ambient measured monitoring data. The eVNA technique was applied to $PM_{2.5}$ component species model predictions in conjunction with measured data to create modeled/measured fused surfaces that leverage measured concentrations at air quality monitor locations and model predictions at locations with no monitoring data.
   4.1. The quarterly average $PM_{2.5}$ component species eVNA spatial fields are created for the 2016 base year with EPA's SMAT-CE software package using 3 years of monitoring data (2015-2017) and the 2016 modeled data.
   4.2. The model-predicted spatial fields (*i.e.*, not the eVNA fields) of quarterly average $PM_{2.5}$ component species in 2016 were paired with the corresponding model-predicted spatial fields in the future year to calculate the ratio of $PM_{2.5}$ component species between 2016 and the future year in each model grid cell.
   4.3. To create a gridded future year eVNA surfaces, the spatial fields of 2016/future year ratios created in step (4.2) were multiplied by the corresponding eVNA spatial fields for 2016 created in step (4.1) to produce an eVNA annual average $PM_{2.5}$ component species spatial field for the future year using (Eq-1).
5. Create spatial fields of total EGU speciated $PM_{2.5}$ contributions for each year/scenario evaluated.
   5.1. Use the annual total NOX, SO2 and PM2.5 emissions for the 2028 baseline scenario and the corresponding future year modeled EGU NOX, SO¬2 and PM2.5 emissions to calculate the ratio of 2028 baseline emissions to future year modeled emissions for each EGU state-fuel contribution tag (*i.e.*, annual NOX, SO2 and PM2.5 scaling factors calculated for each state and fuel combination). These scaling factors are provided in Table J-6 through Table J-11.
   5.2. Calculate adjusted gridded annual $PM_{2.5}$ component species EGU contributions that reflect differences in state-EGU NO_X, SO_2 and primary $PM_{2.5}$ emissions between the modeled future year and the 2028 baseline by multiplying the annual NO_X, SO_2 and $PM_{2.5}$ scaling factors by the corresponding annual gridded $PM_{2.5}$ component species contributions from each state-fuel EGU tag[168].
   5.3. Add together the adjusted $PM_{2.5}$ contributions of for each EGU state-fuel tag to produce spatial fields of adjusted EGU totals for each $PM_{2.5}$ component species.
   5.4. Repeat steps 5.1 through 5.3 for the 2028 final rule scenario and for the baseline and final rule scenarios for each additional analytic year. The scaling factors for all $PM_{2.5}$ component species for the baseline and the final rule scenarios are provided in Table J-6 through Table J-11.
6. Create gridded spatial fields of each $PM_{2.5}$ component species for the 2028 baseline by combining the EGU annual $PM_{2.5}$ component species contributions from step (5.3) with the corresponding contributions

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[168] Scaling factors for components that are formed through chemical reactions in the atmosphere were created as follows: scaling factors for sulfate were based on relative changes in annual SO_2 emissions; scaling factors for nitrate were based on relative changes in annual NO_X emissions. Scaling factors for $PM_{2.5}$ components that are emitted directly from the source (OA, EC, crustal) were based on the relative changes in annual primary $PM_{2.5}$ emissions between the future year modeled emissions and the baseline and the final rule scenarios in each year.

to annual $PM_{2.5}$ component species from all other sources. Repeat for each of the EGU contributions created in step (5.4) to create separate gridded spatial fields for the rest of the baseline and policy scenarios and analytic years.

7. Create gridded spatial fields of total $PM_{2.5}$ mass by combining the component species surfaces for sulfate, nitrate, organic aerosol, elemental carbon and crustal material with ammonium, and particle-bound. Ammonium and particle-bound water concentrations are calculated for each scenario based on nitrate and sulfate concentrations along with the ammonium degree of neutralization in the base year modeling in accordance with equations from the SMAT-CE modeling software.

Steps 5 and 6 result in equation 3 for $PM_{2.5}$ component species: sulfate, nitrate, organic aerosol, elemental carbon and crustal material.

$$PM_{s,g,i,y} = eVNA_{s,g,y} \times \left(\frac{C_{s,g,BC}}{C_{s,g,Tot}} + \frac{C_{s,g,int}}{C_{s,g,Tot}} + \frac{C_{s,g,bio}}{C_{s,g,Tot}} + \frac{C_{s,g,fires}}{C_{s,g,Tot}} + \frac{C_{s,g,USanthro}}{C_{s,g,Tot}} + \sum_{t=1}^{T} \frac{C_{EGUs,g,t}\, S_{s,t,i,y}}{C_{s,g,Tot}} \right) \quad \text{Eq-3}$$

- $PM_{s,g,i,y}$ is the estimated fused model-obs PM component species “s” for grid-cell, “g”, scenario, “i”[169], and year, “y”[170];
- $eVNA_{s,g,future}$ is the future year eVNA PM concentration for component species “s” in grid-cell “g” calculated using Eq-1.
- $C_{s,g,Tot}$ is the total modeled PM component species “s” for grid-cell “g” from all sources in the future year source apportionment modeling
- $C_{s,g,BC}$ is the future year PM component species “s” modeled contribution from the modeled boundary inflow;
- $C_{s,g,int}$ is the future year PM component species “s” modeled contribution from international emissions within the modeling domain;
- $C_{s,g,bio}$ is the future year PM component species “s” modeled contribution from biogenic emissions;
- $C_{s,g,fires}$ is the future year PM component species “s” modeled contribution from fires;
- $C_{s,g,USanthro}$ is the total future year PM component species “s” modeled contribution from U.S. anthropogenic sources other than EGUs;

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[169] Scenario “i" can represent either baseline or the final rule scenario.

[170] Analytic year “y” can represent 2028, 2030, 2035, 2040, 2045, or 2050

- $C_{EGUs,g,t}$ is the future year PM component species “s” modeled contribution from EGU emissions of NO_X, SO_2, or primary $PM_{2.5}$ from tag, “t”; and

- $S_{s,t,i,y}$ is the EGU scaling factor for component species “s”, tag, “t”, scenario “i”, and year, “y”. Scaling factors for nitrate are based on annual NO_X emissions, scaling factors for sulfate are based on annual SO_2 emissions, scaling factors for primary $PM_{2.5}$ components are based on primary $PM_{2.5}$ emissions.

Selected maps showing changes in air quality concentrations between the final rule and the baseline are provided later in this appendix.

J.3 Scaling Factors Applied to Source Apportionment Tags

Table J-4: Baseline and Final Rule Scenario Ozone Scaling Factors for Coal EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
ALMS[a]	1.40	1.65	1.47	1.47	0.38	0.38	1.19	1.65	1.47	1.47	0.38	0.38
AZ	0.01	1.43	1.13	0.00	0.00	0.98	0.01	1.40	1.15	0.00	0.00	0.98
CA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CO	139.01	1.28	1.98	1.98	1.98	1.98	139.01	1.28	1.98	1.98	1.98	1.98
CT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FL	0.47	1.24	0.10	0.10	0.03	0.03	0.44	0.93	0.10	0.10	0.03	0.03
GA	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.43	0.00	0.00	0.00	0.00
IA	1.17	1.18	0.77	0.46	0.42	0.81	1.17	1.18	0.72	0.46	0.42	0.81
ID	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IL	0.97	0.96	0.81	0.14	0.00	0.00	0.97	0.96	0.77	0.10	0.00	0.00
IN	1.35	0.76	0.19	0.19	0.00	0.00	1.35	0.77	0.19	0.19	0.00	0.00
KY	0.79	0.95	0.97	0.83	0.06	0.15	0.65	0.84	0.60	0.57	0.00	0.15
MA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MDPA[b]	3.14	3.17	2.58	1.06	1.30	1.31	3.07	3.07	2.53	1.06	1.30	1.37
ME	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MI	0.75	0.00	0.00	0.00	0.00	0.00	0.73	0.00	0.00	0.00	0.00	0.00
MN	2.41	2.25	0.00	0.00	0.00	0.00	2.41	2.25	0.00	0.00	0.00	0.00
MO	2.72	1.57	0.67	0.31	0.27	0.56	2.68	1.59	0.66	0.28	0.26	0.52
MT	1.07	1.12	1.11	0.99	0.00	0.78	1.07	1.12	1.10	0.99	0.00	0.77
NC	9.89	6.41	2.86	1.50	2.86	3.98	12.69	9.43	2.86	0.00	2.57	3.98
ND	1.09	1.08	0.25	0.24	0.01	0.02	1.08	1.07	0.25	0.24	0.01	0.02
NEKS[c]	1.79	1.87	0.76	0.59	0.41	0.68	1.55	1.61	0.76	0.59	0.39	0.68
NH	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NJ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NM	0.98	0.98	0.01	0.01	0.01	0.01	0.98	0.98	0.01	0.01	0.01	0.01
NV	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NY	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OH	0.58	1.07	0.00	0.00	0.00	0.70	0.57	0.77	0.00	0.00	0.00	0.68
OR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SC	0.81	2.22	3.18	3.18	0.00	0.00	0.48	2.21	3.18	3.18	0.00	0.00
SD	0.87	1.33	0.00	0.00	0.00	0.00	0.87	1.33	0.00	0.00	0.00	0.00
TN	3.89	0.01	0.00	0.00	0.00	0.00	3.79	0.01	0.00	0.00	0.00	0.00
TX-reg[d]	2.69	2.03	1.54	0.95	0.44	1.40	2.64	2.15	1.56	0.95	0.44	1.39

Table J-4: Baseline and Final Rule Scenario Ozone Scaling Factors for Coal EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
UT	1.00	0.06	0.06	0.06	0.04	0.00	1.00	0.06	0.06	0.06	0.04	0.00
VA	0.65	0.45	0.00	0.00	0.00	0.00	0.65	0.41	0.00	0.00	0.00	0.00
VT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WI	1.66	2.16	0.36	0.00	0.00	0.66	1.66	2.16	0.36	0.00	0.00	0.66
WV	0.92	1.16	0.92	0.27	0.10	0.10	0.76	1.00	0.58	0.27	0.10	0.10
WY	1.26	1.12	1.12	0.61	0.53	0.52	1.26	1.12	1.12	0.61	0.53	0.52
ALMS	1.40	1.65	1.47	1.47	0.38	0.38	1.19	1.65	1.47	1.47	0.38	0.38

[a] ALMS: AL, MS

[b] MDPA: MD, PA

[c] NEKS: NE, KS

[d] TX-reg: AR, LA, OK, TX

Table J-5: Baseline and Final Rule Scenario Ozone Scaling Factors for Natural Gas EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
AL	0.53	0.61	0.49	0.39	0.27	0.37	0.52	0.50	0.49	0.38	0.27	0.36
AR	0.65	0.68	0.43	0.20	0.10	0.18	0.65	0.68	0.43	0.19	0.10	0.18
AZ	0.69	0.68	0.67	0.68	0.45	0.69	0.69	0.68	0.67	0.68	0.45	0.69
CA	0.92	0.94	0.85	0.52	0.02	0.04	0.92	0.94	0.85	0.51	0.02	0.04
CO	3.26	0.63	0.50	0.48	0.12	0.17	3.27	0.63	0.50	0.47	0.12	0.17
CT	1.04	0.98	0.89	0.00	0.01	0.01	1.05	0.98	0.89	0.00	0.01	0.01
DC	0.86	0.59	0.33	0.21	0.16	0.16	0.86	0.59	0.33	0.21	0.16	0.16
DE	0.79	0.80	0.38	0.37	0.38	0.43	0.77	0.78	0.38	0.37	0.32	0.42
FL	1.08	1.03	1.04	0.89	0.66	0.65	1.07	1.04	1.03	0.89	0.65	0.64
GA	0.58	0.54	0.52	0.42	0.38	0.41	0.58	0.53	0.52	0.41	0.38	0.41
IA	0.53	0.42	0.16	0.04	0.01	0.04	0.53	0.43	0.15	0.04	0.01	0.05
ID	0.60	0.90	0.90	0.90	0.04	0.09	0.59	0.90	0.88	0.88	0.03	0.09
IL	0.69	0.61	0.42	0.21	0.00	0.00	0.67	0.62	0.41	0.20	0.00	0.00
IN	0.75	0.63	0.38	0.20	0.15	0.21	0.74	0.64	0.38	0.20	0.16	0.21
KS	1.38	1.32	0.25	0.14	0.10	0.03	1.39	1.33	0.33	0.15	0.11	0.03
KY	0.87	0.81	0.69	0.57	0.38	0.49	0.96	0.90	0.83	0.66	0.45	0.59
LA	1.04	1.00	0.72	0.45	0.41	0.56	1.03	1.00	0.71	0.45	0.40	0.56
MA	0.60	0.67	0.66	0.84	0.47	0.64	0.59	0.68	0.66	0.80	0.45	0.64
MD	1.51	1.33	1.12	0.84	0.79	1.04	1.34	1.24	1.10	0.83	0.72	1.04
ME	1.16	1.15	0.59	0.63	0.36	0.56	1.16	1.15	0.59	0.64	0.36	0.56
MI	0.68	0.70	0.55	0.41	0.23	0.40	0.67	0.63	0.54	0.40	0.23	0.40
MN	0.92	0.84	0.34	0.17	0.13	0.21	0.85	0.78	0.34	0.17	0.13	0.21
MO	0.59	0.59	0.20	0.08	0.04	0.06	0.57	0.57	0.20	0.08	0.04	0.06
MS	0.64	0.62	0.50	0.45	0.29	0.34	0.63	0.59	0.50	0.44	0.26	0.33
MT	0.95	1.10	0.08	0.14	0.02	0.24	0.95	0.79	0.08	0.14	0.02	0.34
NC	0.77	0.59	0.68	0.63	0.51	0.59	0.73	0.55	0.69	0.62	0.48	0.59
ND	0.85	1.85	0.34	0.96	0.14	0.66	0.85	1.84	0.34	0.96	0.14	0.16
NE	5.91	5.92	0.28	0.87	0.02	1.02	5.80	5.98	0.33	0.87	0.05	1.02
NH	0.67	0.51	0.41	0.41	0.41	0.40	0.68	0.51	0.41	0.41	0.41	0.40
NJ	0.81	0.85	0.61	0.49	0.46	0.75	0.77	0.85	0.59	0.48	0.45	0.74
NM	1.00	0.84	0.77	0.35	0.47	0.40	1.00	0.84	0.77	0.33	0.48	0.40

Table J-5: Baseline and Final Rule Scenario Ozone Scaling Factors for Natural Gas EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
NV	0.33	0.25	0.19	0.21	0.12	0.09	0.33	0.25	0.19	0.21	0.11	0.09
NY	1.03	0.99	0.65	0.28	0.28	0.28	0.97	0.97	0.62	0.28	0.28	0.28
OH	1.02	0.97	0.84	0.71	0.62	0.80	1.11	1.07	0.94	0.80	0.71	0.81
OK	1.69	1.57	0.48	0.33	0.32	0.32	1.65	1.56	0.48	0.33	0.32	0.33
OR	63.29	0.00	0.00	0.00	0.00	0.00	63.38	0.00	0.00	0.00	0.00	0.00
PA	0.79	0.69	0.34	0.24	0.23	0.35	0.74	0.64	0.35	0.23	0.23	0.35
RI	0.69	0.75	0.71	0.88	0.89	0.46	0.69	0.75	0.72	0.88	0.89	0.46
SC	0.93	0.96	0.59	0.59	0.56	0.83	0.91	0.94	0.58	0.59	0.60	0.83
SD	0.59	0.59	0.17	0.06	0.03	0.07	0.54	0.59	0.16	0.06	0.02	0.07
TN	1.12	1.09	1.07	0.90	0.51	0.72	1.13	1.10	1.05	0.87	0.49	0.64
TX	0.99	0.89	0.47	0.28	0.15	0.32	0.98	0.88	0.47	0.28	0.15	0.32
UT	0.50	0.43	0.34	0.37	0.31	0.41	0.50	0.43	0.34	0.37	0.30	0.41
VA	0.89	0.85	0.54	0.32	0.26	0.12	0.84	0.83	0.54	0.31	0.17	0.12
VT	0.00	0.37	3.53	3.99	0.00	1.58	0.00	0.37	3.53	3.99	0.00	1.58
WA	0.08	0.23	0.79	0.74	0.02	0.02	0.08	0.23	0.85	0.74	0.02	0.02
WI	0.74	0.70	0.58	0.30	0.14	0.24	0.73	0.66	0.41	0.30	0.14	0.23
WV	1.19	1.12	0.33	0.13	0.07	2.97	1.25	1.18	0.39	0.16	0.11	2.99
WY	0.01	0.04	0.06	0.06	0.00	0.05	0.01	0.05	0.06	0.05	0.00	0.05

Table J-6: Baseline and Final Rule Scenario Nitrate Scaling Factors for Coal EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
AL	1.33	1.45	1.65	1.54	0.14	0.23	1.36	1.50	1.65	1.54	0.14	0.23
AR	39.93	8.30	3.83	0.71	0.28	2.49	39.48	8.53	3.83	0.71	0.28	2.51
AZ	0.47	0.97	0.59	0.20	0.15	0.69	0.47	0.97	0.60	0.19	0.15	0.69
CA	0.24	0.36	0.16	0.13	0.00	0.00	0.24	0.36	0.16	0.13	0.00	0.00
CO	25.56	0.97	0.37	0.41	0.37	0.40	25.64	0.97	0.37	0.41	0.37	0.40
CT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FL	0.89	1.20	0.26	0.26	0.14	0.18	0.76	1.01	0.26	0.26	0.14	0.18
GA	0.23	0.12	0.00	0.00	0.00	0.00	0.53	0.35	0.00	0.00	0.00	0.00
IA	1.20	1.16	0.68	0.28	0.19	0.57	1.20	1.19	0.65	0.27	0.19	0.57
ID	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IL	0.98	0.92	0.62	0.14	0.00	0.00	0.98	0.93	0.58	0.10	0.00	0.00
IN	1.29	0.64	0.11	0.11	0.00	0.00	1.36	0.68	0.11	0.11	0.00	0.00
KS	45.15	46.03	3.08	3.08	0.00	0.00	36.98	39.58	3.08	3.08	0.00	0.00
KY	1.38	1.12	1.15	1.00	0.07	0.16	1.19	1.01	0.77	0.70	0.05	0.16
LA	24.63	16.33	25.37	13.43	2.22	16.83	24.63	16.56	26.42	13.43	2.22	16.83
MA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MD	3.54	3.54	3.54	3.54	2.97	3.42	3.54	3.54	3.54	3.54	2.97	3.42
ME	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MI	0.74	0.00	0.00	0.00	0.00	0.00	0.73	0.00	0.00	0.00	0.00	0.00
MN	2.97	2.31	0.00	0.00	0.00	0.00	2.97	2.25	0.00	0.00	0.00	0.00
MO	1.41	1.06	0.43	0.04	0.03	0.09	1.39	1.06	0.43	0.04	0.03	0.08
MS	4.02	3.60	1.06	1.00	1.00	1.00	1.94	3.60	1.06	1.00	1.00	1.00
MT	1.07	1.09	1.08	1.02	0.38	0.79	1.07	1.10	1.08	1.02	0.38	0.79
NC	19.19	11.95	3.66	3.51	3.84	4.16	21.30	11.96	3.68	2.58	3.69	4.16

Table J-6: Baseline and Final Rule Scenario Nitrate Scaling Factors for Coal EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
ND	1.03	1.03	0.25	0.25	0.01	0.02	1.03	1.03	0.26	0.25	0.01	0.02
NE	1.14	1.13	0.61	0.37	0.18	0.46	1.03	1.02	0.61	0.37	0.17	0.46
NH	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NJ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NM	0.99	0.99	0.01	0.01	0.01	0.01	0.99	0.99	0.01	0.01	0.01	0.01
NV	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NY	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OH	0.90	0.94	0.19	0.00	0.00	0.40	0.81	0.84	0.25	0.00	0.00	0.40
OK	12.10	5.08	3.11	3.11	1.03	1.03	11.50	5.19	3.11	3.11	1.03	1.03
OR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PA	3.05	2.94	2.61	1.19	1.16	1.23	2.98	2.88	2.56	1.20	1.15	1.22
RI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SC	1.15	1.92	2.98	2.98	0.00	0.00	0.98	1.91	2.98	2.98	0.00	0.00
SD	0.93	1.11	0.00	0.00	0.00	0.00	0.93	1.11	0.00	0.00	0.00	0.00
TN	7.49	1.00	0.00	0.00	0.00	0.00	7.39	1.00	0.00	0.00	0.00	0.00
TX	1.02	1.13	0.87	0.47	0.12	0.42	1.03	1.20	0.88	0.47	0.12	0.41
UT	3.50	0.09	0.09	0.09	0.06	0.04	3.50	0.09	0.09	0.09	0.06	0.04
VA	0.67	0.41	0.12	0.00	0.00	0.00	0.67	0.31	0.12	0.00	0.00	0.00
VT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WI	1.84	2.07	0.38	0.00	0.00	0.27	1.81	2.10	0.37	0.00	0.00	0.27
WV	1.25	1.30	0.97	0.27	0.09	0.10	1.06	1.16	0.61	0.27	0.09	0.10
WY	1.32	1.15	1.14	0.61	0.48	0.51	1.32	1.15	1.14	0.61	0.48	0.51

Table J-7: Baseline and Final Rule Scenario Nitrate Scaling Factors for Natural Gas EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
AL	0.59	0.60	0.45	0.27	0.16	0.23	0.58	0.53	0.46	0.27	0.16	0.23
AR	0.56	0.68	0.38	0.13	0.06	0.12	0.56	0.68	0.38	0.13	0.06	0.12
AZ	0.73	0.85	0.83	0.75	0.37	0.62	0.73	0.85	0.82	0.74	0.38	0.62
CA	0.76	0.88	0.97	0.67	0.16	0.19	0.76	0.89	0.97	0.67	0.15	0.19
CO	2.02	0.71	0.72	0.76	0.30	0.51	2.02	0.71	0.72	0.74	0.30	0.50
CT	0.92	0.81	0.66	0.00	0.01	0.01	0.92	0.81	0.66	0.00	0.01	0.01
DC	0.63	0.47	0.26	0.18	0.13	0.11	0.63	0.47	0.26	0.17	0.13	0.12
DE	0.79	0.76	0.33	0.29	0.30	0.42	0.77	0.70	0.33	0.29	0.26	0.41
FL	1.11	1.06	1.01	0.73	0.49	0.51	1.10	1.05	1.00	0.72	0.49	0.50
GA	0.68	0.63	0.54	0.29	0.22	0.26	0.67	0.62	0.54	0.29	0.22	0.26
IA	0.49	0.42	0.13	0.03	0.01	0.04	0.49	0.42	0.13	0.03	0.01	0.04
ID	1.02	1.36	1.39	1.24	0.60	0.84	1.00	1.35	1.36	1.21	0.59	0.84
IL	0.54	0.54	0.29	0.12	0.00	0.00	0.53	0.54	0.29	0.12	0.00	0.00
IN	0.67	0.59	0.34	0.12	0.08	0.12	0.65	0.59	0.34	0.12	0.09	0.12
KS	0.96	0.87	0.20	0.07	0.05	0.02	0.96	0.92	0.25	0.08	0.06	0.02
KY	0.81	0.76	0.46	0.25	0.15	0.22	0.88	0.80	0.55	0.30	0.17	0.27
LA	0.96	0.94	0.61	0.27	0.24	0.34	0.95	0.93	0.60	0.27	0.24	0.34
MA	0.64	0.66	0.54	0.61	0.33	0.52	0.63	0.67	0.54	0.58	0.32	0.52
MD	1.47	1.35	1.05	0.72	0.66	0.82	1.36	1.27	1.03	0.72	0.61	0.85
ME	1.64	1.34	0.63	0.58	0.34	0.55	1.64	1.37	0.63	0.60	0.34	0.55
MI	0.65	0.71	0.43	0.30	0.15	0.28	0.65	0.64	0.43	0.28	0.15	0.27

Table J-7: Baseline and Final Rule Scenario Nitrate Scaling Factors for Natural Gas EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
MN	1.02	0.95	0.36	0.15	0.09	0.18	0.97	0.90	0.36	0.15	0.09	0.18
MO	0.52	0.52	0.19	0.06	0.03	0.05	0.50	0.51	0.19	0.06	0.03	0.05
MS	0.61	0.56	0.36	0.24	0.15	0.19	0.58	0.53	0.35	0.23	0.13	0.18
MT	0.66	0.80	0.05	0.08	0.01	0.14	0.66	0.61	0.05	0.08	0.01	0.20
NC	0.89	0.67	0.72	0.55	0.47	0.62	0.85	0.64	0.72	0.54	0.45	0.62
ND	0.66	1.32	0.26	0.60	0.09	0.41	0.66	1.33	0.26	0.60	0.09	0.10
NE	2.05	1.80	0.13	0.31	0.01	0.28	2.04	1.84	0.14	0.30	0.01	0.28
NH	0.78	0.59	0.44	0.38	0.36	0.41	0.79	0.58	0.43	0.38	0.36	0.41
NJ	0.82	0.83	0.51	0.34	0.39	0.67	0.78	0.81	0.48	0.34	0.38	0.66
NM	0.74	0.66	0.64	0.33	0.39	0.36	0.74	0.66	0.64	0.32	0.39	0.37
NV	0.50	0.39	0.44	0.40	0.23	0.18	0.50	0.39	0.44	0.40	0.23	0.18
NY	0.91	0.89	0.55	0.16	0.16	0.17	0.88	0.89	0.54	0.16	0.16	0.17
OH	1.00	0.98	0.87	0.59	0.42	0.61	1.10	1.08	0.96	0.66	0.48	0.60
OK	1.43	1.20	0.34	0.21	0.20	0.21	1.38	1.18	0.34	0.21	0.20	0.21
OR	5.58	0.96	0.50	0.00	0.00	0.00	5.58	0.96	0.49	0.00	0.00	0.00
PA	0.69	0.61	0.35	0.21	0.18	0.31	0.66	0.57	0.35	0.20	0.18	0.31
RI	0.76	0.76	0.64	0.71	0.68	0.45	0.77	0.77	0.65	0.71	0.68	0.45
SC	0.94	0.96	0.67	0.56	0.55	0.83	0.88	0.94	0.67	0.56	0.55	0.83
SD	0.55	0.55	0.16	0.06	0.04	0.08	0.51	0.57	0.15	0.06	0.04	0.08
TN	1.02	0.97	0.79	0.41	0.23	0.34	1.02	0.96	0.77	0.40	0.22	0.30
TX	0.97	0.88	0.42	0.17	0.08	0.20	0.97	0.88	0.42	0.17	0.08	0.20
UT	0.52	0.62	0.56	0.58	0.46	0.61	0.52	0.62	0.55	0.57	0.46	0.61
VA	0.84	0.80	0.43	0.20	0.15	0.09	0.80	0.75	0.42	0.20	0.10	0.09
VT	0.10	0.16	1.53	1.73	0.00	0.68	0.10	0.16	1.53	1.73	0.00	0.68
WA	0.43	0.36	0.72	0.97	0.44	0.27	0.43	0.36	0.74	0.97	0.43	0.26
WI	0.66	0.67	0.45	0.18	0.08	0.14	0.65	0.63	0.34	0.18	0.08	0.14
WV	1.02	0.89	0.22	0.08	0.04	3.06	1.10	0.95	0.30	0.14	0.09	3.06
WY	0.01	0.04	0.06	0.06	0.00	0.05	0.01	0.05	0.06	0.05	0.00	0.05

Table J-8: Baseline and Final Rule Scenario Sulfate Scaling Factors for Coal EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
AL	4.96	5.39	7.07	5.96	0.34	0.55	5.29	5.56	6.77	6.49	0.34	0.55
AR	118.10	7.02	4.45	1.09	0.42	2.83	116.64	7.40	4.45	1.09	0.42	2.85
AZ	0.48	1.42	1.16	0.32	0.31	1.47	0.48	1.42	1.16	0.32	0.31	1.47
CA	0.33	0.50	0.26	0.19	0.00	0.00	0.33	0.50	0.26	0.19	0.00	0.00
CO	14.31	0.98	0.20	0.22	0.21	0.23	14.40	0.98	0.20	0.22	0.21	0.23
CT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FL	0.98	1.16	0.50	0.50	0.38	0.50	0.89	1.03	0.50	0.50	0.38	0.50
GA	0.04	0.09	0.00	0.00	0.00	0.00	0.10	0.23	0.00	0.00	0.00	0.00
IA	1.31	1.25	0.78	0.32	0.21	0.66	1.31	1.27	0.75	0.31	0.21	0.66
ID	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IL	1.01	0.73	0.48	0.10	0.00	0.00	1.01	0.74	0.46	0.08	0.00	0.00
IN	0.89	0.56	0.12	0.13	0.00	0.00	0.91	0.60	0.12	0.13	0.00	0.00
KS	52.35	51.92	11.39	11.39	0.00	0.00	43.14	45.52	11.39	11.39	0.00	0.00
KY	2.68	2.12	1.88	1.71	0.09	0.21	2.41	2.01	1.47	1.39	0.06	0.21

Table J-8: Baseline and Final Rule Scenario Sulfate Scaling Factors for Coal EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
MA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MD	3.54	3.54	3.54	3.54	2.97	3.42	3.54	3.54	3.54	3.54	2.97	3.42
ME	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MI	0.85	0.00	0.00	0.00	0.00	0.00	0.85	0.00	0.00	0.00	0.00	0.00
MN	1.68	1.47	0.00	0.00	0.00	0.00	1.68	1.43	0.00	0.00	0.00	0.00
MO	2.20	1.08	0.71	0.10	0.12	0.36	2.17	1.09	0.70	0.09	0.11	0.35
MS	4.02	3.60	1.06	1.00	1.00	1.00	1.94	3.60	1.06	1.00	1.00	1.00
MT	1.85	2.06	1.92	1.30	0.39	0.86	1.85	2.07	1.89	1.30	0.39	0.86
NC	7.31	5.14	1.88	1.67	2.03	1.38	8.56	4.95	1.89	1.36	1.90	1.38
ND	0.94	1.00	0.94	0.93	0.03	0.03	0.94	1.01	0.94	0.93	0.03	0.03
NE	0.96	0.95	0.58	0.35	0.18	0.57	0.92	0.91	0.57	0.35	0.17	0.57
NH	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NJ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NM	1.00	1.00	0.01	0.01	0.01	0.01	1.00	1.00	0.01	0.01	0.01	0.01
NV	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NY	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OH	0.78	0.61	0.29	0.00	0.00	0.36	0.63	0.65	0.16	0.00	0.00	0.35
OK	37.84	4.77	2.54	2.54	1.68	1.68	37.24	4.85	2.54	2.54	1.68	1.68
OR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PA	4.25	4.06	3.94	1.63	1.83	1.72	4.26	4.15	4.02	1.67	1.85	1.73
RI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SC	0.73	1.22	1.76	1.76	0.00	0.00	0.65	1.22	1.76	1.76	0.00	0.00
SD	1.05	1.27	0.00	0.00	0.00	0.00	1.06	1.27	0.00	0.00	0.00	0.00
TN	20.55	1.57	0.00	0.00	0.00	0.00	20.19	1.57	0.00	0.00	0.00	0.00
TXLA[a]	1.86	2.39	2.25	1.61	0.42	1.29	1.86	2.45	2.28	1.60	0.42	1.28
UT	0.93	0.06	0.06	0.05	0.04	0.02	0.94	0.06	0.06	0.05	0.04	0.02
VA	0.11	0.07	0.02	0.00	0.00	0.00	0.11	0.05	0.02	0.00	0.00	0.00
VT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WI	3.50	3.83	1.15	0.00	0.00	0.69	3.93	3.88	1.11	0.00	0.00	0.69
WV	1.40	1.39	1.08	0.36	0.12	0.13	1.31	1.21	0.75	0.35	0.12	0.13
WY	1.26	0.98	0.97	0.49	0.37	0.37	1.26	0.98	0.97	0.49	0.37	0.37

Note: Emissions of Louisiana are less 10 tpy in the original source apportionment modeling. Air quality impacts and emissions from Texas and Louisiana were combined.

[a] TXLA: Louisiana and Texas

Table J-9: Baseline and Final Rule Primary PM$_{2.5}$ Scaling Factors for Coal EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
AL	1.20	1.31	1.43	1.33	0.14	0.22	1.21	1.36	1.43	1.33	0.14	0.22
AR	20.02	7.10	3.14	0.08	0.03	2.20	19.77	7.32	3.14	0.08	0.03	2.22
AZ	0.38	1.17	0.61	0.18	0.16	0.76	0.38	1.18	0.61	0.17	0.16	0.76
CA	0.24	0.36	0.16	0.13	0.00	0.00	0.24	0.36	0.16	0.13	0.00	0.00
CO	13.37	1.19	0.51	0.54	0.51	0.53	13.47	1.19	0.51	0.54	0.51	0.53
CT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FL	1.40	1.84	0.25	0.25	0.13	0.17	1.32	1.82	0.25	0.25	0.13	0.17

Table J-9: Baseline and Final Rule Primary PM$_{2.5}$ Scaling Factors for Coal EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
GA	0.03	0.06	0.00	0.00	0.00	0.00	0.06	0.14	0.00	0.00	0.00	0.00
IA	1.17	1.14	0.67	0.28	0.19	0.57	1.17	1.16	0.64	0.27	0.19	0.57
ID	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IL	1.17	0.95	0.57	0.03	0.00	0.00	1.17	0.95	0.56	0.02	0.00	0.00
IN	1.28	0.60	0.20	0.20	0.00	0.00	1.32	0.63	0.20	0.20	0.00	0.00
KY	1.30	1.19	0.77	0.36	0.16	0.36	1.03	1.07	0.42	0.34	0.10	0.36
MA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MD	3.54	3.54	3.54	3.54	2.97	3.42	3.54	3.54	3.54	3.54	2.97	3.42
ME	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MI	0.83	0.00	0.00	0.00	0.00	0.00	0.82	0.00	0.00	0.00	0.00	0.00
MN	3.50	2.70	0.00	0.00	0.00	0.00	3.51	2.62	0.00	0.00	0.00	0.00
MO	3.04	1.33	0.54	0.11	0.10	0.26	2.96	1.34	0.54	0.10	0.10	0.25
MS	4.02	3.60	1.06	1.00	1.00	1.00	1.94	3.60	1.06	1.00	1.00	1.00
MT	0.98	0.98	0.98	0.98	0.38	0.79	0.98	0.98	0.98	0.98	0.38	0.78
NC	21.57	17.32	6.08	6.14	6.26	8.67	19.27	14.75	6.12	4.19	6.10	8.67
ND	0.94	0.98	0.78	0.72	0.04	0.08	0.94	0.98	0.78	0.72	0.04	0.08
NEKS[a]	3.70	3.68	0.80	0.50	0.15	0.43	2.81	2.91	0.80	0.50	0.14	0.43
NH	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NJ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NM	0.98	0.99	0.01	0.01	0.01	0.01	0.98	0.99	0.01	0.01	0.01	0.01
NV	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NY	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OH	0.83	1.08	0.19	0.00	0.00	0.46	0.93	1.04	0.24	0.00	0.00	0.46
OK	14.75	8.14	8.94	8.94	1.00	1.00	14.17	8.57	8.94	8.94	1.00	1.00
OR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PA	3.12	3.04	2.28	1.14	1.14	1.10	2.74	2.71	1.91	1.05	1.03	1.01
RI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SC	1.03	2.17	3.78	3.78	0.00	0.00	0.91	2.16	3.78	3.78	0.00	0.00
SD	0.93	1.11	0.00	0.00	0.00	0.00	0.93	1.11	0.00	0.00	0.00	0.00
TN	16.88	1.00	0.00	0.00	0.00	0.00	16.63	1.00	0.00	0.00	0.00	0.00
TXLA[b]	1.10	1.30	1.15	0.65	0.14	0.55	1.11	1.37	1.16	0.65	0.14	0.54
UT	2.92	0.06	0.06	0.06	0.04	0.02	2.89	0.06	0.06	0.06	0.04	0.02
VA	0.46	0.29	0.08	0.00	0.00	0.00	0.46	0.21	0.08	0.00	0.00	0.00
VT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WI	2.11	2.36	0.46	0.00	0.00	0.33	2.10	2.39	0.45	0.00	0.00	0.33
WV	1.29	1.45	1.23	0.56	0.06	0.06	1.29	1.47	1.13	0.55	0.06	0.06
WY	1.03	1.10	1.08	0.54	0.44	0.43	1.03	1.10	1.08	0.54	0.44	0.43

Note: Emissions of Louisiana and Kansas are less 10 tpy in the original source apportionment modeling. Air quality impacts and emissions from those states were combined with nearby states.

[a] NEKS: Nebraska and Kansas

[b] TXLA: Louisiana and Texas

Table J-10: Baseline and Final Rule Primary PM$_{2.5}$ Scaling Factors for Natural Gas EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
AL	0.85	0.84	0.71	0.46	0.31	0.39	0.84	0.82	0.71	0.45	0.31	0.39
AR	0.63	0.82	0.43	0.10	0.07	0.10	0.63	0.81	0.43	0.10	0.06	0.10

Table J-10: Baseline and Final Rule Primary PM$_{2.5}$ Scaling Factors for Natural Gas EGU Tags

State Tag	Baseline						Final Rule					
	2028	2030	2035	2040	2045	2050	2028	2030	2035	2040	2045	2050
AZ	0.70	0.85	0.86	0.74	0.39	0.79	0.70	0.85	0.86	0.73	0.38	0.79
CA	0.96	1.06	0.98	0.77	0.20	0.24	0.96	1.07	0.97	0.77	0.20	0.24
CO	1.23	0.74	0.77	0.75	0.32	0.51	1.22	0.74	0.77	0.73	0.32	0.50
CT	0.78	0.67	0.60	0.00	0.00	0.03	0.78	0.67	0.60	0.00	0.00	0.03
DC	0.15	0.13	0.11	0.10	0.08	0.07	0.15	0.13	0.11	0.09	0.08	0.08
DE	0.62	0.64	0.31	0.27	0.30	0.48	0.59	0.53	0.30	0.26	0.26	0.47
FL	0.97	0.98	0.95	0.77	0.55	0.57	0.97	0.98	0.94	0.77	0.55	0.57
GA	0.84	0.81	0.72	0.41	0.30	0.37	0.84	0.80	0.72	0.41	0.30	0.37
IA	0.50	0.48	0.20	0.06	0.01	0.08	0.50	0.47	0.20	0.07	0.01	0.08
ID	1.22	1.65	1.68	1.49	0.76	1.04	1.21	1.63	1.65	1.47	0.74	1.03
IL	0.49	0.55	0.28	0.13	0.00	0.00	0.49	0.55	0.28	0.13	0.00	0.00
IN	0.67	0.67	0.44	0.15	0.10	0.15	0.66	0.67	0.43	0.15	0.11	0.15
KS	1.11	1.01	0.19	0.08	0.04	0.03	1.12	1.05	0.21	0.09	0.04	0.03
KY	0.75	0.72	0.49	0.34	0.18	0.30	0.90	0.86	0.66	0.45	0.24	0.37
LA	0.79	0.80	0.64	0.29	0.19	0.31	0.79	0.79	0.63	0.28	0.19	0.31
MA	0.48	0.46	0.34	0.28	0.19	0.26	0.48	0.46	0.34	0.28	0.18	0.26
MD	1.05	1.08	0.85	0.63	0.61	0.75	1.01	0.99	0.83	0.63	0.58	0.77
ME	1.75	1.44	0.51	0.50	0.29	0.45	1.74	1.49	0.52	0.52	0.29	0.44
MI	0.75	0.87	0.63	0.48	0.28	0.43	0.75	0.81	0.63	0.46	0.27	0.43
MN	0.57	0.52	0.21	0.08	0.05	0.09	0.53	0.49	0.21	0.08	0.05	0.09
MO	0.30	0.33	0.10	0.03	0.01	0.02	0.28	0.33	0.10	0.02	0.01	0.02
MS	0.88	0.84	0.51	0.32	0.18	0.24	0.86	0.79	0.50	0.31	0.16	0.23
MT	0.17	0.21	0.03	0.03	0.00	0.05	0.17	0.17	0.03	0.03	0.00	0.07
NC	0.87	0.70	0.76	0.60	0.55	0.73	0.86	0.68	0.76	0.59	0.54	0.74
ND	0.47	0.92	0.19	0.43	0.06	0.22	0.47	0.86	0.17	0.43	0.06	0.07
NE	2.35	2.21	0.30	0.78	0.01	0.74	2.32	2.24	0.36	0.78	0.05	0.74
NH	0.59	0.43	0.31	0.27	0.25	0.29	0.59	0.42	0.31	0.27	0.25	0.29
NJ	0.82	0.84	0.52	0.40	0.42	0.77	0.78	0.81	0.47	0.40	0.42	0.76
NM	0.52	0.52	0.89	0.99	0.86	1.34	0.52	0.53	0.89	1.00	0.89	1.36
NV	0.72	0.84	0.83	0.85	0.36	0.28	0.72	0.83	0.83	0.85	0.35	0.28
NY	0.86	0.85	0.59	0.26	0.27	0.28	0.85	0.86	0.58	0.26	0.27	0.28
OH	0.95	0.95	0.89	0.63	0.42	0.63	1.05	1.04	0.97	0.68	0.48	0.63
OK	1.00	0.79	0.22	0.07	0.06	0.06	0.97	0.78	0.22	0.07	0.06	0.06
OR	3.29	0.74	0.39	0.00	0.00	0.00	3.29	0.74	0.39	0.00	0.00	0.00
PA	0.83	0.80	0.60	0.37	0.33	0.51	0.83	0.80	0.61	0.36	0.33	0.51
RI	0.83	0.78	0.65	0.38	0.35	0.34	0.84	0.80	0.66	0.38	0.35	0.34
SC	0.80	0.86	0.64	0.51	0.53	0.77	0.77	0.85	0.63	0.52	0.54	0.77
SD	0.73	0.73	0.25	0.13	0.11	0.21	0.72	0.73	0.19	0.18	0.10	0.22
TN	1.08	1.05	0.88	0.46	0.26	0.39	1.08	1.04	0.86	0.45	0.26	0.35
TX	0.90	0.83	0.45	0.19	0.09	0.24	0.89	0.82	0.45	0.19	0.09	0.24
UT	0.66	0.87	0.84	0.88	0.69	0.92	0.66	0.87	0.84	0.88	0.68	0.92
VA	0.81	0.73	0.47	0.26	0.17	0.12	0.79	0.71	0.47	0.23	0.14	0.12
VT	0.00	0.00	0.03	0.03	0.00	0.01	0.00	0.00	0.03	0.03	0.00	0.01
WA	0.44	0.48	0.58	0.59	0.39	0.36	0.44	0.48	0.58	0.59	0.39	0.36
WI	0.56	0.66	0.43	0.18	0.08	0.15	0.55	0.64	0.36	0.18	0.08	0.15
WV	0.51	0.38	0.10	0.12	0.09	4.54	0.63	0.50	0.23	0.21	0.15	4.54
WY	0.01	0.04	0.03	0.03	0.00	0.01	0.01	0.05	0.03	0.01	0.00	0.01

Table J-11: Baseline and Final Rule Scaling Factors for Other EGU Tags

	Baseline						Final Rule					
State Tag	**2028**	**2030**	**2035**	**2040**	**2045**	**2050**	**2028**	**2030**	**2035**	**2040**	**2045**	**2050**
Seasonal NO_X	1.16	1.16	1.10	1.04	1.03	1.08	1.16	1.16	1.10	1.04	1.03	1.16
Annual NO_X	1.17	1.17	1.11	1.03	1.00	1.06	1.17	1.17	1.11	1.03	1.00	1.17
Annual SO_2	1.00	1.01	1.00	0.90	0.87	0.87	1.00	1.01	1.00	0.90	0.87	1.00
Annual $PM_{2.5}$	1.37	1.37	1.32	1.27	1.20	1.49	1.37	1.37	1.32	1.27	1.20	1.37

J.4 Air Quality Surface Results

The spatial fields of baseline AS-MO3 and Annual Average $PM_{2.5}$ in 2028 are presented in Figure J-8 and J-9, respectively. It is important to recognize that ozone is a secondary pollutant, meaning that it is formed through chemical reactions of precursor emissions in the atmosphere. As a result of the time necessary for precursors to mix in the atmosphere and for these reactions to occur, ozone can either be highest at the location of the precursor emissions or peak at some distance downwind of those emissions sources. The spatial gradients of ozone depend on a multitude of factors including the spatial patterns of NOx and VOC emissions and the meteorological conditions on a particular day. Thus, on any individual day, high ozone concentrations may be found in narrow plumes downwind of specific point sources, may appear as urban outflow with large concentrations downwind of urban source locations or may have a more regional signal. However, in general, because the AS-MO3 metric is based on the average of concentrations over more than 180 days in the spring and summer, the resulting spatial fields are rather smooth without sharp gradients, compared to what might be expected when looking at the spatial patterns of MDA8 ozone concentrations on specific high ozone episode days. $PM_{2.5}$ is made up of both primary and secondary components. Secondary $PM_{2.5}$ species sulfate and nitrate often demonstrate regional signals without large local gradients while primary $PM_{2.5}$ components often have heterogenous spatial patterns with larger gradients near emissions sources. Both secondary and primary $PM_{2.5}$ contribute to the spatial patterns shown in Figure J-9 as demonstrated by the extensive areas of elevated concentrations over much of the Eastern US which have large secondary components and hotspots in urban areas which are impacted by primary PM emissions.

Figure J-10 through Figure J-15 present the model-predicted changes in the AS-MO3 between the baseline and the final rule for 2028, 2030, 2035, 2040, 2045, and 2050 calculated as final rule minus the baseline. Figures J-16 to J-21 present the model-predicted changes in annual average $PM_{2.5}$ between the baseline and final rule for 2028, 2030, 2035, 2040, 2045, and 2050 calculated as the final rule minus the baseline. The spatial patterns shown in the figures are a result of (1) of the spatial distribution of EGU sources that are predicted to have changes in emissions and (2) of the physical or chemical processing that the model simulates in the atmosphere. While SO_2, NO_x and primary $PM_{2.5}$ emissions changes all contributed to the $PM_{2.5}$ changes depicted in Figures J-16 through J-21, the $PM_{2.5}$ component species with the larger changes was sulfate and consequently the SO_2 emissions changes have the largest impact on predicted changes in $PM_{2.5}$ concentrations through sulfate, ammonium and particle-bound water impacts. The spatial fields used to create these maps serve as an input to the benefits analysis.

Figure J-8: Map of AS-MO3 in the 2028 Baseline

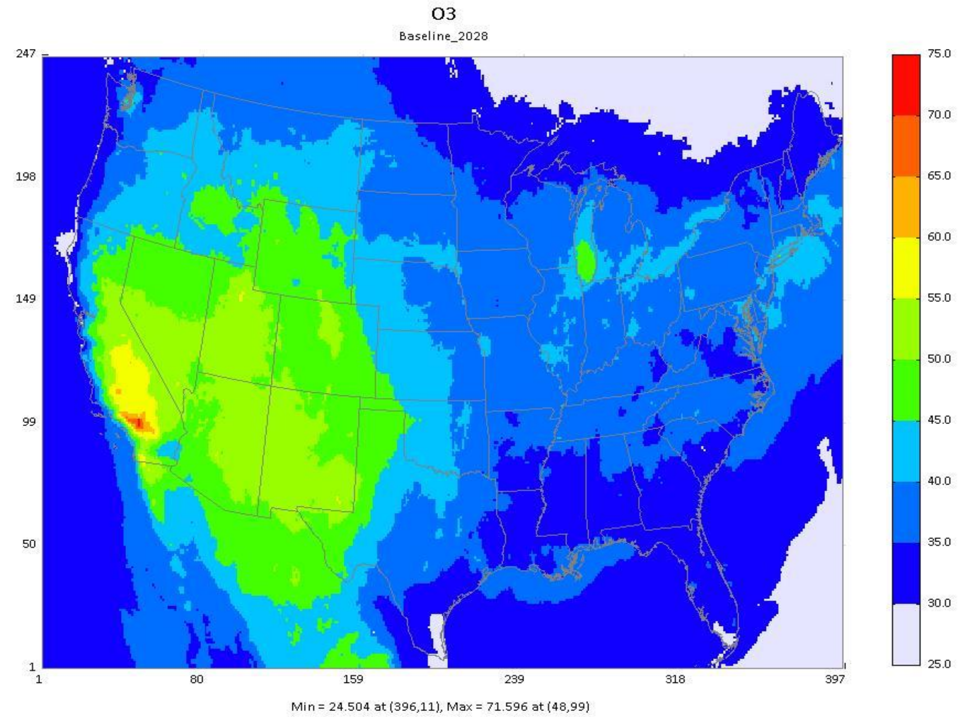


Figure J-9: Map of Annual Average PM$_{2.5}$ in the 2028 Baseline

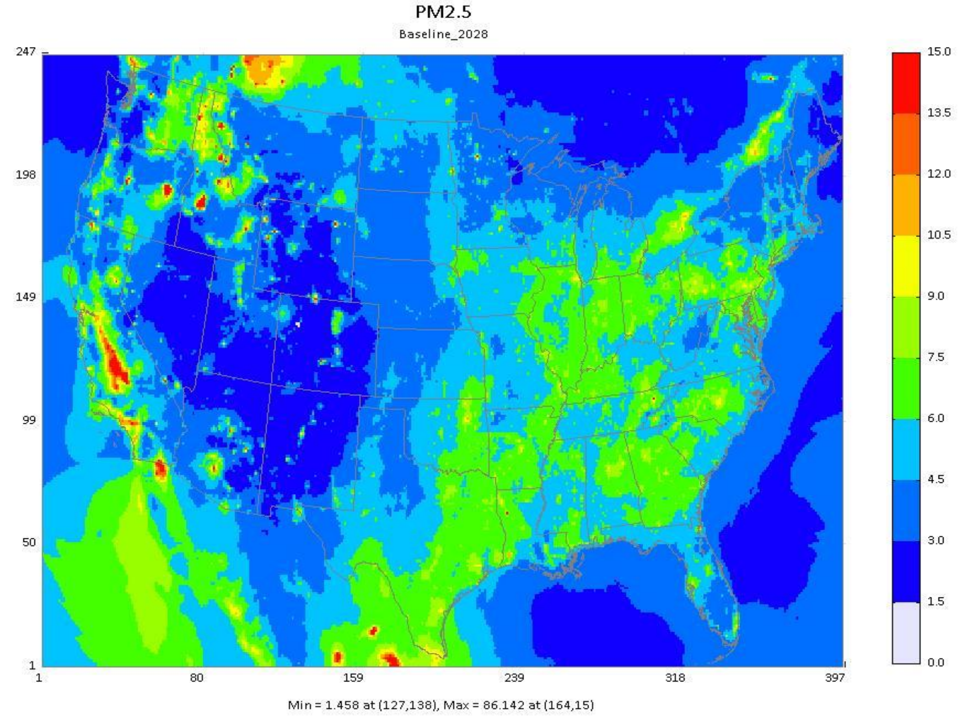


Figure J-10: Map of Change in Apr-September MDA8 Ozone (ppb): 2028 Final Rule – Baseline

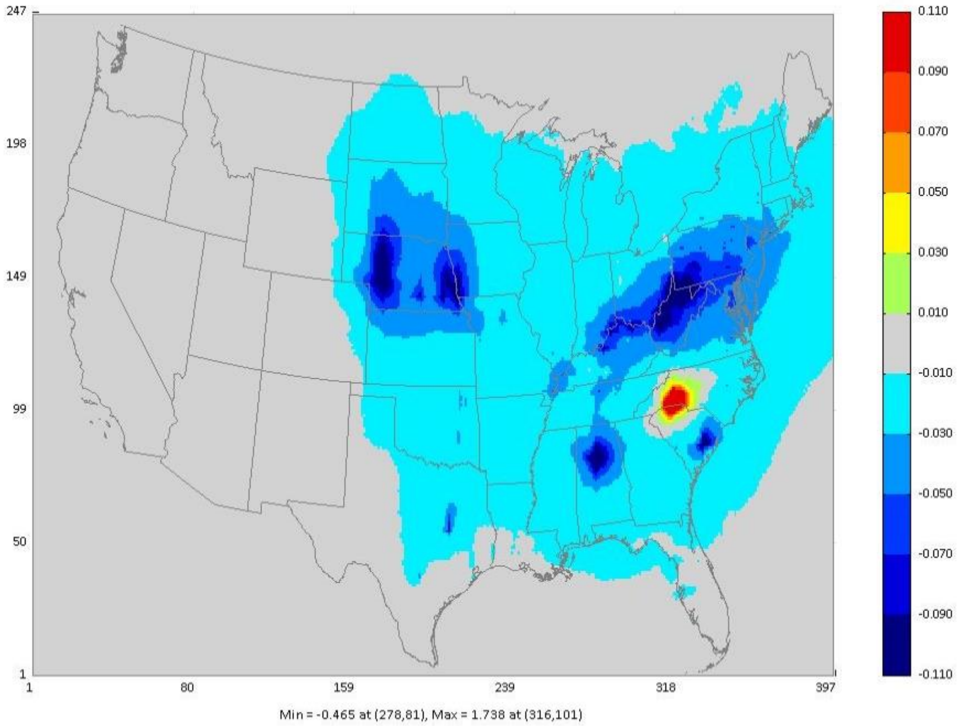


Figure J-11: Map of Change in Apr-September MDA8 Ozone (ppb): 2030 Final Rule – Baseline

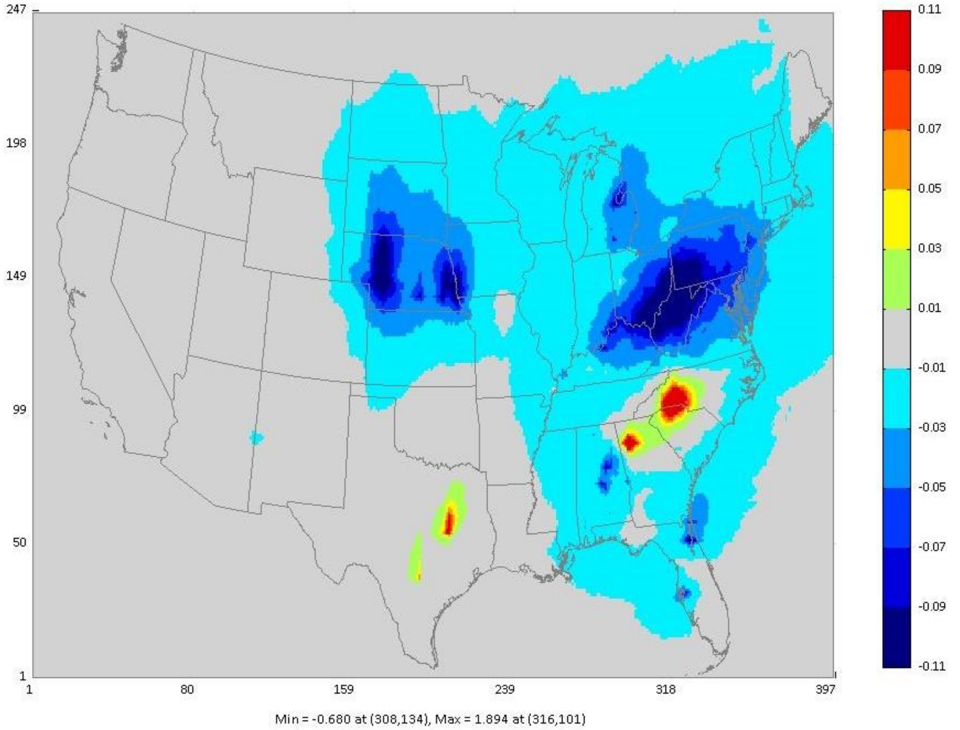


Figure J-12: Map of Change in Apr-September MDA8 Ozone (ppb): 2035 Final Rule – Baseline

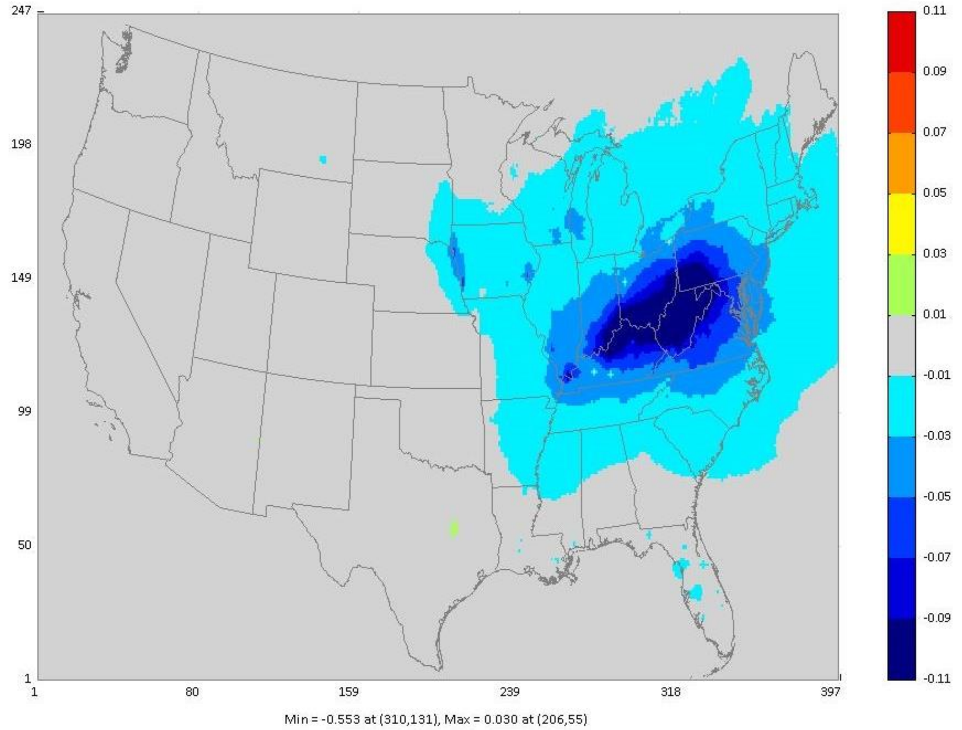


Figure J-13: Map of Change in Apr-September MDA8 Ozone (ppb): 2040 Final Rule – Baseline

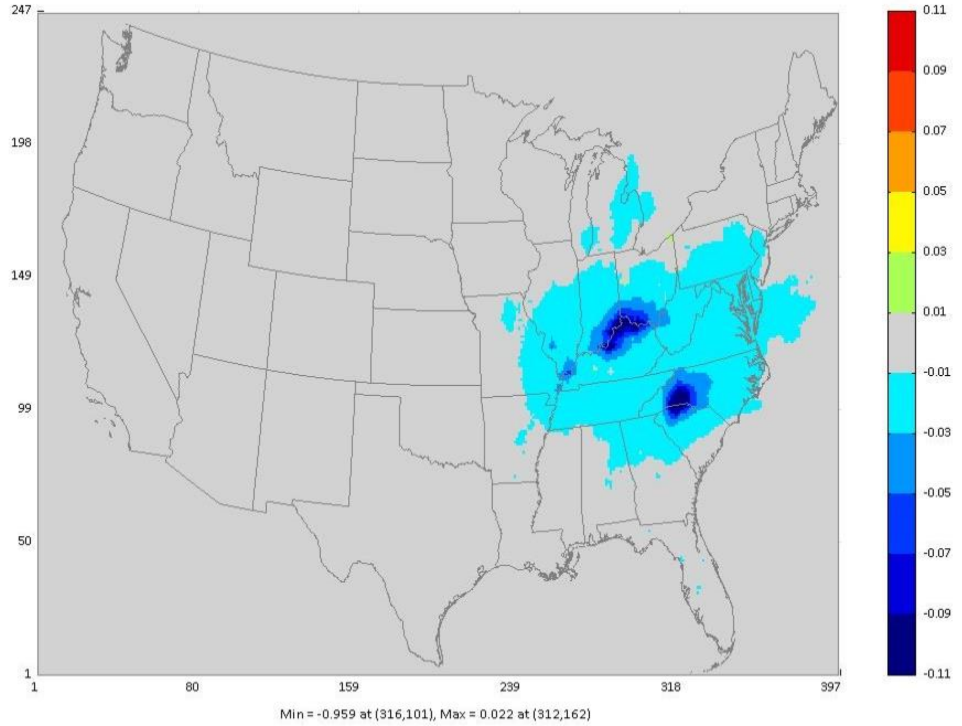
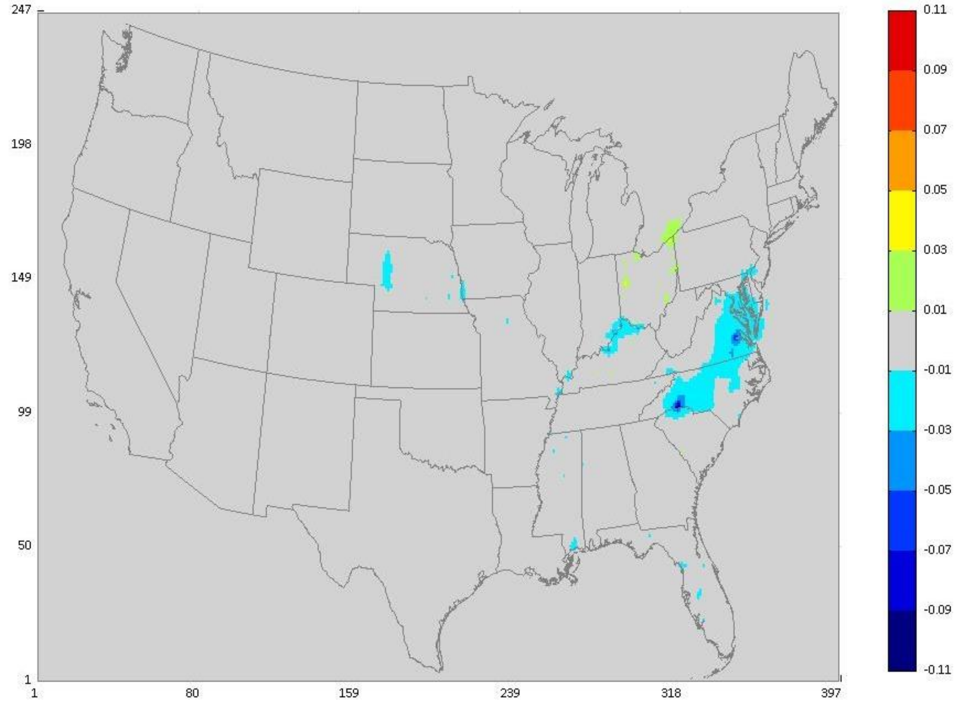
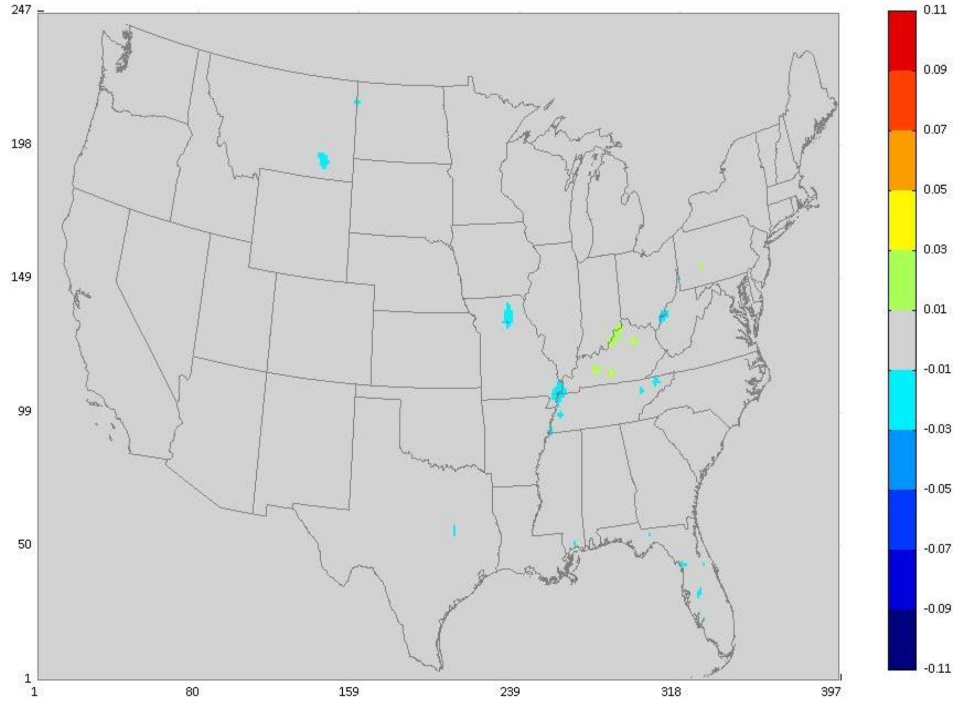


Figure J-14: Map of Change in Apr-September MDA8 Ozone (ppb): 2045 Final Rule – Baseline



Min = -0.186 at (316,101), Max = 0.036 at (290,147)

Figure J-15: Map of Change in Apr-September MDA8 Ozone (ppb): 2050 Final Rule – Baseline



Min = -0.043 at (257,106), Max = 0.042 at (275,114)

Figure J-16: Map of Change in Annual Mean $PM_{2.5}$ ($\mu g/m^3$): 2028 Final Rule – Baseline

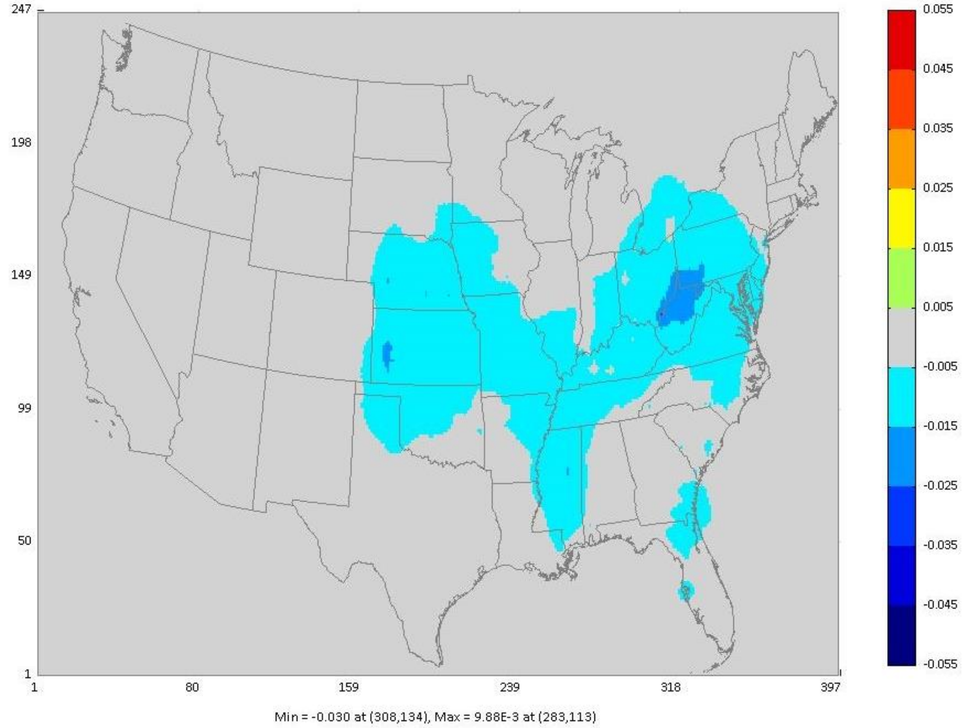


Figure J-17: Map of Change in Annual Mean $PM_{2.5}$ ($\mu g/m^3$): 2030 Final Rule – Baseline

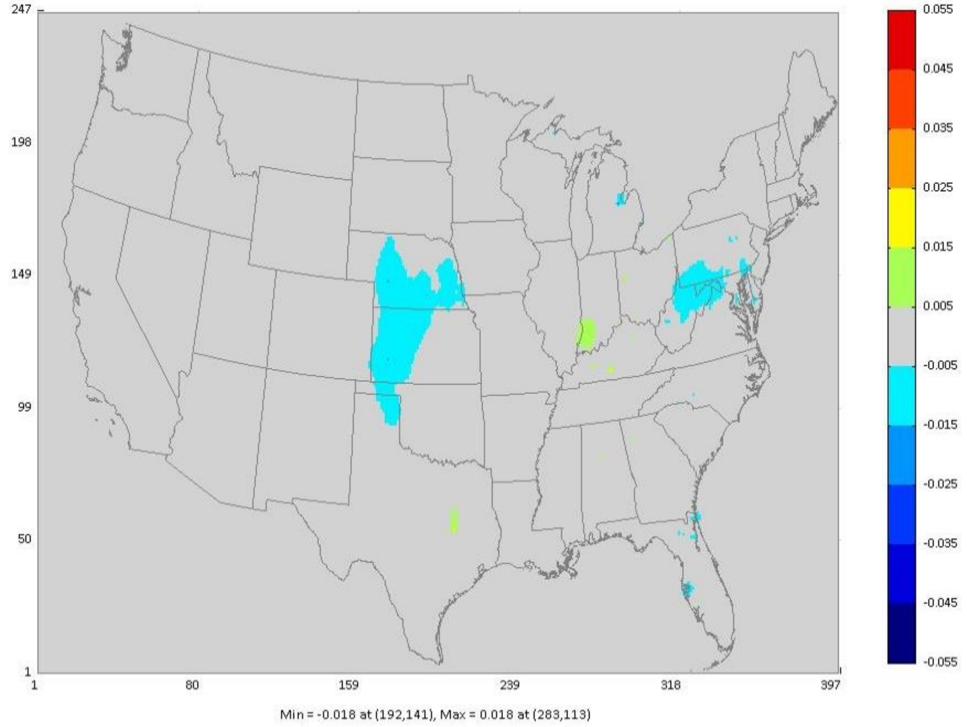
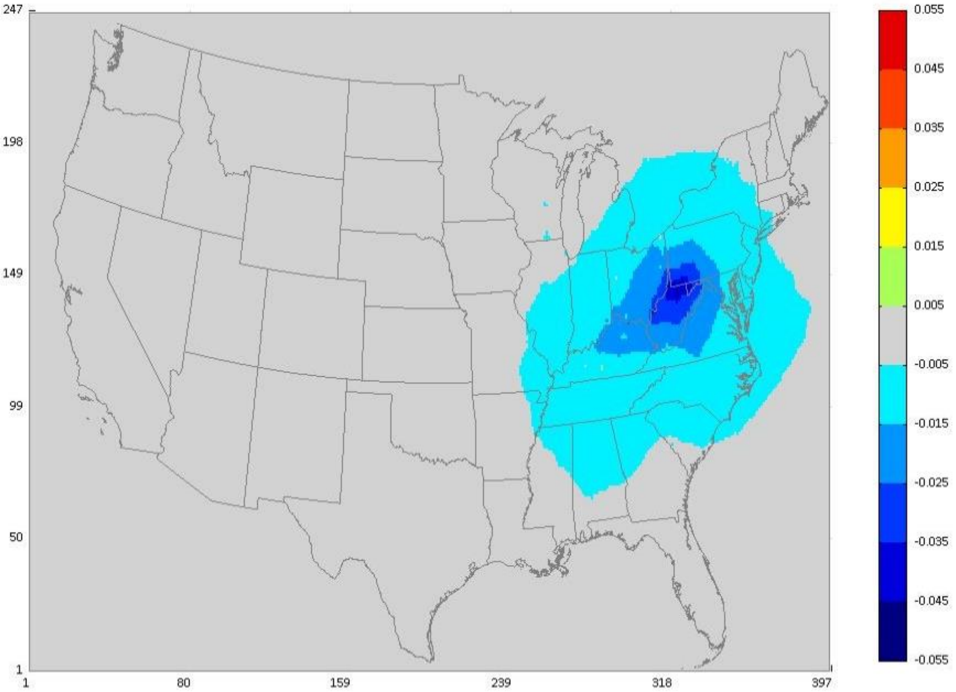
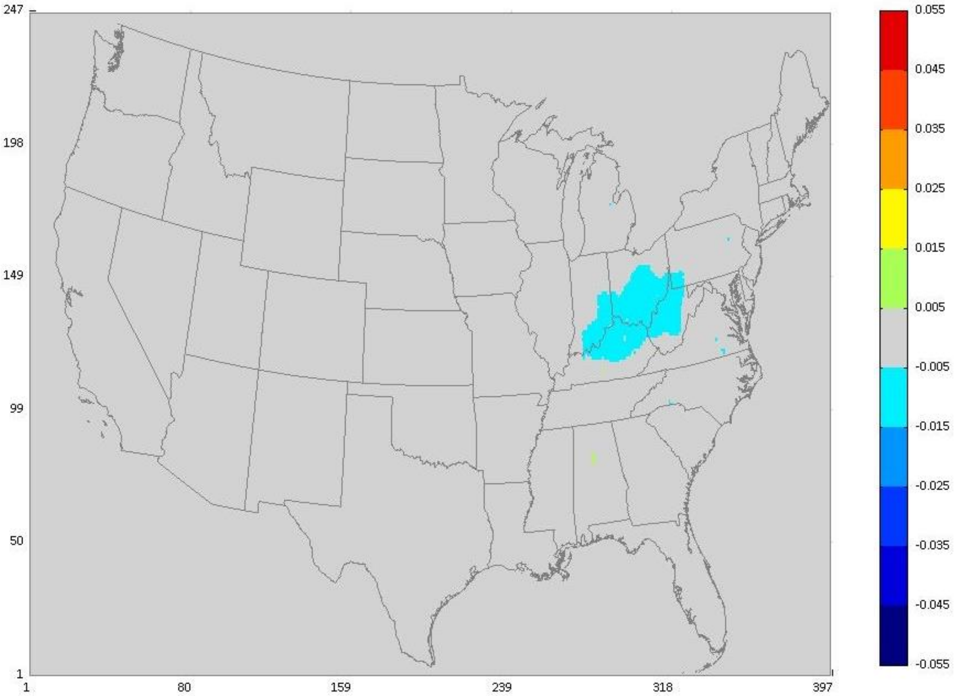


Figure J-18: Map of Change in Annual Mean $PM_{2.5}$ ($\mu g/m^3$): 2035 Final Rule – Baseline



Min = -0.055 at (320,141), Max = 6.38E-3 at (283,113)

Figure J-19: Map of Change in Annual Mean $PM_{2.5}$ ($\mu g/m^3$): 2040 Final Rule – Baseline



Min = -0.012 at (296,130), Max = 0.012 at (278,81)

Figure J-20: Map of Change in Annual Mean $PM_{2.5}$ ($\mu g/m^3$): 2045 Final Rule – Baseline

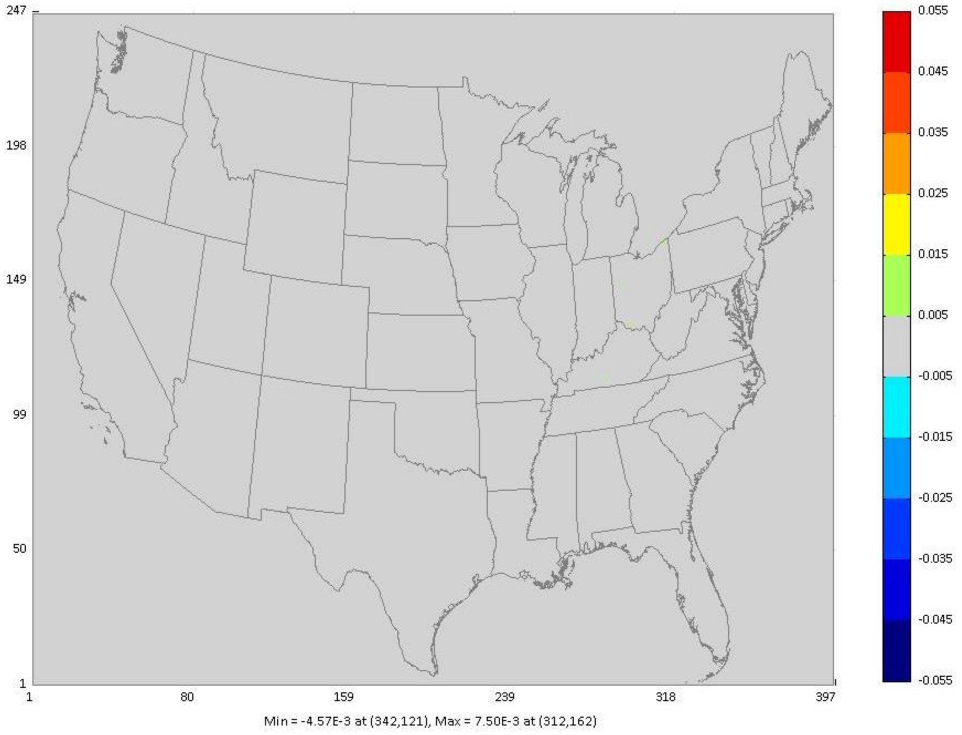
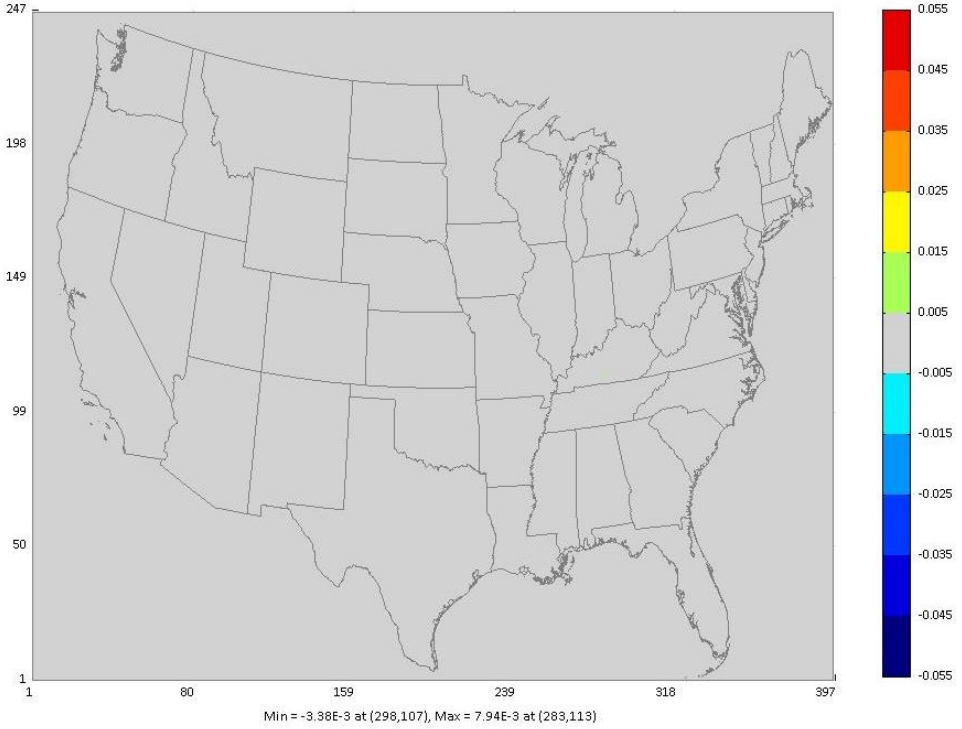


Figure J-21: Map of Change in Annual Mean $PM_{2.5}$ ($\mu g/m^3$): 2050 Final Rule – Baseline



J.5 Uncertainties and Limitations of the Air Quality Methodology

One limitation of the scaling methodology for creating ozone and $PM_{2.5}$ surfaces associated with the baseline or final rule scenarios described above is that the methodology treats air quality changes from the tagged sources as linear and additive. It therefore does not account for nonlinear atmospheric chemistry and does not account for interactions between emissions of different pollutants and between emissions from different tagged sources. The method applied in this analysis is consistent with how air quality estimations have been made in several prior regulatory analyses (U.S. EPA, 2012, 2019h, 2020d). We note that air quality is calculated in the same manner for the baseline and for the final rule, so any uncertainties associated with these assumptions is propagated through results for both the baseline and final rule scenarios in the same manner. In addition, emissions changes between baseline and the final rule are relatively small compared to modeled future year emissions that form the basis of the source apportionment approach described in this appendix. Previous studies have shown that air pollutant concentrations generally respond linearly to small emissions changes of up to 30 percent (Cohan & Napelenok, 2011; Cohan et al., 2005; Dunker et al., 2002; Koo, Dunker & Yarwood, 2007; Napelenok et al., 2006; Zavala et al., 2009). A second limitation is that the source apportionment contributions are informed by the spatial and temporal distribution of the emissions from each source tag as they occur in the future year modeled case. Thus, the contribution modeling results do not allow us to consider the effects of any changes to spatial distribution of EGU emissions within a state-fuel tag between the future year modeled case and the baseline and final rule scenarios analyzed in this RIA. Finally, the future year CAMx-modeled concentrations themselves have some uncertainty. While all models have some level of inherent uncertainty in their formulation and inputs, the base-year 2016 model outputs have been evaluated against ambient measurements and have been shown to adequately reproduce spatially and temporally varying concentrations.