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

United States Environmental Protection Agency

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U.S. Environmental Protection Agency
Office of Water (4303T)
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Abbreviations

ACE	Affordable Clean Energy
ACS	American Community Survey
ADD	Average daily dose
AFSC	Alaska Fisheries Science Center
ASMFC	Atlantic States Marine Fisheries Commission
As	Arsenic
BA	Bottom ash
BAT	Best available technology economically achievable
BCA	Benefit-cost-analysis
BEA	Bureau of Economic Analysis
BenMAP	Environmental Benefits Mapping and Analysis Program
BLS	Bureau of Labor Statistics
BMP	Best management practices
BOD	Biochemical oxygen demand
BPT	Best practicable control technology currently available
BW	Body weight
C&D	Construction and development
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
CO_2	Carbon dioxide
COD	Chemical oxygen demand
COI	Cost-of-illness
COPD	Chronic obstructive pulmonary disease
CPI	Consumer Price Index
CSF	Cancer slope factor
CVD	Cardiovascular disease
CWA	Clean Water Act
D-FATE	Downstream Fate and Transport Equations
DBP	Disinfection byproduct
DBPR	Disinfectants and Disinfection Byproduct Rule
DCN	Document Control Number
DHHS	Department of Health and Human Services
DO	Dissolved oxygen
DOE	Department of Energy
E2RF1	Enhanced River File 1
EA	Environmental Assessment
ECI	Employment Cost Index
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
FC	Fecal coliform
FCA	Fish consumption advisories
FGD	Flue gas desulfurization
FR	Federal Register
GDP	Gross Domestic Product
GHG	Greenhouse gas
GIS	Geographic Information System
HAA	Haloacetic acids
Hg	Mercury
HISA	Highly influential scientific assessment
HRTR	High Residence Time Reduction
HUC	Hydrologic unit code
IAM	Integrated assessment model
ICR	Information Collection Rule
IEUBK	Integrated Exposure, Uptake, and Biokinetics
IPCC	Intergovernmental Panel on Climate Change
IPM	Integrated Planning Model
ISA	Integrated science assessment
IRIS	Integrated Risk Information System
IQ	Intelligence quotient
LADD	Lifetime average daily dose
LML	Lowest measured level
LRTR	Low Residence Time Reduction
MCL	Maximum contaminant level
MCLG	Maximum contaminant level goal
MGD	Million gallons per day
MRM	Meta-regression model
MWTP	Marginal willingness-to-pay
NCHS	National Center for Health Statistics
NEFSC	Northeast Fisheries Science Center
NERC	North American Electric Reliability Corporation
NHD	National Hydrography Dataset
NLCD	National Land Cover Dataset
NMFS	National Marine Fisheries Service
NOAA	National Oceanic and Atmospheric Administration
NO_X	Nitrogen oxides
NPDES	National Pollutant Discharge Elimination System
NRWQC	National Recommended Water Quality Criteria
NWIS	National Water Information System
OAQPS	Office of Air Quality Planning and Standards
O&M	Operation and maintenance
OMB	Office of Management and Budget

OSHA	Occupational Safety and Health Administration
OTSA	Oklahoma Tribal Statistical Area
PAM	Below the poverty level and minority
Pb	Lead
PbB	Blood lead concentration
PIFSC	Pacific Islands Fisheries Science Center
PM	Particulate matter
POM	Below the poverty level or minority
ppm	parts per million
PSES	Pretreatment Standards for Existing Sources
PWS	Public water system
QA	Quality assurance
QC	Quality control
RIA	Regulatory Impact Analysis
RSEI	Risk-Screening Environmental Indicators
SAB	Science Advisory Board
SBREFA	Small Business Regulatory Enforcement Fairness Act
SCC	Social cost of carbon
SC-CO_2	Domestic social cost of carbon
SDWIS	Safe Drinking Water Information System
Se	Selenium
SEER	Surveillance, Epidemiology, and End Results
SEFSC	Southeast Fisheries Science Center
SO_2	Sulfur dioxide
SPARROW	SPAtially Referenced Regressions On Watershed attributes
STORET	STOrage and RETrieval Data Warehouse
SWAT	Surface Water Analytical Tool
SWFSC	Southwest Fisheries Science Center
T&E	Threatened and endangered
TDD	Technical Development Document
TDS	Total dissolved solids
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-compliance water quality index
WQL	Water quality ladder
WTP	Willingness-to-pay

Executive Summary

The U.S. Environmental Protection Agency (EPA) is proposing a regulation that would revise the technology-based effluent limitations guidelines and standards (ELGs) for the steam electric power generating point source category, 40 CFR part 423, which the EPA promulgated in November 2015 (80 FR 67838). The regulatory options would revise certain best available technology (BAT) effluent limitations and pretreatment standards for existing sources (PSES) for two wastestreams: flue gas desulfurization (FGD) wastewater and bottom ash transport water.

Regulatory Options

The EPA analyzed four regulatory options, summarized in Table ES-1. The baseline for the analyses reflects ELG requirements (in absence of any new final EPA action).[1] The Agency calculated the difference between the baseline and the regulatory options to determine the net incremental effect (as positive or negative change) of the regulatory options. The EPA is proposing Option 2. The incremental effects between the baseline and Option 2 are very small and are expected to yield very small benefits (positive or negative).

Table ES-1: Regulatory Options

Wastestream	Subcategory	Technology Basis for BAT/PSES Regulatory Options[a]				
		2015 Rule (Baseline)	Option 1	Option 2	Option 3	Option 4
FGD Wastewater	NA[b]	Chemical Precipitation + HRTR Biological Treatment	Chemical Precipitation	Chemical Precipitation + LRTR Biological Treatment	Chemical Precipitation + LRTR Biological Treatment	Membrane Filtration
	High FGD Flow Facilities: Plant-level scrubber purge flow >4 MGD	NS	NS	Chemical Precipitation	Chemical Precipitation	Chemical Precipitation
	Low Utilization Boilers: All units have net generation ≤ 876,000 MWh	NS	NS	Chemical Precipitation	NS	NS
	Boilers retiring by 2028	NS	Surface Impoundment	Surface Impoundment	Surface Impoundment	Surface Impoundment
FGD Wastewater Voluntary Incentives Program (Direct Dischargers Only)		Chemical Precipitation + Evaporation	Membrane Filtration	Membrane Filtration	Membrane Filtration	NA
Bottom Ash Transport Water	NA[b]	Dry Handling / Closed loop	Dry Handling or High Recycle Rate Systems	Dry Handling or High Recycle Rate Systems	Dry Handling or High Recycle Rate Systems	Dry Handling or High Recycle Rate Systems
	Low Utilization Boilers: All units have net generation ≤ 876,000 MWh	NS	NS	Surface Impoundment + BMP Plan	NS	NS
	Boilers retiring by 2028	NS	Surface Impoundment	Surface Impoundment	Surface Impoundment	Surface Impoundment

[1] This includes the 2015 rule as well as the September 2017 postponement rule which delayed the earliest compliance date for the ELGs applicable to FGD wastewater and bottom ash transport water.

Table ES-1: Regulatory Options						
		Technology Basis for BAT/PSES Regulatory Options[a]				
Wastestream	**Subcategory**	**2015 Rule (Baseline)**	**Option 1**	**Option 2**	**Option 3**	**Option 4**

Abbreviations: BMP = Best Management Practice; HRTR = High Residence Time Reduction; LRTR = Low Residence Time Reduction; NS = Not subcategorized; NA = Not applicable

a. See *Supplemental TDD* for a description of these technologies.

b. The 2015 rule subcategorized units with nameplate capacity 50 MW or less and the EPA is not revising requirements for these units in this proposal.

Source: U.S. EPA Analysis, 2019

Benefits of Regulatory Options

The EPA estimated the potential social welfare effects of the regulatory options and, where possible, quantified and monetized the benefits (see Chapters *3* through *11* for details of the methodology and results). Table ES-2 and Table ES-3 summarize the benefits that the EPA quantified and monetized using 3 percent and 7 percent discounts, respectively. In the tables, positive values indicate improvements in social welfare, relative to the baseline, whereas negative values reflect forgone benefits of the regulatory options, *i.e.*, social welfare losses. In general, the estimated effects of implementing the regulatory options are small compared to those estimated in 2015 (see U.S. EPA, 2015a).

The EPA quantified but did not monetize other welfare effects of the regulatory options, including expected changes of pollutant concentrations in excess of human health-based NRWQC limits, and discusses other potential welfare effects qualitatively, including impacts to commercial fisheries or changes in the marketability of coal ash for beneficial use; the EPA evaluated these effects qualitatively in *Chapter 2*.

Table ES-2: Summary of Total Annualized Benefits at 3 Percent (Millions; 2018$)

Benefit Category	Option 1[a]			Option 2[a]			Option 3[a]			Option 4[a]		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Human Health		**-$0.7**			**$34.8**			**$39.7**			**$82.8**	
Changes in IQ losses in children from exposure to lead[b]		<$0.0			<$0.0			<$0.0			<$0.0	
Changes in IQ losses in children from exposure to mercury		-$0.3			-$2.8			-$2.9			-$1.5	
Changes in cancer risk from DBPs in drinking water		-$0.4			$37.6			$42.6			$84.3	
Ecological Conditions and Recreational Uses Changes	**-$10.0**	**-$12.5**	**-$55.5**	**$11.8**	**$16.7**	**$65.6**	**$16.3**	**$22.5**	**$90.7**	**$19.8**	**$27.3**	**$110.2**
Use and nonuse values for water quality changes	-$10.0	-$12.5	-$55.5	$11.8	$16.7	$65.6	$16.3	$22.5	$90.7	$19.8	$27.3	$110.2
Market and Productivity	**-$0.1**	**-$0.1**	**-$0.1**	**-$0.2**	**-$0.2**	**-$0.2**	**-$0.1**	**-$0.1**	**-$0.1**	**$0.6**	**$0.6**	**$0.7**
Changes in dredging costs	-$0.1	-$0.1	-$0.1	-$0.1	-$0.2	-$0.2	-$0.1	-$0.1	-$0.1	$0.6	$0.6	$0.7
Reduced water withdrawals[b]		$0.0			<$0.0			$0.0			$0.0	
Air-related effects		**-$30.3**			**-$31.6**			**-$20.9**			**-$4.8**	
Changes in CO_2 air emissions[c]		-$30.3			-$31.6			-$20.9			-$4.8	
Total[d]	**-$41.0**	**-$43.6**	**-$86.6**	**$14.8**	**$19.6**	**$68.5**	**$35.1**	**$41.3**	**$109.4**	**$98.4**	**$105.9**	**$188.9**

Table ES-2: Summary of Total Annualized Benefits at 3 Percent (Millions; 2018$)

Benefit Category	Option 1[a]			Option 2[a]			Option 3[a]			Option 4[a]		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High

a. Negative values represent forgone benefits and positive values represent realized benefits.

b. "<$0.0" indicates that monetary values are greater than -$0.1 million but less than $0.00 million.

c. The EPA estimated the air-related benefits for Option 2 using the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE). EPA extrapolated estimates for Options 1 and 3 air-related benefits from the estimate for Option 2 that is based on IPM-ACE outputs. The values for Option 4 air-related benefits were estimated using the IPM analysis scenario that does not include the ACE rule in the baseline.

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

Source: U.S. EPA Analysis, 2019

Table ES-3: Summary of Total Annualized Benefits at 7 Percent (Millions; 2018$)

Benefit Category	Option 1[a]			Option 2[a]			Option 3[a]			Option 4[a]		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Human Health		**-$0.3**			**$23.6**			**$26.9**			**$54.0**	
Changes in IQ losses in children from exposure to lead[b]		<$0.0			<$0.0			<$0.0			<$0.0	
Changes in IQ losses in children from exposure to mercury[b]		-$0.1			-$0.6			-$0.6			-$0.3	
Changes in cancer risk from DBPs in drinking water		-$0.2			$24.2			$27.5			$54.3	
Ecological Conditions and Recreational Uses Changes	**-$8.6**	**-$10.9**	**-$48.1**	**$10.1**	**$14.3**	**$56.1**	**$14.0**	**$19.4**	**$77.8**	**$17.0**	**$23.6**	**$94.6**
Use and nonuse values for water quality changes	-$8.6	-$10.9	-$48.1	$10.1	$14.3	$56.1	$14.0	$19.4	$77.8	$17.0	$23.6	$94.6
Market and Productivity	**-$0.1**	**-$0.1**	**-$0.1**	**-$0.1**	**-$0.2**	**-$0.2**	**$0.0**	**-$0.1**	**-$0.1**	**$0.5**	**$0.5**	**$0.7**
Changes in dredging costs	-$0.1	-$0.1	-$0.1	-$0.1	-$0.1	-$0.2	$0.0	-$0.1	-$0.1	$0.5	$0.5	$0.7
Reduced water withdrawals[b]		$0.0			<$0.0			$0.0			$0.0	
Air-related Effects		**-$4.8**			**-$5.2**			**-$3.7**			**-$0.9**	
Changes in CO_2 air emissions[c]		-$4.8			-$5.2			-$3.7			-$0.9	
Total[d]	**-$13.7**	**-$16.0**	**-$53.3**	**$28.4**	**$32.6**	**$74.4**	**$37.1**	**$42.5**	**$100.9**	**$70.6**	**$77.2**	**$148.4**

a. Negative values represent forgone benefits and positive values represent realized benefits.

b. "<$0.0" indicates that monetary values are greater than -$0.1 million but less than $0.00 million.

c. The EPA estimated the air-related benefits for Option 2 using the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE). EPA extrapolated estimates for Options 1 and 3 air-related benefits from the estimate for Option 2 that is based on IPM-ACE outputs. The values for Option 4 air-related benefits were estimated using the IPM analysis scenario that does not include the ACE rule in the baseline.

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

Source: U.S. EPA Analysis, 2019

Social Costs of Regulatory Options

Table ES-5 presents the incremental costs attributable to the regulatory options, calculated as the difference between each option and the baseline. The regulatory options generally result in cost savings across the four options and discount rates, with the exception of Option 4 which results in additional costs at 3 percent discount rate. *Chapter 12* describes the social cost analysis. The compliance costs of the regulatory options are detailed in the Regulatory Impact Analysis (RIA) document.

Comparison of Benefits and Social Costs of Regulatory Options

In accordance with the requirements of Executive Order 12866: Regulatory Planning and Review and Executive Order 13563: Improving Regulation and Regulatory Review, the EPA compared the benefits and costs of each regulatory option. Table ES-5 presents the incremental monetized benefits and incremental social costs attributable to the regulatory options, calculated as the difference between each option and the baseline.

Table ES-5: Total Annualized Benefits and Social Costs by Regulatory Option and Discount Rate (Millions; 2018$)

Regulatory Option	Total Monetized Benefits			Total Costs
	Low	Mid	High	
3% Discount Rate				
Option 1	-$41.0	-$43.6	-$86.6	-$130.6
Option 2	$14.8	$19.6	$68.5	-$136.3
Option 3	$35.1	$41.3	$109.4	-$90.1
Option 4	$98.4	$105.9	$188.9	$11.9
7% Discount Rate				
Option 1	-$13.7	-$16.0	-$53.3	-$154.0
Option 2	$28.4	$32.6	$74.4	-$166.2
Option 3	$37.1	$42.5	$100.9	-$119.5
Option 4	$70.6	$77.2	$148.4	-$27.3

Source: U.S. EPA Analysis, 2019.

1 Introduction

The EPA is proposing a regulation that would revise the technology-based ELGs for the steam electric power generating point source category, 40 CFR part 423, which the EPA promulgated in November 2015 (80 FR 67838). The proposed rule would revise certain effluent limitations based on BAT and pretreatment standards for existing sources for two wastestreams: FGD wastewater and bottom ash transport water (BA).

This document presents an analysis of the social benefits and social costs of the regulatory options, including the proposed option (Option 2), and complements other analyses the EPA conducted in support of this proposal, described in separate documents:

- *Supplemental Environmental Assessment for the Reconsideration of the Effluent Guidelines and Standards for the Steam Electric Power Generating Point Source Category* (Supplemental EA; U.S. EPA, 2019a). The *Supplemental EA* summarizes the environmental and human health improvements that are expected to result from implementation of the proposed ELGs.

- *Supplemental Technical Development Document for the Reconsideration of the Effluent Guidelines and Standards for the Steam Electric Power Generating Point Source Category* (Supplemental TDD; U.S. EPA, 2019b). The *Supplemental TDD* provides background on the ELGs; industry description; wastewater characterization and identification of pollutants of concern; and treatment technologies and pollution prevention techniques. It also documents the EPA's engineering analyses to support the regulatory options including plant-specific compliance cost estimates, pollutant loadings, and non-water quality impact assessment.

- *Regulatory Impact Analysis for Proposed Revisions to the Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category* (RIA; U.S. EPA, 2019c). The RIA describes the 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 12* 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 13211 on Actions Concerning Regulations That Significantly Affect Energy Supply, Distribution, or Use, and others.

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

The analyses of the regulatory options are based on data generated or obtained in accordance with the EPA's Quality Policy and Information Quality Guidelines. The 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 the 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 CFR 423.10).

Based on data the EPA obtained from the U.S. Department of Energy (DOE) (U.S. DOE, 2017), the 2010 Questionnaire for the Steam Electric Power Generating Effluent Guidelines (industry survey; U.S. EPA, 2010c) and other sources (see *Supplemental TDD*, U.S. EPA, 2019b), as well as adjustments to the 2015 rule universe to account for actual or announced unit and plant retirements or conversions, the EPA estimates that there are 951 plants in the steam electric power generating industry. Of these, only a subset may incur compliance costs under the regulatory options: coal fired power plants that discharge bottom ash transport water or FGD wastewater. See *Supplemental TDD* and *RIA* for details (U.S. EPA, 2019b; 2019c).

1.2 Baseline and Regulatory Options Analyzed

The EPA presents four regulatory options (see Table 1-1). These options differ in the stringency of controls and applicability of these controls to units or plants based on generation capacity, net power generation, and scrubber purge flow (see *Supplemental TDD* for a detailed discussion of the options and the associated treatment technology bases). Additionally, under Options 1, 2 and 3, steam electric power plants may elect to participate in the Voluntary Incentive Program (VIP) which requires them to meet more stringent limits for FGD wastewater in exchange for additional time to comply with those limits.

The baseline for this analysis reflects applicable requirements (in absence of any new final EPA action).[2] The agency estimated and presents in this report the water quality and other environmental effects of bottom ash transport water and FDG wastewater discharges under both this 2015 rule baseline and each of the four regulatory options presented in Table 1-1. The Agency calculated the difference between the baseline and the regulatory options to determine the net effect of any regulatory options. The changes attributable to the regulatory options are the difference between each option and the baseline.

2 This includes the 2015 rule as well as the September, 2017 postponement rule which delayed the earliest compliance date for the ELGs applicable to FGD wastewater and bottom ash transport water.

Table 1-1: Regulatory Options

Wastestream	Subcategory	Technology Basis for BAT/PSES Regulatory Options[a]				
		2015 Rule (Baseline)	**Option 1**	**Option 2**	**Option 3**	**Option 4**
FGD Wastewater	NA[b]	Chemical Precipitation + HRTR Biological Treatment	Chemical Precipitation	Chemical Precipitation + LRTR Biological Treatment	Chemical Precipitation + LRTR Biological Treatment	Membrane Filtration
	High FGD Flow Facilities: Plant-level scrubber purge flow >4 MGD	NS	NS	Chemical Precipitation	Chemical Precipitation	Chemical Precipitation
	Low Utilization Boilers: All units have net generation ≤ 876,000 MWh	NS	NS	Chemical Precipitation	NS	NS
	Boilers retiring by 2028	NS	Surface Impoundment	Surface Impoundment	Surface Impoundment	Surface Impoundment
FGD Wastewater Voluntary Incentives Program (Direct Dischargers Only)		Chemical Precipitation + Evaporation	Membrane Filtration	Membrane Filtration	Membrane Filtration	NA
Bottom Ash Transport Water	NA[b]	Dry Handling / Closed loop	Dry Handling or High Recycle Rate Systems	Dry Handling or High Recycle Rate Systems	Dry Handling or High Recycle Rate Systems	Dry Handling or High Recycle Rate Systems
	Low Utilization Boilers: All units have net generation ≤ 876,000 MWh	NS	NS	Surface Impoundment + BMP Plan	NS	NS
	Boilers retiring by 2028	NS	Surface Impoundment	Surface Impoundment	Surface Impoundment	Surface Impoundment

Abbreviations: BMP = Best Management Practice; HRTR = High Residence Time Reduction; LRTR = Low Residence Time Reduction; NS = Not subcategorized; NA = Not applicable

a. See *Supplemental TDD* for a description of these technologies.

b. The 2015 rule subcategorized units with nameplate capacity 50 MW or less and the EPA is not revising requirements for these units in this proposal.

Source: U.S. EPA Analysis, 2019

1.3 Analytic Framework

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

1. All values are presented in 2018 dollars;
2. Future benefits and costs are discounted using rates of 3 percent and 7 percent back to 2020, which is the projected promulgation year for a final rule;
3. Benefits and costs are analyzed over a 27-year period (2021 to 2047);
4. Benefits and costs are annualized;
5. Positive values represent improvements in environmental conditions, whereas negative values represent forgone benefits of the regulatory options compared to the baseline; and
6. Future values account for annual U.S. population and income growth, unless noted otherwise.

These components are discussed in the sections below.

The EPA's analysis of the regulatory options generally follows the methodology the Agency used previously to analyze the 2015 rule (see *Benefit and Cost Analysis for the Final Effluent Limitations Guidelines and Standards for the Steam Electric Power Generating Point Source Category* (U.S. EPA, 2015a). In analyzing the regulatory options, however, the EPA made several changes relative to the analysis of the 2015 rule:

- The EPA used revised inputs that reflect the costs and loads estimated for the regulatory options (see *TDD* and *RIA* for details).
- The EPA updated the baseline information to incorporate changes in the universe and operational characteristics of steam electric power plants such as electricicty generating unit retirements and fuel conversions since the analysis of the 2015 rule. The EPA also incorporated updated information on the technologies and other controls that plants employ. See the *Supplemental TDD* for details on the changes (U.S. EPA, 2019b). The current analysis focuses only on the two wastestreams addressed in this proposal: bottom ash transport water and FGD wastewater..
- Given the changes in the universe of steam electric power plants since the 2015 rule was promulgated and advances in treatment technologies, and that this proposal is specific to a subset of wastestreams from the 2015 rule, the EPA first modeled the compliance response, pollutant loadings, costs, and benefit estimates for the baseline requirements (see *Supplemental TDD* for a detailed discussion of the baseline). The EPA then modeled the same for each regulatory option.
- The EPA revised assumptions to use more recent data (*e.g.*, analysis year, compliance period, dollar year adjustments).

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

- Finally, the EPA made certain changes to the methodologies to address environmental stressors not quantified as part of the 2015 rule analysis, be consistent with approaches used by the Agency for other rules, and/or incorporate recent advances in the health risk and resource valuation research.

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

1.3.1 Constant Prices

This BCA applies a year 2018 constant price level to all future monetary values of costs and benefits. 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).[4]

1.3.2 Discount Rate and Year

This BCA estimates the annualized value of future benefits using two discount rates: 3 percent and 7 percent. The 3 percent discount rate reflects society's valuation of differences in the timing of consumption; the 7 percent discount rate reflects the opportunity cost of capital to society. In Circular A-4, the Office of Management and Budget (OMB) recommends 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 (OMB, 2003; updated 2009). The same discount rates are used for both benefits and costs.

All future cost and benefit values are discounted back to 2020, which is the anticipated rule promulgation year.[5]

1.3.3 Period of Analysis

Benefits are expected to begin accruing when each plant implements the control technologies needed to comply with any applicable BAT effluent limits or pretreatment standards. As discussed in the *RIA* (in *Chapter 3: Compliance Costs*), for the purpose of the economic impact and benefit analysis, the EPA generally assumes that plants would implement for bottom ash transport water control technologies to meet the applicable rule limitations and standards as their permits are renewed over the period of 2021 through 2023. However, some regulatory options provide a longer period to meet FGD effluent limits. Under Options 1, 2 and 3 plants may implement FGD controls as late as 2028[6] and under Option 4, plants have until 2028 to meet FGD wastewater controls based on the membrane technology.[7] This schedule reflects differing levels of

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4 To update the value of a Statistical Life (VSL), the 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 2010a). The EPA used the GDP deflator to update the value of an IQ point, CPI to update the WTP for surface water quality improvements, cost of illness (COI) estimates, and the price of water purchase, and the CCI to update the cost of dredging navigational waterways and reservoirs.

5 In its analysis of the 2015 rule, the EPA presented benefits in 2013 dollars and discounted these benefits costs to 2015 (see U.S. EPA, 2015a).

6 The VIP program under Options 1, 2 and 3 allows facilities to implement FGD controls as late as 2028. Plants that are not participating in the VIP program may implement FGD controls as late as 2023 under Option 1 and as late as 2025 under Options 2 and 3.

7 Other dates may apply to subcategories of facilities as described in *Section 3.2.1*.

controls that may be needed to meet limits under different options as compared to the baseline and recognizes that control technology implementation is likely to be staggered over time across the universe of steam electric power plants.

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, the EPA used the annual average of loadings or other environmental changes (*e.g.*, air emissions, water withdrawals) projected over the analysis period (2021-2047) and assumed that any resulting benefits would begin in 2021.

The period of analysis extends to 2047 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 2028.

1.3.4 Annualization of future costs and benefits

Consistent with the analysis of the costs, the EPA assumes that plants implement necessary technologies to meet the specified limits at the start of each year. The EPA used 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 (3 percent or 7 percent), and *n* is the number of years (27 years).

1.3.5 Direction of Environmental Changes and Benefits

The technology bases or subcategorizations shown in Table 1-1 for some regulatory options yield effluent limits that may be less stringent than the baseline. This is true, for example, for options that base FGD effluent limits on chemical precipitation only, or for subcategory options under which some plants can use best management practices (BMP) to control bottom ash wastewater discharges. Additionally, the delayed effective deadline for FGD limits under some options, such as the 2028 deadline for meeting FGD limits based on membrane technology under Option 4, prolong the period when plants would continue to operate their existing systems and discharge at current levels. The combination of these factors means that some options can be expected to provide negative benefits (disbenefits) when compared to the baseline. This document uses the generic term “benefits” whether the changes are truly beneficial or are detrimental to society (reduce social welfare). The sign, positive or negative, communicates the direction of the effects. Under this convention, positive benefit values indicate improvements in social welfare under the option as compared to the baseline. This effect is typically in the opposite direction as the change in environmental effects. For example, lower effluent pollutant concentrations (negative changes) reduce the incidence of the health effects being quantified (negative changes) and avoid excess mortality resulting from the exposure (positive changes).

1.3.6 Population and Income Growth

To account for future population growth or decline, the EPA used the U.S. Census Bureau population forecasts for the United States from 2017 through 2060 (U.S. Census Bureau, 2017a). The EPA used the growth projections for each year to adjust affected population estimates for future years (*i.e.*, from 2021 to 2047).

Also, since WTP is expected to increase as income increases, the 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 (WQ) improvements. To develop adjustment factors for VSL, the EPA first used income growth factors in the Environmental Benefits Mapping and Analysis Program (BenMAP) database between 1990 and 2024 to estimate a linear regression model. Using coefficient estimates from the linear regression, the EPA extrapolated the income growth factors for years 2025-2047. The EPA applied the projected income data along with the income elasticity for the respective models (VSL and meta-regression) to adjust the VSL and WQ meta-analysis estimates of WTP in future years.[8]

1.4 Organization of the Benefit and Cost Analysis Report

This BCA report presents the 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 proposed regulatory options.
- *Chapter 3* describes the EPA's estimates of the environmental changes resulting from the regulatory options, including water quality modeling that underlays estimates of several categories of benefits.
- *Chapters 4* and *5* details the methods and results of the EPA's analysis of human health benefits from changes in pollutant exposure via the drinking water and fish ingestion pathways, respectively.
- *Chapter 6* discusses the EPA's analysis of the nonmarket benefits of changes in surface water quality resulting from the regulatory options.
- *Chapter 7* discusses expected changes in benefits to threatened and endangered (T&E) species.
- *Chapter* 8 describes the 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* discusses benefits arising from changes in groundwater withdrawals.
- *Chapter 10* describes benefits from changes in maintenance dredging of navigational channels and reservoirs.

[8] These extrapolated income growth factors were originally developed for the EPA's COBRA tool (http://epa.gov/statelocalclimate/resources/cobra.html). The latest public version is 3,2 released in May 2018.

- *Chapter 11* summarizes monetized benefits across benefit categories.
- Chapter 12 summarizes the social costs of the four regulatory options.
- *Chapter 13* addresses the requirements of Executive Orders that the EPA is required to satisfy for this proposal, notably Executive Order 12866, which requires the EPA to compare the benefits and social costs of its actions.
- *Chapter 14* details the EPA's analysis of the distribution of benefits across socioeconomic groups to fulfill requirements under Executive Order (E.O.) 12898 on Environmental Justice.
- *Chapter 15* provides references cited in the text.

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 welfare effects to society resulting from changes in pollutant loadings due to implementation of the regulatory options. The EPA expects the regulatory options to change discharge loads of various categories of pollutants when fully implemented. The categories of pollutants include conventional (such as total suspended solids (TSS), biochemical oxygen demand (BOD), and oil and grease), priority (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 under full implementation of the effluent limits for the baseline and the four regulatory options. The *Supplemental TDD* provides further detail on the loading changes (U.S. EPA, 2019b).

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

Regulatory Option	Estimated Total Industry Pollutant Loadings (pounds per year)	Estimated Changes[a] in Pollutant Loadings from Baseline (pounds per year)
Baseline	1,670,000,000	NA
1	1,680,000,000	13,400,000
2	1,560,000,000	-104,000,000
3	1,390,000,000	-276,000,000
4	342,000,000	-1,320,000,000

NA: Not applicable to the baseline

Note: Pollutant loadings values are rounded to three significant figures. See EA for details (U.S. EPA, 2019a).

a. Negative values represent loading reductions and positive values represent loading increases, compared to the baseline.

Source: U.S. EPA Analysis, 2019

As discussed in *Section 1.3.4*, some of the options may increase pollutant loads for some plants, wastestreams, pollutants, or years, when compared to the baseline. Consequently, technology options resulting in overall increase in pollutant loads would result in forgone benefits to society while options resulting in load reduction would result in realized benefits. Furthermore, whether a regulatory option increases or reduces loadings depends on the particular plant, pollutant, and timing of the comparison to baseline conditions. *Section 3.2* discusses the temporal profile of pollutant loads in further detail.

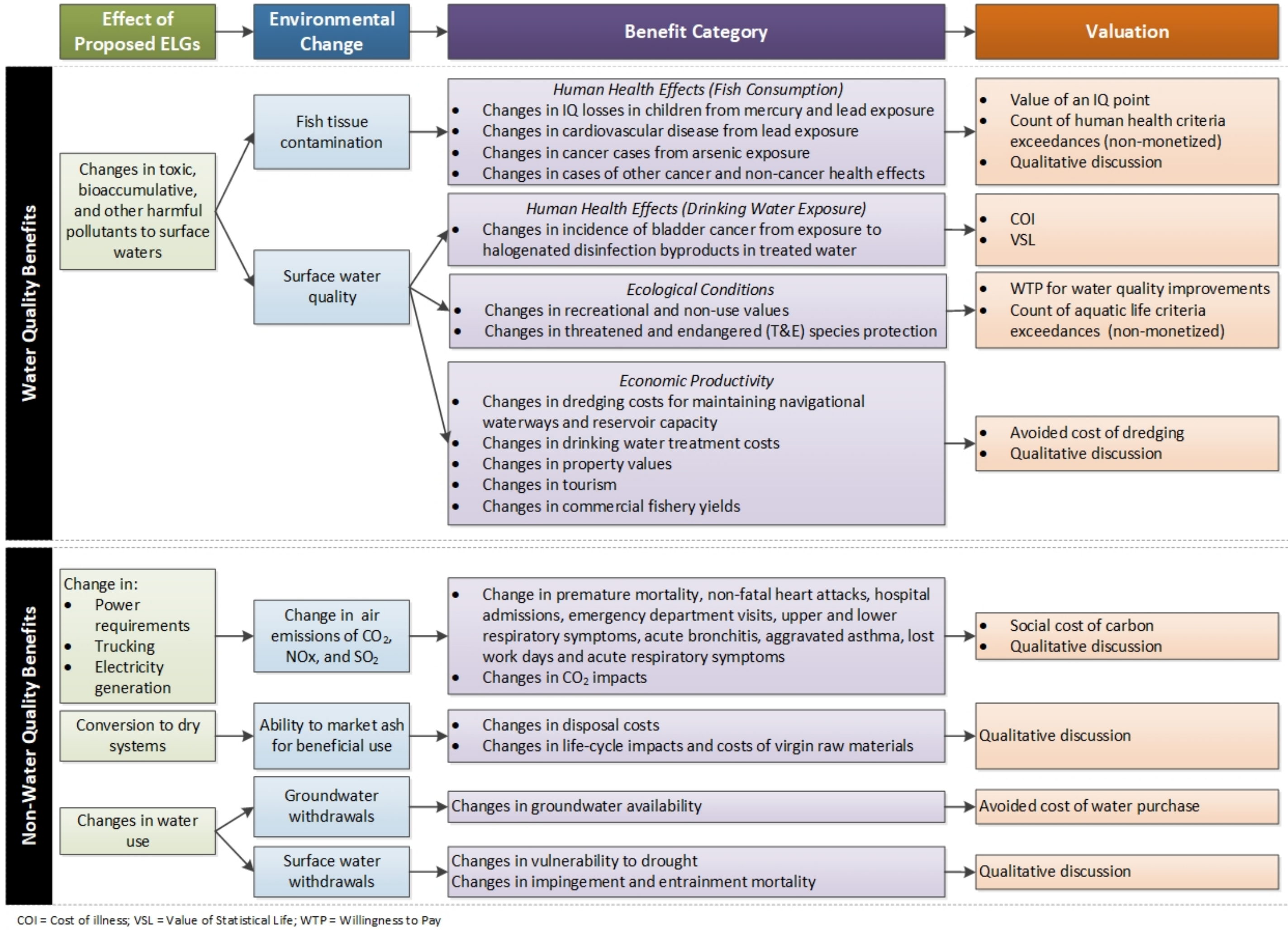
Changes estimated for proposed Option 2 and Option 3 include effects of the VIP. Because the VIP is voluntary, the set of plants participating in the program is uncertain. For the purpose of the costs and benefits analyses, the EPA estimated VIP participants by comparing the estimated costs of the two technologies for each affected facility and assuming that a plant owner would select the less costly of the two. The Agency estimated that 18 steam electric power plants may choose to participate in the VIP under Option 2 and 23 plants may choose to participate in the VIP under Option 3. The facilities which the EPA estimates VIP may be the least-cost option range in FGD wastewater flows, nameplate capacity, capacity utilization, and location. The EPA cost estimates for the VIP tend to be lower at facilities where no treatment has been installed beyond surface impoundments, however even for this group of facilities biological systems are still often least-cost.

Effects of the regulatory options in comparison to the 2015 rule also include other effects of the implementation of control technologies or other changes in plant operations, such as changes in emissions of air pollutants (*e.g.*, carbon dioxide (CO_2), nitrogen oxides (NO_X), and sulfur dioxide (SO_2)) which result in benefits forgone to society in the form of increased mortality and CO_2 impacts on environmental quality and economic activities. Other effects include changes in water use, which provide benefits in the form of increased availability of surface water and groundwater.

This chapter also provides a brief discussion of the effects of pollutants found in bottom ash transport water and FGD wastewater addressed by the regulatory options on human health and ecosystem services, and a framework for understanding the benefits expected to be achieved by these options. For a more detailed description of steam electric pollutants, their fate, transport, and impacts on human health and environment, see the *Supplemental EA* document (U.S. EPA, 2019a).

Figure 2-1 summarizes the potential effects of the regulatory options, the expected environmental changes, and categories of social welfare effects as well as the EPA's approach to analyzing those welfare effects. The 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. The 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 effect categories applicable to this rule, including human health effects, ecological effects, economic productivity, and changes in air pollution, solid waste generation, and water withdrawals. Some estimates of the monetary value of social welfare changes presented in this document rely on models with a variety of assumptions, limitations and uncertainties discussed in more detail in *Chapters 3* through *10* for the relevant benefit categories.

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



Source: U.S. EPA Analysis, 2019.

2.1 Human Health Impacts Associated with Changes in Surface Water Quality

Pollutants present in steam electric power plant discharges can cause a variety of adverse human health effects. *Chapter 3* describes the approach the 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, 2015b; 2019a).

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 2.4*.

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 oral 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). For example, bromide and other halogens are precursors to the formation of trihalomethanes, a group of potentially carcinogenic contaminants.

Public drinking water supplies are subject to legally enforceable maximum contaminant levels (MCLs) established by EPA (U.S. EPA, 2018a). 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. The 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 Goal for Selected Pollutants in Steam Electric FGD Wastewater or Bottom Ash Transport Water 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

Table 2-2: Drinking Water Maximum Contaminant Levels and Goal for Selected Pollutants in Steam Electric FGD Wastewater or Bottom Ash Transport Water Discharges

Pollutant	MCL (mg/L)	MCLG (mg/L)
Copper[a]	1.3	1.3
Cyanide (free cyanide)	0.2	0.2
Lead[a]	0.015	0
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 available
bromodichloromethane	Not available	0
bromoform	Not available	0
dibromochloromethane	Not available	0.06
chloroform	Not available	0.07

a. MCL value is based on action level.

b. Bromide, a constituent found in steam electric power plant effluent, is a trihalomethane precursor.

Source: 40 CFR 141.53 as summarized in U.S. EPA (2018a): 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. The EPA assumed compliance with existing MCLs. Nevertheless, for some pollutants that have an MCL above the MCLG, there may be incremental benefits from reducing concentrations below the MCL. Examples include arsenic, lead, and total trihalomethanes (TTHM).

As shown in Table 2-2, there are no “safe levels” for some these pollutants. Therefore, any reduction in exposure to these pollutants is expected to yield benefits. The EPA estimated the changes in levels of bromide, a trihalomethane precursor, downstream from steam electric power plant outfalls and estimated the resulting changes in the incidence of bladder cancers associated with TTHM exposure. These benefits are discussed in *Section 4.4.* The EPA did not evaluate potential benefits associated with other health endpoints (*e.g.*, reproductive effects, fetal development, and other cancers resulting from reduced TTHM exposure).

The value of health benefits is the monetary value that society is willing to pay to avoid the adverse health effects. WTP to avoid morbidity or mortality is generally considered to be a comprehensive measure of the costs of health care, losses in income, and pain and suffering of affected individuals and their caregivers. For example, the value of a statistical life is based on estimates of society’s WTP to avoid the risk of premature mortality. The cost-of-illness (COI) approach is a less comprehensive measure: it allows valuation of a particular type of non-fatal illness by placing monetary values on metrics, such as lost productivity and the cost of health care and medications that can be monetized. The EPA used the VSL and COI to estimate the benefits of changing excess mortality and morbidity associated with incremental bladder cancers in the population estimated to be exposed to trihalomethanes attributable to of bottom ash transport water and/or FGD wastewater bromide discharges. Arsenic and lead benefits were not modeled due to the very small concentration changes in downstream reaches with drinking water intakes and, furthermore, because lead found in supplied water is generally associated with water distribution rather than source water quality. See *Chapter 4* for details of this analysis.

2.1.2 Fish Consumption

Recreational anglers 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. The EPA analyzed the following direct measures of change in risk to human health from exposure to contaminated fish tissue:

1. Neurological effects to children ages 0 to 7 from exposure to lead;
2. Neurological effects to infants from in-utero exposure to mercury;
3. Incidence of skin cancer from exposure to arsenic[9]; and
4. Reduced risk of other cancer and non-cancer toxic effects.

The Agency evaluated changes in potential intellectual impairment, or intelligence quotient (IQ), resulting from changes in childhood and in-utero exposures to lead and mercury. The EPA also translated changes in the incidence of skin cancer into changes in the number of skin cancer cases.

For constituents with human health ambient water quality criteria, the change in the risk of other cancer and non-cancer toxic effects from fish consumption is addressed indirectly in the EPA's assessment of changes in exceedances of these criteria (see *Section 5.7)*.

In the 2015 rule, the EPA used VSL to estimate the value of changes in the risk of premature mortality from cardiovascular disease (CVD). The EPA performed a screening analysis of the regulatory options using the same approach used in the 2015 analysis. This analysis showed very small changes in CVD mortality based on changes in lead exposure under the options. See memorandum in the rule record for details (U.S. EPA, 2019g). The Agency is aware of more recent studies linking lead exposure and CVD, but determined that the changes in lead exposure under the regulatory options are so small as to be unlikely to yield benefits. The EPA used a COI approach to estimate the value of changes in the incidence of skin cancer, which are generally non-fatal (see *Section 5.5*). 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 since available economic research provides little empirical data on society's WTP to avoid IQ losses. Instead, the 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 exposure to lead and mercury.

[9] The EPA is currently revising its cancer assessment of arsenic to reflect new data on internal cancers including bladder and lung cancers associated with arsenic exposure via oral ingestion (U.S. EPA, 2010b). Because cancer slope factors for internal organs have not been finalized, the Agency did not consider these effects in the analysis of the proposed ELG.

The EPA expects that there could also be health impacts via the fish consumption pathway arising from changes in discharges of other steam electric pollutants, such as cadmium, selenium, and zinc. Analyses of these health effects are not possible due to lack of data on a quantitative relationship between ingestion rate and potential adverse health effects.

Despite numerous studies conducted by the EPA and other researchers, dose-response functions are available only for a handful of health endpoints associated with steam electric pollutants. In addition, the available research does not always allow complete economic evaluation, even for quantifiable health effects. For example, the EPA's analysis omits the following health effects: low birth weight and neonatal mortality from in-utero exposure to lead, decreased postnatal growth in children ages one to 16, delayed puberty, immunological effects, decreased hearing and motor function (U.S. EPA, 2009a; 2019h); effects to adults from exposure to lead (*e.g.*, cardiovascular diseases, decreased kidney function, reproductive effects, immunological effects, cancer and nervous system disorders) (U.S. EPA, 2009d; 2013a; 2019h); effects to adults from exposure to mercury, including vision defects, hand-eye coordination, hearing loss, tremors, cerebellar changes, and others (Mergler et al., 2007; CDC, 2009); and other cancer and non-cancer effects from exposure to other steam electric pollutants. Therefore, the total monetary value of changes in human health effects included in this analysis represent only a subset of the potential health benefits (or forgone benefits) that are expected to result from the regulatory options.

2.1.3 Complementary Measure of Human Health Impacts

The 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 a measure 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 5.7*).

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.

2.2 Ecological Impacts Associated with Changes in Surface Water Quality

The composition of steam electric power plant wastewater depends on a variety of factors, such as fuel composition, air pollution control technologies used, and wastewater management techniques used. Wastewater often contains toxic pollutants such as aluminum, arsenic, boron, cadmium, chromium, copper, iron, lead, manganese, mercury, nickel, selenium, thallium, vanadium, and zinc (U.S. EPA, 2019a). 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, 2019a). 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 is quite small. Still, EPA expects the ecological impacts from the regulatory options may include habitat changes 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 may affect ecosystem productivity in waterways and the health of resident species, including threatened and endangered species. The proposed regulation may affect the general health of fish and invertebrate populations, their propagation to waters, and fisheries for both commercial and recreational purposes. Changes in water quality could also affect recreational activities such as swimming, boating, fishing, and water skiing. Finally, the proposed regulation may affect nonuse values (*e.g.*, option, existence, and bequest values) of the affected water resources.

2.2.1 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 are affected by steam electric power plant discharges. Society values changes in ecosystem services by a number of mechanisms, including increased frequency of use and quality of the improved habitat for recreational activities (*e.g.*, fishing, swimming, and boating). Individuals also value the protection of habitats and species that may be adversely affected by FGD wastewater and bottom ash transport water discharges, even when those individuals do not use or anticipate future use of the affected waterways for recreational or other purposes, resulting in nonuse values.

The EPA quantified potential ecological impacts from the regulatory options by estimating in-waterway concentrations of bottom ash transport water and FGD wastewater pollutants and translating water quality estimates into a single numerical indicator (water quality index (WQI)). The EPA used the estimated change in WQI as a quantitative estimate of ecological changes for this regulatory analysis. *Section 3.4* of this report provides detail on the parameters used in formulating the WQI and the WQI methodology and calculations. In addition to estimating changes using the WQI, the EPA compared estimated pollutant concentrations to freshwater chronic NRWQC for aquatic life (see Section *3.4.1.1*). The *Supplemental EA* (U.S. EPA, 2019a) details comparisons of the estimated concentrations in immediate receiving and downstream reaches to the freshwater chronic NRWQC for aquatic life for individual pollutants.

A variety of primary methods exist for estimating recreational use values, including both revealed and stated preference methods (Freeman, 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, 2010a; U.S. OMB, 2003). Stated preference methods rely on carefully designed surveys, which either (1) ask people about their WTP for particular ecological improvements, such as increased protection of aquatic species or habitats with particular attributes, or (2) ask people to choose between competing hypothetical "packages" of ecological improvements and household cost (Bateman et al., 2006). 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 and Johnston, 2007). 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 et al. 2002, p. 134). It involves adapting research conducted for another purpose to estimate values within a particular policy context (Bergstrom and De Civita, 1999). The EPA followed the same methodology used in analyzing the 2015 rule (U.S. EPA, 2015a) and relied on a benefit transfer approach based on a meta-analysis of surface water valuation studies to estimate the use and non-use benefits of improved surface water quality resulting from the proposal. This analysis is presented in *Chapter 6*. Valuation of water quality changes is an area of on-going research. The EPA will update the methods employed to reflect the inclusion of rigorous and timely studies that will shed light on household values of water quality changes and changes in the methods in the economics literature. Further research may also include efforts to examine the feasibility of conducting regional water quality valuation studies that are designed to be aggregated up to the national level where the study designs are consistent with the best practices of the economics literature as well as the OMB Circular A-4 requirements.

2.2.2 Impacts on Threatened and Endangered Species

For threatened and endangered (T&E) species, even minor changes to reproductive rates and small levels of mortality may represent a substantial portion of annual population growth. By changing the discharge of steam electric pollutants to aquatic habitats, the regulatory options may affect 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.[10]

The EPA quantified but did not monetize the potential effects of the regulatory options on T&E species. The EPA constructed databases to determine which species are found in waters that may be affected by changes in pollutant discharge from steam electric power plants. The 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 exceed aquatic life-based NRWQC under regulatory options, or vice versa. 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 risk to T&E species and potential improvement in species population. Conversely, increasing the frequency of exceedances may increase risk to T&E species and jeopardize their survival or recovery. Therefore, to estimate the benefits of the regulatory options, the EPA identified the inhabited waterbodies that see changes in achievement of wildlife NRWQC as a consequence of the regulatory options and used these data as a proxy for locations where T&E species recovery could be affected. This analysis and results are presented in *Chapter 7*.

2.2.3 Changes in Sediment Contamination

Effluent discharges from steam electric power plants can also contaminate waterbody sediments. For example, adsorption of arsenic, selenium, and other pollutants found in FGD wastewater and bottom ash transport water 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

[10] The Federal 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

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, the EPA examined potential exposures of ecological receptors (*i.e.*, sediment biota) to pollutants in contaminated sediment. Benthic organisms are affected primarily by discharges of mercury, nickel, selenium, and cadmium (U.S. EPA, 2015b; 2019a). The chemicals 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. In 2015, the EPA 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 changing discharges of pollutants to receiving reaches, the regulatory options may affect the future contamination of waterbody sediments, thereby impacting benthic organisms and changing 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, the EPA did not quantify or monetize the associated benefits.

2.3 Economic Productivity

The economic productivity changes estimated to result from the regulatory options may include changes in beneficial use of coal ash and the resulting reduction in disposal costs. Other potential economic productivity effects may stem from changes in contamination of public drinking water supplies and irrigation water; changes in sediment deposition in reservoirs and navigational waterways; changes in tourism, commercial fish harvests, and property values. Due to the small magnitude of changes in water quality estimated in the *Supplemental EA*, the latter three categories are not monetized or discussed further in this document.

2.3.1 Marketability of Coal Ash for Beneficial Use

The regulatory options may prompt certain plants to convert from wet handling of bottom ash to dry handling. This change could in turn allow plants to more readily market the CCR to beneficial uses. In particular, bottom ashes can be used as substitutes for sand and gravel in fill applications. There are economic productivity benefits from plants avoiding certain costs associated with disposing of the ashes as waste and from society or users of the ash avoiding the cost and life-cycle effects associated with the displaced virgin material. In the analysis of the 2015 rule, the EPA quantified the benefits from increased dry handling of fly ash and bottom ash (see *Chapter 10* in U.S. EPA, 2015a). That analysis showed that the economic value was greatest for fly ash used in concrete production, and smallest for fly ash or bottom ash used as fill material.

Among the regulatory options considered for this proposal, Option 1 would not affect fly ash, the wastestream responsible for the vast majority of projected benefits in this category in the 2015 rule (see U.S. EPA, 2015a), while Options 2, 3, and 4 could affect fly ash to the extent facilities decide to encapsulate membrane filtration brine with fly ash that is currently beneficially used. Since the EPA could not estimate which facilities might use fly ash for encapsulation versus an alternative brine management method (*e.g.*, deep well injection), this potential change in fly ash beneficial use was not quantified, and represents an uncertainty in the analysis. With respect to bottom ash, the EPA estimates that only Option 2 would affect the quantity of bottom ash handled wet when compared to the baseline, and for that option the estimated increase in bottom ash handled wet is small (total of 310,671 tons per year at 20 plants). See the *Supplemental TDD* for details (U.S. EPA, 2019b). Given the uncertainties surrounding changes in fly ash, the small changes in bottom ash, and the uncertainty associated with projecting plant-specific changes in marketed bottom ash, the EPA did not quantify this benefit category in the analysis of the proposed Option 2.

2.3.2 Water Supply and Use

The regulatory options are expected to change loading of steam electric pollutants to surface waters by small amounts relative to the 2015 rule estimates (see U.S. EPA, 2015a), and thus may affect uses of these waters for drinking water supply and agriculture:

- *Drinking water treatment costs*. The regulatory options have the potential to affect costs of drinking water treatment (*e.g.*, filtration and chemical treatment) by changing pollutant concentrations and eutrophication in source waters (also see discussion of changes in bromide concentrations below). Eutrophication is one of the main causes of taste and odor impairment in drinking water, which has a major negative impact on public perceptions of drinking water safety. Additional treatment to address foul tastes and odors can significantly increase the cost of public water supply. The Agency conducted screening-level assessment to evaluate the potential for changes in costs incurred by public drinking water systems and concluded that such changes, while they may exist, are likely to be insignificant. 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, the EPA determined that there are no drinking water systems drawing water at levels that exceed an MCL for metals and other toxics listed in Table 2-2 such as selenium and cyanide under either the baseline or the four regulatory options, and only one drinking water intake is drawing water from a reach with nitrate concentrations exceeding an MCL (10 mg/L) under the baseline. No changes in MCL exceedances are expected under the regulatory options. At many drinking water treatment facilities, treatment system operations do not generally respond to small incremental water quality changes for one pollutant or a small subset of pollutants. Furthermore, associated operations costs are not expected to change significantly due to small incremental changes in water quality. Accordingly, the EPA did not conduct analysis of cost changes in publicly operated treatment systems.

- *Reduction in bromide concentrations*. Existing treatment technologies in the majority of public drinking water sources are not designed to remove bromide (a constituent of FGD wastewater and bottom ash transport waters) from raw surface waters. Bromide and other halogens found in source water can react during routine drinking water treatment to generate harmful disinfection byproducts (DBPs) (U.S. EPA, 2016). The 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. Public water systems (PWS) may adjust their current 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, 2005a, page 7-19). Where those low-cost changes are not sufficient 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, and 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 had to upgrade their treatment systems as a direct result of bromide discharges from steam electric power plants (U.S. vs. Duke Energy, 2015; Rivin, 2015). In extreme cases, if water treatment is not sufficient, an alternate water source needs to be substituted or developed (Watson et al., 2012). Thus, increased bromide 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 bromide levels in source waters can reduce the health risk, even where treatment changes have already occurred.[11] In some cases, operation and maintenance (O&M) costs may also be reduced. The EPA did not have data on drinking water treatment technologies at potentially affected PWS or cost estimates for those technologies given changes in bromide concentrations in source water. Since cost data were insufficeint, and treatment costs and human health benefits overlap, the Agency estimated only the human health benefits of changes in bromide discharges (see *Section 2.1.1* for a discussion of this benefit category and *Chapter 4* for the analysis).

- *Irrigation and other agricultural uses*: Changes in steam electric pollutants discharges can affect agricultural productivity by improving water quality used for irrigation and livestock watering (Clark et al., 1985). Although elevated nutrient concentrations in irrigation water would not adversely affect its usefulness for plants, concerns exist for potential residual effects due to steam electric pollutants, such as arsenic, mercury, lead,cadmium, and selenium, entering the food chain. Further, eutrophication promotes 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. The EPA did not quantify or monetize effects of quality changes in agricultural water sources arising from the regulatory options due to data limitations and small estimated changes in water quality.

- *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 cause buildup of silt layers over time, 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 et al., 1985). The EPA expects that by reducing TSS concentrations, the regulatory options could provide cost savings by reducing dredging activity to reclaim capacity at existing reservoirs. Conversely, an increase in TSS concentrations could lead to an increase in dredging costs (see *Chapter 10* for detail).

2.3.3 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. Navigable channels are prone to reduced functionality due to sediment build-up, which can reduce the navigable depth and width of the waterway (Clark et al., 1985). For many navigable waters, periodic dredging is necessary to remove sediment and keep them passable. Dredging of navigable waterways can be costly.

[11] Regli et al (2015) estimated benefits of reducing bromide across various types of water treatment systems.

The EPA expects that the regulatory options would reduce sediment loadings to surface waters and reduce dredging of navigational waterways under Option 4. The EPA quantified and monetized these benefits based on the avoided cost for expected future dredging volumes. Small increases in sediment loads under Options 1, 2, and 3 would result in a modest increase in dredging costs in navigational waterways. *Chapter 10* describes this analysis.

2.3.4 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. In some cases, excessive pollutant loadings can lead to the closures of shellfish beds, thereby reducing shellfish harvests. 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 harvest, which in turn could lead to an increase in producer and consumer surplus. Conversely, an increase in pollutant loadings under some regulatory options could lead to negative impacts on fish and shellfish harvest.

The EPA did not quantify or monetize impacts to commercial fisheries from the regulatory options. The EPA's *Supplemental EA* (U.S. EPA, 2019a) shows that eight steam electric power plants discharge bottom ash transport water or FGD wastewater directly to the Great Lakes or to estuaries. Although estimated increases or decreases in annual average pollutant loads under the regulatory options may have an impact on local fish populations and commercial harvest, the overall effects to commercial fisheries arising from the regulatory options are likely to be negligible. Most species of fish have numerous close substitutes. The literature suggests that when there are plentiful substitute fish products, numerous fishers, and a strong ex-vessel market, individual fishers are generally price takers. Therefore, the measure of consumers welfare (consumer surplus) is unlikely to change as a result of small changes in fish landings, such as those the EPA expects under the regulatory options.

2.3.5 Tourism

Discharges of pollutants may also affect the tourism industries (*e.g.*, sales of fishing equipment) and, as a result, local economies in the areas surrounding affected waters due to changes in recreational opportunities. 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 and vice versa. Due to the estimated small magnitude of water quality changes expected from the regulatory options (see *Section 3.4* for detail) and availability of substitute sites the overall effects on tourism and, as a result, social welfare is likely to be trivial. Therefore, the EPA did not quantify or monetize this benefit category.

2.3.6 Property Values

Discharges of pollutants may affect the aesthetic quality of land and water resources by changing pollutant discharges and thus 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 these differences could have an effect on water eutrophication, algae production, and water turbidity, among others. Several studies (Boyle et al., 1999; Poor et al., 2001; Leggett and Bockstael, 2000; Gibbs et al., 2002; Bin and Czakowski, 2013; Walsh et al., 2011; Tuttle and

Heintzelman, 2014; Netusil et al., 2014; Liu et al., 2017; Klemick et al., 2018; Kung et al., 2018) suggest that waterfront property is more desirable when located near unpolluted water. Therefore, the value of properties located in proximity to waters contaminated with steam electric pollutants may increase or decrease due to changes in the composition of bottom ash transport water or FGD wastewater discharges.

Due to data limitations, the EPA was not able to quantify or monetize the potential change in property values associated with the regulatory options. The magnitude of the potential change depends on many factors, including the number of housing units located in the vicinity of the affected waterbodies, community characteristics (*e.g.*, residential density) and housing stock (*e.g.*, single family or multiple family) and the effects of steam electric pollutants on aesthetic quality of surface water. Given the small changes in aesthetic quality of surface waters that may result from the small changes in pollutant concentrations under the regulatory options, the EPA expects impacts on property values to be small. In addition, there may be overlap between shifts in property values and the estimated total WTP for surface water quality changes summarized in *Section 2.2.1*.

2.4 Changes in Air Pollution

The regulatory options are expected to affect air pollution through three main mechanisms: 1) changes in energy use by steam electric power plants to operate wastewater treatment, ash handling, and other systems needed to comply with the regulatory options; 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 compliance costs for the regulatory options (or conversely, lower generation costs for plants incurring cost savings under the rule options). The different profile of generation can result in lower or higher air pollutant emissions due to differences in emission factors for coal or natural gas combustion, or nuclear or hydroelectric power generation.

Of the three mechanisms above, the change in the emissions profile of electricity generation at the market level is the only one that increases under Option 2. As described in *Chapter 5* of the RIA, the EPA used the Integrated Planning Model (IPM®), a comprehensive electricity market optimization model that can evaluate impacts of the proposed ELG options within the context of regional and national electricity markets. The EPA analyzed proposed Option 2 and Option 4 using IPM.

Electricity market analyses using IPM indicate that in 2030 under Option 2, coal fired electric power generation may increase by 0.6 percent and under Option 4 may increase by 0.2 percent, when compared to the baseline without ACE (see RIA; U.S. EPA, 2019c). These small changes in generation result in air emsission increases that are also relatively small. Changes in coal-based electricity generation as a result of the regulatory options are compensated by changes in generation using other fuels or energy sources — natural gas, nuclear power, solar, and wind power. The changes in air emissions reflect the differences in emissions factors for these other fuels, as compared to coal-fueled generation. Overall for the three mechanisms (auxiliary services, transportation, and market-level generation), the EPA estimates a net increase in CO_2 and SO_2, and NO_X emissions under all regulatory options as compared to the baseline.

Following the promulgation of the ACE rule finalized in June 19, 2019, the EPA also conducted a sensitivity analysis of the impacts of proposed Option 2 relative to a baseline that includes the Affordable Clean Energy (ACE) final rule (see U.S. EPA, 2019f). Appendix C in the RIA details this sensitivity analysis.

CO_2 is the most prevalent of the greenhouse gases, which are air pollutants that the EPA has determined endangers public health and welfare through their contribution to climate change. The EPA used estimates of the domestic social cost of carbon (SC-CO_2) to monetize the benefits of changes in CO_2 emissions as a result of this proposal. The SC-CO2 is a metric that estimates the monetary value of projected impacts associated with marginal changes in CO2 emissions in a given year. It includes a wide range of anticipated climate impacts, such as net changes in agricultural productivity and human health, property damage from increased flood risk, and changes in energy system costs, such as reduced costs for heating and increased costs for air conditioning. *Chapter 8* details this analysis.

The air-related benefit estimates presented in *Chapter 8* rely on IPM projections from a sensitivity analysis of proposed Option 2, which includes the effects of the ACE rule in the baseline, and from an analysis of proposed Option 4 completed before the ACE rule was finalized (and which therefore does not include the ACE rule).

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). The EPA quantified changes in emissions of $PM_{2.5}$ precursors NO_X and SO_2 but did not monetize the estimated changes in secondary PM exposure that would result from changes in NO_X, and SO_2 emissions at this time. To map those emission changes to air quality changes across the country, full scale air quality modeling is needed. Prior to this proposal, the EPA's modeling capacity was fully allocated to supporting other regulatory and policy efforts and as a result we did not do an air quality impact assessment and quantify the air disbenefits of this proposal, were it to become a final regulation. For the final rule, the EPA intends to conducting full scale air quality modeling to provide spatially explicit estimates of concentration changes, which is required for characterizing uncertainty in mortality risk from changes in $PM_{2.5}$ concentrations at different levels of baseline $PM_{2.5}$ exposure.

The Agency did not estimate the number or economic value of forgone benefits from increased exposure to $PM_{2.5}$ associated with increased SO_2 and NO_X emissions using a benefit per-ton (BPT) approach. Over the last year and a half, the EPA systematically compared the changes in benefits, and concentrations where available, from its BPT technique and other reduced-form techniques to the changes in benefits and concentrations derived from full-form photochemical model representation of a few different specific emissions scenarios. Reduced form tools are less complex than the full air quality modeling, requiring less agency resources and time. That work, in which we also explore other reduced form models is referred to as the "Reduced Form Tool Evaluation Project" (Project), began in 2017, and the initial results were available at the end of 2018. The Agency's goal was to better understand the suitability of alternative reduced-form air quality modeling techniques for estimating the health impacts of criteria pollutant emissions changes in EPA's benefit-cost analysis. This research suggests that, for purposes of estimating the impacts of current emissions changes in the EGU sector, the 2012 BPT approach (which was based off a 2005 inventory) may yield estimates of $PM_{2.5}$ benefits that are as much as 25 percent greater than those estimated when using full air quality modeling. EPA continues to work to develop refined reduced-form approaches for estimating $PM_{2.5}$ benefits. The scenario-specific emission inputs developed for this project are currently available online.[12] The study design and methodology will be thoroughly described in the final report summarizing the results of the project, which is planned to be completed by the end of 2019. The agency intends to monetize the changes in PM2.5 and their precursor emissions by conducting the full air quality modeling in the final rule.

2.5 Reduced Water Withdrawals

The regulatory options may change water withdrawals associated with wet bottom ash transport and wet FGD scrubbers. In comparison to the baseline, these changes are estimated to be small. The regulatory options are expected to increase water withdrawals from aquifers under Option 2 and from surface waterbodies under Options 1, 2, and 3. The estimated increase in water withdrawal ranges from 0.22 billion gallons per year (0.61 million gallons per day) under Option 3 to 7.7 billion gallons per year (21 million gallons per day) under Option 2 (see *Supplemental TDD* for details). The EPA estimates that power plants would reduce water withdrawals by 3.4 billion gallons per year (9.4 million gallons per day) under Option 4.

Increased water use from groundwater sources by steam electric power plants under the regulatory options could reduce availability of groundwater supplies for alternative uses. One power plant affected by this proposal relies on groundwater sources. The EPA's analysis of potential costs associated with an increase in groundwater withdrawal are presented in *Chapter 9*.

A change in surface water intake would affect impingement and entrainment mortality. An increase in surface water withdrawal under Options 1, 2, and 3 would increase impingement and entrainment mortality. Although the overall increase in water withdrawal is modest, the significance of local ecological impacts is uncertain and will depend on the overall health of the affected species population as well as species vulnerability to impingement and entrainment (*e.g.*, if water intakes affect a nursery habitat). A reduction in water withdrawal under Option 4 may benefit fish species affected by impingement and entrainment mortality. Due to data limitations and uncertainty, the EPA did not quantify and monetize these benefits as part of this analysis.

2.6 Summary of Benefits Categories

Table 2-3 summarizes the potential social welfare effects of the regulatory options 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 (in which case the table identifies the section of the report that discusses the analysis). The monetized welfare effects include changes in some human health risks, use and non-use values from changes in surface water quality, changes in costs for dredging navigational waterways, increased air pollution, and changes in water withdrawals. Other welfare effect categories, including expected changes of pollutant concentrations in excess of human health-based NRWQC limits, can be quantified but not monetized. Finally, the EPA was not able to quantify or monetize other welfare effects, including impacts to commercial fisheries or changes in the marketability of coal ash for beneficial use; the EPA evaluated these effects qualitatively as discussed above in *Sections 2.1* through *2.5*.

[12] The scenario-specific emission inputs developed for this project are currently available online at: https://github.com/epa-kpc/RFMEVAL. Upon completion and publication of the final report, the final report and all associated documentation will be online and available at this URL.

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

Category	Effect of Regulatory Options	Benefits Analysis: Quantified	Benefits Analysis: Monetized	Benefits Analysis: Methods (Report Chapter or Section where Analysis is Detailed)
Human Health Benefits from Surface Water Quality Improvements				
Incidence of bladder cancer	Changes in exposure to TTHM in drinking water	✓	✓	VSL and COI (*Section 2.1.1*)
IQ losses to children ages 0 to 7	Changes in childhood exposure to lead from fish consumption	✓	✓	IQ point valuation (*Section 5.3*)
Need for specialized education	Changes in childhood exposure to lead from fish consumption	✓	✓	Avoided cost (*Section 5.3)*
Incidence of cardiovascular disease	Changes in exposure to lead from fish consumption			Qualitative discussion
IQ losses in infants	Changes in-utero mercury exposure from maternal fish consumption	✓	✓	IQ point valuation (*Section 5.4*)
Incidence of cancer	Changes in exposure to arsenic from fish consumption	✓	✓	COI (*Section 5.5*)
Other adverse health effects (cancer and non-cancer)	Changes in exposure to other pollutants (arsenic, lead, etc.) via fish consumption or drinking water	✓		Human health criteria exceedances (*Section 5.7*)
Reduced adverse health effects	Changes in exposure to pollutants from recreational water uses			Qualitative discussion
Ecological Conditions and Effects on Recreational Use from Surface Water Quality Changes				
Aquatic and wildlife habitat[a]	Changes in ambient water quality in receiving reaches	✓	✓	Benefit transfer (*Chapter 6*)
Water-based recreation[a]	Changes in swimming, fishing, boating, and near-water activities from water quality changes	✓	✓	Benefit transfer (*Chapter 6*)
Aesthetics[a]	Changes in aesthetics from shifts in water clarity, color, odor, including nearby site amenities (residing, working, traveling)	✓	✓	Benefit transfer (*Chapter 6*)
Non-use values[a]	Changes in existence, option, and bequest values from improved ecosystem health	✓	✓	Benefit transfer (*Chapter 6*)
Aquatic and wildlife[a]	Changes in risks to aquatic life from exposure to steam electric pollutants	✓	✓	Benefit transfer (*Chapter 6*)
Protection of T&E species	Changes in T&E habitat and thus potential effects on T&E population	✓		Qualitative discussion (*Chapter 7*)
Sediment contamination	Changes in deposition of toxic pollutants to sediment			Qualitative discussion
Market and Productivity Benefits				
Dredging costs	Changes in costs for maintaining navigational waterways and reservoir capacity	✓	✓	Cost of dredging (*Chapter 10*)
Beneficial use of ash	Changes in disposal costs and avoided lifecycle impacts from displaced virgin material			Qualitative discussion

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 or Section where Analysis is Detailed)
Water treatment costs for drinking water and irrigation water	Changes in quality of source water used for drinking and irrigation			Qualitative discussion
Commercial fisheries	Changes in fisheries yield and harvest quality due to aquatic habitat changes			Qualitative discussion
Tourism industries	Changes in participation in water-based recreation			Qualitative discussion
Property values	Increased property values from water quality improvements			Qualitative discussion
Air-Related Effects				
Air emissions of NO_X and SO_2	Changes in mortality and morbidity from exposure to particulate matter ($PM_{2.5}$) linked to changes in NO_X and SO_2 emissions	✓		Changes in tons of NO_X and SO_2 emitted (Chapter 8)
Air emissions of CO_2	Climate change impacts	✓	✓	Domestic social cost of carbon (SC-CO_2) (Chapter 8)
Air emissions of other pollutants	Changes in human health and other effects from pollutants emissions			Qualitative discussion
Changes in Water Withdrawal				
Groundwater withdrawals	Decreased availability of groundwater resources	✓	✓	Cost per gallon of water withdrawn (Chapter 9)
Surface water withdrawals	Changes in vulnerability to drought and impingement and entrainment mortality			Qualitative discussion

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

Source: U.S. EPA Analysis, 2019

3 Water Quality Effects of Regulatory Options

Changes in the quality of surface waters, aquatic habitats and ecological functions due to the regulatory options depend on a number of factors, including the operational characteristics of steam electric power plants, treatment technologies implemented to control pollutant levels, the timing required for plants to comply with the regulatory options, 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. The EPA modeled water quality based on loadings estimated for the baseline and for each of the four regulatory options (Options 1-4). The differences in predicted 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*.

The analyses use pollutant loading estimates detailed in in the *Supplemental TDD* (U.S. EPA, 2019b) and expand upon the analysis of immediate receiving waters described in the *Supplemental EA* document (U.S EPA, 2019a) by estimating changes in both receiving and downstream reaches. The *Supplemental 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

The regulatory options affect pollutant discharges to receiving waters downstream of 116 steam electric power plants. The 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, 2018c) to characterize these waters.

Of the 116 plants modeled, 112 had non-zero pollutant discharges under the baseline or the regulatory options. [13] In the aggregate, these plants discharge bottom ash transport water or FGD wastewater to 112 waterbodies (as categorized in NHDPlus), including lakes, rivers, and estuaries. NHDPlus also provides the Strahler Stream Order[14] for each reach, where the order increases as one moves from headwaters (order 1) to downstream segments (orders 2-9). Table 3-1 summarizes Strahler Stream Order for the 112 receiving reaches. Stream order is one of the factors considered in evaluating potential uses of reaches (*e.g.*, whether the reach is likely to be fishable), when estimating benefits of water quality changes.

Table 3-1: Strahler Stream Order Designation for Reaches Receiving Steam Electric Power Plant Discharges

Stream Order	Number of Reaches
1	15
2	9
3	6
4	9

[13] Two plants have multiple receiving waters to which different waste streams are discharged — one receiving inputs from FGD discharges and the other from BA discharges. There are also two reaches that receive discharges from two separate plants.

[14] Strahler Stream Order is a numerical measure of stream branching complexity. First order streams are the origin or headwaters of a flowline. The confluence of two first order streams forms a second order stream, the confluence of two second order streams forms a third order stream, and so on.

Table 3-1: Strahler Stream Order Designation for Reaches Receiving Steam Electric Power Plant Discharges

Stream Order	Number of Reaches
5	9
6	18
7	17
8	20
9	3
Not classified	6

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[15] for analysis of the fate and transport of steam electric power plant discharges (*Section 3.3*). While eight steam electric power plants discharge bottom ash transport water and/or FGD wastewater to tidal reaches or the Great Lakes,[16] the EPA did not assess pollutant loadings and water quality changes associated with these waterbodies because of the lack of a defined flow path in NHDPlus, the complexity of flow patterns, and the relatively small changes in concentrations expected.[17] The EPA did not quantify the water quality changes and resulting benefits (or forgone benefits) to these systems. Thus, the total number of plants for which the EPA estimated downstream water quality changes is 104 (112 plants with nonzero pollutant discharges minus the eight plants discharging to the Great Lakes or tidal waterbodies).

3.2 Changes in Pollutant Loadings

The EPA estimated post-compliance pollutant loadings for each plant under the baseline and the four regulatory options. The TDD details the methodology (U.S. EPA, 2019b). The sections below discuss the approach the EPA used to develop a profile of loading changes over time and summarize the results.

3.2.1 Timing of ELG Implementation

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, 2003). As described in the proposal, the regulatory options incorporate varying compliance deadlines for meeting the revised limits depending on the wastestream and technology basis, including providing more time to plants that participate in the VIP to meet more stringent FGD wastewater effluent limits.

Table 3-2 summarizes the expected implementation schedules for the baseline and the four regulatory options. This implementation schedule means that plants may be installing wastewater treatment technologies in different years across the industry and potentially even within a given plant (*e.g.*, complying with bottom ash transport water requirements in 2021 and FGD wastewater requirements in 2028). This in turn can translate into variations in pollutant loads to waters over time.

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15 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.

16 Six reaches, one of which receives discharges from two steam electric power plants, are located in the Great Lakes (four reaches along or near Lake Michigan, one reach along Lake Erie, and one reach on Saginaw Bay near Lake Huron). One additional reach is located in Hillsborough Bay and is influenced by tidal processes.

17 The 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 EA document for details; U.S. EPA, 2015a).

To support estimating the benefits of the regulatory options, the EPA estimated the annual average loadings discharged by each plant during the period of analysis (2021-2047), accounting for when each plant would implement technologies to comply with the regulatory options. Using average annual values instead of a year-by-year profile masks potential transitional effects of the regulatory options, including temporary increases in loadings relative to the 2015 final rule baseline due to an extended status quo from delayed implementation of new requirements. However, because the categories of benefits that the EPA is analyzing generally result from changes in long-term processes (*e.g.,* bladder cancer from chronic exposure to trihalomethanes), annual average pollutant levels are likely an appropriate measure of changes in environmental stressors under the regulatory options.

As discussed in the *RIA* (U.S. EPA, 2019c), there is uncertainty in the exact timing when individual steam electric power plants would be implementing technologies to meet the ELGs. This benefits analysis uses the same plant-specific technology installation years used in the cost and economic impact analysis. 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.

Table 3-2: Implementation Schedule by Wastestream and Regulatory Option

	Bottom Ash Transport Water					FGD Wastewater				
Year(s)	**Baseline**	**Option 1**	**Option 2**	**Option 3**	**Option 4**	**Baseline**	**Option 1**	**Option 2**	**Option 3**	**Option 4**
2020	**Current**	Current	Current	Current	Current	**Current**	Current	Current	Current	Current
2021	**Transition**	Transition	Transition	Transition	Transition	**Transition**	Transition (non-VIP plants)	Transition (non-VIP plants)	Transition (non-VIP plants)	Current
2022	**Transition**	Transition	Transition	Transition	Transition	**Transition**	Transition (non-VIP plants)	Transition (non-VIP plants)	Transition (non-VIP plants)	Current
2023	**Transition**	Transition	Transition	Transition	Transition	**Transition**	Transition (non-VIP plants)	Transition (non-VIP plants)	Transition (non-VIP plants)	Current
2024	**Revised ELG**	Revised ELG	Revised ELG	Revised ELG	Revised ELG	**Revised ELG**	Transition (non-VIP plants)	Transition (non-VIP plants)	Transition (non-VIP plants)	Transition
2025	**Revised ELG**	Revised ELG	Revised ELG	Revised ELG	Revised ELG	**Revised ELG**	Transition (non-VIP plants)	Transition (non-VIP plants)	Transition (non-VIP plants)	Transition
2026	**Revised ELG**	Revised ELG	Revised ELG	Revised ELG	Revised ELG	**Revised ELG**	Interim Loads	Interim Loads	Interim Loads	Transition
2027	**Revised ELG**	Revised ELG	Revised ELG	Revised ELG	Revised ELG	**Revised ELG**	Interim Loads	Interim Loads	Interim Loads	Transition
2028	**Revised ELG**	Revised ELG	Revised ELG	Revised ELG	Revised ELG	**Revised ELG**	Transition (VIP plants)	Transition (VIP plants)	Transition (VIP plants)	Transition
2029-2048	**Revised ELG**	Revised ELG	Revised ELG	Revised ELG	Revised ELG	**Revised ELG**	Revised ELG	Revised ELG	Revised ELG	Revised ELG

Current = Current loadings

Transition = Some plants meet the revised limits, based on permitting schedule (see *Section 3.1.3* in the *RIA* (U.S. EPA, 2019c) for details on the modeled plant-specific compliance schedule). Aggregate loadings are lower than under current conditions but greater than under the revised ELG.

Interim loads = Non-VIP plants have reached the steady-state post-compliance loadings, but loadings for VIP plants are still at the current level.

Revised ELG = All plants meet revised limits. Loadings are at their minimum steady-state post-compliance level.

Source: U.S. EPA Analysis, 2019

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) means that changes in pollutant loads between the regulatory options and the baseline vary over the period of analysis. Table 3-3 summarizes the average annual changes in FGD wastewater, bottom ash transport water, and total loads for selected pollutants that inform the EPA's analysis of the benefits discussed in *Chapters 4* through *7*. Negative values in the table indicate *reductions* in pollutant loadings under an option as compared to the baseline. As shown in the table, total aggregate annual average pollutant loads increase under Option 1 across all pollutants. Options 2 and 3 show a decline in total bromide loads, with Option 3 also reducing total phosphorus and thallium loads. Option 4 reduces total loadings of additional pollutants, but still shows increases in total nitrogen, selenium, and zinc, among others. While this is not apparent from the total values, the direction of the changes for a particular pollutant is not necessarily uniform across all plants under a given option. For example, plants that participate in the VIP program under Options 2 and 3 may see reduced pollutant loadings in their FGD wastewater when compared to the baseline, whereas pollutant loads may increase for non-VIP plants implementing chemical precipitation with LRTR biological treatment control technologies. Additionally, while Option 4 reduces total bromide loads, plants with bottom ash wastestreams only may discharge greater quantities of bromide under Option 4 than under the baseline. These differences are expected to have varying impacts on benefit estimates depending on the location of the plants and their proximity to sensitive populations or environmental receptors.

Table 3-3: Annual Average Changes in Total Pollutant Loading in 2021-2047 for Selected Pollutants in Steam Electric Power Plant Discharges, Relative to Baseline (lb/year)

Pollutant	Option 1[a]			Option 2[a]			Option 3[a]			Option 4[a]		
	FGD	Bottom Ash	Total	FGD	Bottom Ash	Total	FGD	Bottom Ash	Total	FGD	Bottom Ash	Total
Arsenic	0	86.9	86.9	-20.9	579	558	-31.3	86.9	55.6	-204	86.9	-117
Bromide	0	50,000	50,000	-10,200,000	338,000	-9,890,000	-11,100,000	50,000	-11,100,000	-23,900,000	50,000	-23,900,000
Cadmium	0	6.73	6.73	287	44.7	332	409	6.73	416	337	6.73	344
Chromium	0	47.4	47.4	3.46	315	319	3.33	47.4	50.8	-182	47.4	-135
Copper	0	36.8	36.8	33.9	245	279	47.5	36.8	84.4	-55.7	36.8	-18.8
Lead	0	97.2	97.2	-11.5	647	635	-17.2	97.2	80.0	-117	97.2	-20.3
Mercury	5.14	0.954	6.09	23.3	6.33	29.6	32.1	0.954	33.1	35.0	0.954	35.9
Nickel	164	163	327	2,490	1,090	3,570	3,510	163	3,670	3,770	163	3,930
Nitrogen, Total	5,550,000	24,600	5,570,000	2,040,000	164,000	2,210,000	1,710,000	24,600	1,740,000	2,150,000	24,600	2,180,000
Phosphorus, Total	0	2,070	2,070	-1,420	13,900	12,500	-2,100	2,070	-35.9	-11,700	2,070	-9,660
Selenium	54,000	114	54,100	21,100	766	21,900	18,000	114	18,100	24,400	114	24,500
Thallium	0	10.6	10.6	-32.4	70.7	38.2	-48.8	10.6	-38.2	-340	10.6	-330
TSS	0	125,000	125,000	16,400	840,000	856,000	21,200	125,000	146,000	-228,000	125,000	-103,000
Zinc	0	316	316	3,780	2,100	5,880	5,400	316	5,710	5,480	316	5,800

a. Negative values represent a reduction in pollutant loadings as compared to the baseline.

Source: U.S. EPA Analysis, 2019.

3.3 Water Quality Downstream from Steam Electric Power Plants

The EPA used the estimated annual average changes in total pollutant loadings to estimate concentrations downstream from each plant. The methodology uses two main models to estimate downstream concentrations:

- A dilution model to estimate pollutant concentrations downstream from the plants. The approach, which for the purpose of this analysis is referred to as the D-FATE model (Downstream Fate And Transport Equations), involves calculating concentrations in each downstream medium-resolution NHD reach assuming conservation of mass and annual average Enhanced Runoff Method (EROM) flows from NHDPlus v2. The calculations are similar to the methodology the EPA used in 2015 ELG rule analysis (U.S. EPA, 2015a), but use updated data (*e.g.*, flow). *Appendix A* summarizes differences between the 2015 rule analysis and the present analysis.
- USGS's SPAtially Referenced Regressions On Watershed attributes (SPARROW) to estimate flow-weighted nutrient and sediment concentrations. The SPARROW models provided baseline and post-compliance concentrations of total nitrogen, total phosphorus, and total suspended solids. These calibrated national models are the same models used by the EPA in the 2015 ELG rule analysis. Refer to the BCA document for the 2015 rule for more details on this analysis (U.S. EPA, 2015a).

The models include only discharges to rivers and streams, which represent the vast majority of plants affected by the regulatory options (104 plants out of 116 plants affected by the regulatory options). As discussed in *Section 3.1*, the EPA omitted steam electric power plants that discharge to the Great Lakes or to estuaries from this analysis.

In the D-FATE model, the EPA used stream routing and flow 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. The model assumes that the discharges do not affect in-stream flows. The 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.[18]

Following the approach used in the analysis of the 2015 rule (U.S. EPA, 2015a) to estimate pollutant concentrations, the EPA included loadings from major dischargers (in addition to the steam electric power plants) that reported to the 2016 Toxics Release Inventory (TRI). TRI data were available for a subset of toxics: arsenic, barium, chromium, copper, lead, manganese, mercury, nickel, selenium, thallium, and zinc. The EPA summed reach-specific background 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 analyze nonmarket benefits

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

of water quality improvements (see *Chapter 6*) and to derive fish tissue concentrations used to analyze human health effects from consuming self-caught fish (See *Chapter 5*).

3.4 Overall Water Quality Changes

Overall water quality changes modeled as a result of all evaluated options is relatively small compared to the 2015 rule analysis. Following the approach used in the analysis of the 2015 ELG (U.S. EPA, 2015a), the EPA used a WQI to link water quality changes from reduced metal, 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) concentrations) that are indicative of various aspects of water quality, into a single numerical indicator. The WQI value, which is measured on a scale from 0 to 100, reflects varying water quality, with 0 for poor quality and 100 for excellent.

As detailed in U.S. EPA (2015a), the WQI includes seven parameters: DO, BOD, fecal coliform (FC), TN, TP, TSS, 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 2016 TRI dischargers and that have chronic aquatic life-based NRWQC. Pollutants that meet these qualifications include arsenic, chromium, copper, lead, manganese, mercury, nickel, selenium, and zinc.[19] The only update from the suite of pollutants used for the 2015 rule analysis is the addition of copper exceedances in the toxics subindex, meaning the subindex reflects nine toxics instead of eight. As a result, 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, the EPA used modeled NRWQC exceedances for toxics (using concentrations from D-FATE) and modeled concentrations for TN, TP, and TSS (from the respective SPARROW models). The USGS National Water Information System (NWIS) provided concentration data from 2007-2017 for three parameters that are assumed to remain constant between the baseline and options: 1) fecal coliform, 2) dissolved oxygen, and 3) biochemical oxygen demand (see *Section 3.4.1.2*).[20]

3.4.1.1 Exceedances of Water Quality Standards and Criteria

For each regulatory option, the EPA identified reaches that do not meet national recommended chronic water quality criteria for aquatic life.[21] There are 18 reaches with NRWQC exceedances in the baseline; five of

[19] Barium and thallium are included in the 2016 TRI dataset but do not have chronic NRWQC in EPA's Aquatic Life Criteria Table and thus are excluded from the aggregate toxics subindex.

[20] USGS's NWIS dataset 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/

[21] 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

these reaches show improved water quality for at least one pollutant under the regulatory options. There are 22 reaches with no NRWQC exceedance in the baseline that have exceedances under one or more of the regulatory options; 12 of these reaches have NRWQC exceedances for at least one pollutant under all four of the regulatory options. Refer to the *Supplemental EA* for additional discussion of comparisons of receiving and downstream water pollutant concentrations to acute and chronic aquatic NRWQCs (U.S. EPA, 2019a).

3.4.1.2 Sources for Ambient Water Quality

The EPA used average monitoring values for fecal coliform, dissolved oxygen, and biochemical oxygen demand for 2007-2017 where available. Where more recent data were not available, the EPA used the same averages as for the 2015 rule analysis. The 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 (HUC)8, HUC6, HUC4, and HUC2) to fill in all missing data.[22] This approach assumes that reaches located in the same watershed generally share similar characteristics. Using this estimation approach, the 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 other rules and previously subject to public comment.

3.4.1.3 Spatial Reference for Water Quality Index Calculations

The EPA used two different reach classification frameworks to assess in-stream water quality under the baseline and each of the regulatory options: the medium-resolution NHD network[23] and the USGS's Enhanced River File 1 (E2RF1). Pollutant concentrations and exceedances were estimated for reaches indexed to the NHD network, the SPARROW data are available for reaches indexed to the E2RF1 network, and NWIS and STOrage and RETrieval Data Warehouse (STORET) data (U.S. EPA, 2008a) were averaged to USGS's HUC watersheds. The WQI and benefits are ultimately calculated at the resolution of NHD reaches, but with adjustments made to data available only at the E2RF1 level to reflect differences in spatial scale. Thus, to reconcile the two levels of resolution, the EPA mapped all modeled reaches from the E2RF1 to the NHD network using GIS.

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derived using short term (48-hour to 96-hour) toxicity tests (U.S. EPA, 2017b). More information on aquatic NRWQC can be found at https://www.epa.gov/wqc/national-recommended-water-quality-criteria-aquatic-life-criteria-table.

22 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 21), the next pair the subregion (total of 222), the third pair the basin or cataloguing unit (total of 352), and the fourth pair the subbasin, or accounting unit (total of 2,262) (USGS, 2007). Digits after the first eight offer more detailed information, but are not always available for all waters. 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.

23 The Watershed Boundary Dataset (WBD) is a companion dataset to the NHD and, therefore, was not considered a separate hydrologic unit classification framework.

The water quality analysis included a total of 10,315 medium-resolution NHD reaches that are potentially affected by steam electric power generating plants under the baseline. Of these 10,315 NHD reaches, the EPA estimated concentrations for 10,284 reaches, selected based on their Strahler stream order and mean annual flow rates. Table 3-4 summarizes the data sources used to estimate baseline and post-compliance values by water quality parameters.

Table 3-4: Water Quality Data used in Calculating WQI for the Baseline and Regulatory Options

Parameter	Baseline	Regulatory Option
TN	Concentrations calculated using SPARROW (baseline run) at the E2RF1 level and indexed to NHD reaches	Concentrations calculated using SPARROW (regulatory option run) at the E2RF1 level and indexed to NHD reaches
TP	Concentrations calculated using SPARROW (baseline run) at the E2RF1 level and indexed to NHD reaches	Concentrations calculated using SPARROW (regulatory option run) at the E2RF1 level and indexed to NHD reaches
TSS	Concentrations calculated using SPARROW (baseline run) at the E2RF1 level and indexed to NHD reaches	Concentrations calculated using SPARROW (regulatory option run) at the E2RF1 level and indexed to NHD reaches
DO	Observed values averaged at the WBD watershed level[a]	No change. Regulatory option value set equal to baseline value
BOD	Observed values averaged at the WBD watershed level[a]	No change. Regulatory option value set equal to baseline value
Fecal Coliform	Observed values averaged at the WBD watershed level[a]	No change. Regulatory option value set equal to baseline value
Toxics	Baseline exceedances calculated using D-FATE model at the NHD level	Regulatory option exceedances calculated using D-FATE model at the NHD level

WBD = Watershed Boundary Dataset

a. Values based on STORET and NWIS data, averaged for progressively larger geographical units (HUC8, HUC6, HUC4, and HUC2), as needed to fill in all missing data.

Source: U.S. EPA Analysis, 2019.

3.4.2 WQI Calculation

The EPA used the approach described in the BCA document for the 2015 rule (U.S. EPA, 2015a) to estimate WQI values for each reach under the baseline and each option. 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 to calculate the WQI value for the baseline (*i.e.*, the 2015 rule), and for each analyzed regulatory option. See details of the calculations in *Appendix B*, including the subindex curves used to transform levels of individual parameters.

3.4.3 Baseline WQI

Based on the estimated WQI value under the baseline scenario (WQI-BL), the EPA categorized each of these 10,284 NHD reaches using five WQI ranges (WQI < 25, 25≤WQI<45, 45≤WQI<50, 50≤WQI<70, and 70≤WQI) (Table 3-5). WQI values of less than 25 indicate that water is not suitable for boating (the recreational use with the lowest required WQI), whereas WQI values greater than 70 indicate that waters are swimmable (the recreational use with the highest required WQI).[24]

Table 3-5: Estimated Percentage of Potentially Affected Inland 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
Unusable	WQI<25	5	0.0%	2	0.0%
Suitable for Boating	25≤WQI<45	366	3.6%	349	3.4%
Suitable for Rough Fishing	45≤WQI<50	410	4.0%	343	3.3%
Suitable for Game Fishing	50≤WQI<70	3,364	32.7%	3,206	30.8%
Suitable for Swimming	70≤WQI	6,139	59.7%	6,494	62.5%
Total		**10,284**	**100.0%**	**10,393**	**100.0%**

Source: U.S. EPA Analysis, 2019

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

To estimate benefits of water quality improvements expected to result from the regulatory options, the EPA calculated the change in WQI for each analyzed regulatory option as compared to the baseline. As discussed in *Section 3.3*, the EPA estimated changes in ambient concentrations of TN, TP and TSS using the USGS's SPARROW model and toxics concentrations using the D-FATE model. In calculating the option WQI (WQI-PC), the Agency used option-specific toxics, TN, TP, and TSS concentrations. 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 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 options. Table 3-6 presents water quality change ranges under the four regulatory options. The largest proportion (more than 90 percent) of potentially affected reaches have negative ΔWQI, indicating degrading water quality, or no changes in WQI under Options 1 through 3. In particular, under Option 1, none of the reaches would experience a positive change in WQI value. However, under Option 4, over 25 percent of reaches would experience a positive ΔWQI. Note that the changes are based on annual average concentrations over the period of 2021 through 2047 and reflect conditions both before and after plants implement technologies to meet revised effluent limits.

[24] The 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 (*i.e.*, changes in bromide loadings) are addressed separately in *Chapter 4*.

Table 3-6: Ranges of Estimated Water Quality Changes for Regulatory Options

Options	Minimum ΔWQI[a]	Maximum ΔWQI	Median ΔWQI	ΔWQI Interquartile Range
Option 1	-5.29	0.00	-1.02×10-3	0.01
Option 2	-2.95	1.30	-4.69×10-4	1.68×10-3
Option 3	-2.95	1.30	-2.29×10-4	7.79×10-4
Option 4	-2.62	1.31	-2.30×10-5	1.25×10-3

a. Negative changes in WQI values indicate degrading water quality.

Source: U.S. EPA Analysis, 2019

3.5 Limitations and Uncertainty

The methodologies and data used in the estimation of environmental effects of regulatory options involve limitations and uncertainties. Table 3-7 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 data, see U.S EPA (2018c). Regarding the uncertainties associated with estimated loads, see the TDD (U.S. EPA, 2019b).

Table 3-7: Limitations and Uncertainties in Estimating Environmental Effects of Regulatory Options

Uncertainty/Assumption	Effect on Environmental 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 measured data also reflect other sources such as bottom sediments, air deposition, and other point and non-point sources of pollution. 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 EA for the 2015 rule for discussion of model validation for selected case studies (U.S. EPA, 2015a)
In-stream concentrations assume that stream flows are unaffected by steam electric power plant discharges	Overestimate	The degree of overestimation, if any, would be small given that steam electric power plant discharge flows tend to be very small as compared to stream flows in modeled receiving and downstream reaches.
In-stream toxics concentrations are based only on loadings from steam electric power plants and other TRI discharges.	Underestimate	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.
Annual loadings are estimated based on estimated plant-specific technology implementation years	Uncertain	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. The effect of this uncertainty is limited to the early years of the analysis since loads reach a steady-state level by the compliance deadlines applicable to the regulatory options (*e.g.*, by 2028)

Table 3-7: Limitations and Uncertainties in Estimating Environmental Effects of Regulatory Options

Uncertainty/Assumption	Effect on Environmental Effects Estimation	Notes
The EPA used constant values for fecal coliform, dissolved oxygen, and biochemical oxygen demand.	Uncertain	The use of constant values for these parameters omits the potential impacts of changes in stream electric plant discharges under the regulatory options on these water quality indicators, most notably dissolved oxygen.
The EPA used regional averages of monitoring data from 2007-2017 for fecal coliform, dissolved oxygen, and biochemical oxygen demand, when location-specific data were not available. In cases where more recent data were not available, the EPA used the same averages as used in the 2015 rule analysis (U.S. EPA, 2015a).	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 in-stream sediment and nutrient concentrations into subindex scores (see *Section 3.4.2* and *Appendix B*) 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 benefit in the analysis described later in Chapter 6.

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

The EPA expects that the small changes in pollutant loadings from the regulatory options relative to the 2015 analysis (U.S. EPA, 2015a) 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 *Supplemental EA* (U.S. EPA, 2019a) provides details on the health effects of steam electric pollutants.

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 and fish ingestion. This chapter addresses the first exposure pathway: drinking water. *Chapter 5* addresses the fish consumption pathway.

Section 4.1 presents background information regarding the potential impacts of bromide discharges on drinking water quality and human health. *Sections 4.2* through *4.4* present the 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.

In general, the estimated effects of the proposed regulatory option, Option 2, on pollutant exposure via drinking water pathways are small compared to those estimated in 2015 (U.S. EPA, 2015a).

4.1 Background

Bottom ash transport water and FGD wastewater 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 and VanBriesen, 2016, 2017; McTigue et al., 2014; Ruhl et al., 2012; States et al., 2013; U.S. EPA, 2017a, 2019d) and have attributed measured changes in bromide levels to the installation of wet FGD devices at an increasing number of 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 and 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 (WHO, 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[25] (THM4, also referred to as total trihalomethanes (TTHM) in this discussion) and two of the five regulated haloacetic acids[26] (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, 2016).

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 (see U.S. EPA, 2016 for a review of recent studies). Bromodichloromethane and bromoform are likely to be carcinogenic to humans by all exposure routes and there is evidence suggestive of dibromochloromethane's carcinogenicity (National Toxicology Program, 2018; U.S. EPA, 2016). 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 (2019a).

4.2 Overview of the Analysis

Figure 4-1 illustrates the 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 four 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 changes to changes in the incidence of bladder cancers in the exposed population (Step 3); and estimating the associated monetary value of benefits (Step 4).

The approach in Step 3 builds on the approach the Agency previously used to analyze the effects of the Stage 2 Disinfectants and Disinfection Byproduct Rule (DBPR) (U.S. EPA, 2005a) and incorporates studies, data, and methodological advances that have become available following the promulgation of the DBPR. Specifically, this analysis includes findings from a peer-reviewed paper by Regli et al (2015) that built on the approach taken in the DBPR to derive a slope factor to relate changes in lifetime bladder cancer risk to changes in TTHM exposure. The paper was published after promulgation of the DBPR and includes many of the methodological components that supported the DBPR, such as the pooled analysis of Villanueva et al. (2004). The approach used for this analysis also incorporates more recent 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 proposed rule options, and survival outcomes. The life table modeling approach used by the EPA to estimate changes in health outcomes is a widely used method in public health, insurance, medical research, and other studies and was used by the EPA in the analysis of lead-associated health effects in the 2015 Rule (U.S. EPA, 2015a) and of $PM_{2.5}$-related health effects in revisions to the National Ambient Air Quality Standards for ground-level ozone (U.S. EPA, 20087; 2008b). Other examples include the Occupational Safety and Health Administration (OSHA)'s use of

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

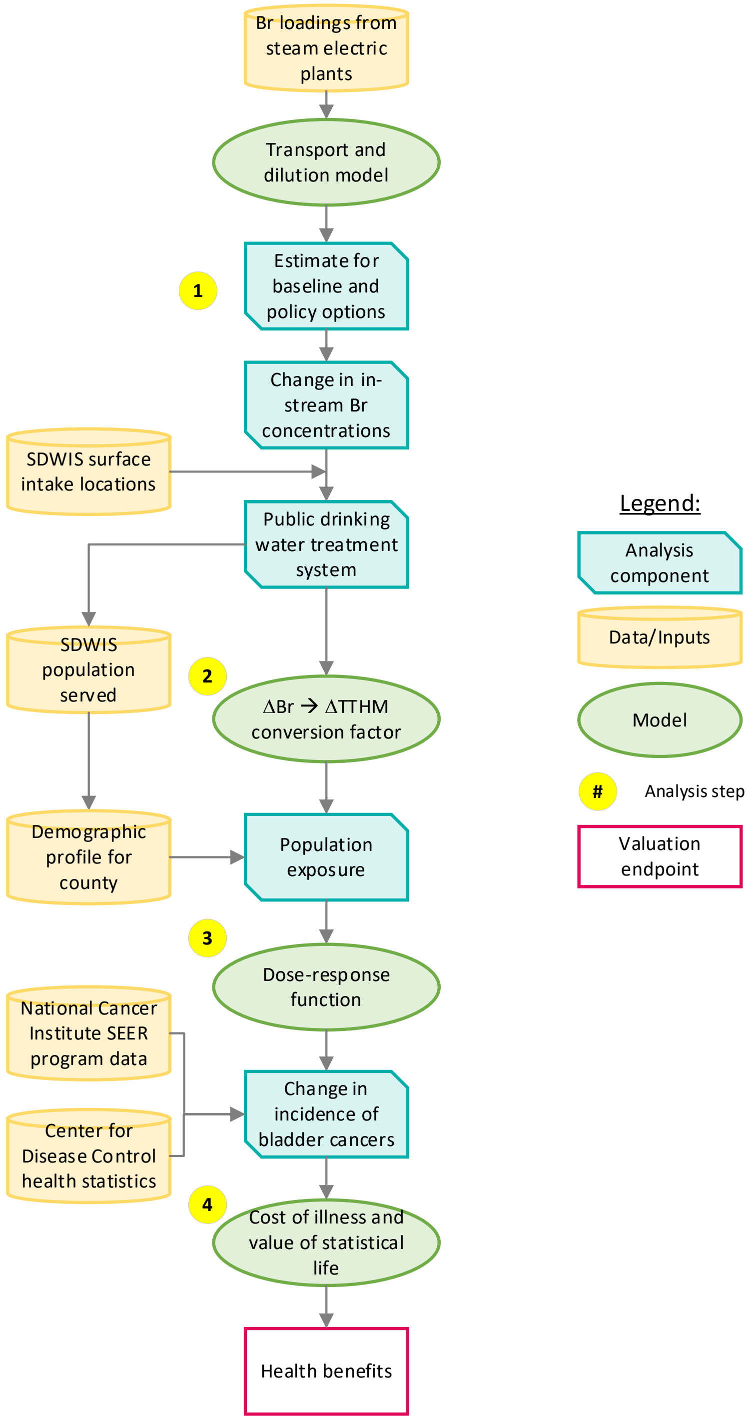
[26] The five regulated haloacetic acids are dibromoacetic acid, dichloroacetic acid, monobromoacetic acid, monochloroacetic acid, and trichloroacetic acid.

a life table approach to estimate lifetime excess lung cancer, NMRD mortality, and silicosis risks from exposure to respirable crystalline silica (81 FR 16285, March 25, 2016; OSHA, undated). The main advantage of the life table approach is that it explicitly accounts for age and cancer stage-specific patterns in cancer outcomes, as well as for other causes of mortality in the affected population.

The TTHM MCL is set higher than the health-based trihalomethane MCLGs in order to balance protection from human health risks from DBP exposure with the need for adequate disinfection to control human health risks from microbial pathogens. Actions that reduce TTHM levels below the MCL can therefore further reduce human health risk. The EPA's analysis quantifies the human health effects associated with incremental changes between the MCL and the MCLG. Recent TTHM compliance monitoring data indicate that the drinking water treatment facilities contributing most significantly to total estimated benefits for the proposal have TTHM levels below the MCL but in excess of the MCLGs for trihalomethanes.

This qualitative relationship between bladder cancer and bromide demonstrates the relative size of the benefit to other benefits associated with this proposal. Should this analysis be used to justify an economically significant rulemaking, EPA intends to peer review the analysis consistent with OMB's Information Quality Bulletin for Peer Review. That review would include robust examination of the strengths and limitations of the methods and an exploration of the sensitivity of the results to the assumptions made. If the analysis is designated a highly influential scientific assessment (HISA), one way the EPA may seek such a review is via the EPA's Science Advisory Board (SAB), which is particularly well suited to provide a peer review of HISAs. The EPA's SAB is a statutorily established committee with a broad mandate to provide advice and recommendations to the Agency on scientific and technical matters.

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



Source: U.S. EPA Analysis, 2019.

4.3 Analysis Steps

4.3.1 Step 1: Modeling Bromide Concentrations in Surface Water

As described in the *Supplemental TDD* (U.S. EPA, 2019b), the EPA estimated steam electric power plant-level bromide loadings associated with bottom ash transport water and FGD wastewater for the baseline and four regulatory options. Total plant loadings are calculated as the sum of bottom ash transport water and FGD wastewater loadings under each scenario. This chapter presents benefits estimated using the EPA's best estimate of changes in bromide loadings under each of the four regulatory options. *Appendix C* includes results of a sensitivity analysis using alternative loading estimates.

The EPA used the D-FATE model described in *Section 3.3* to estimate in-stream bromide concentrations downstream from 104 steam electric power plants with estimated non-zero bromide loads under the analyzed scenarios. The EPA first estimated the annual average bromide load over the period of analysis. The EPA then estimated concentrations in the receiving reach and each downstream reach, assuming conservation of mass, until the load reaches the network terminus (*e.g.*, Great Lake, estuary).[27] The EPA summed individual contributions from all plants to estimate total in-stream concentrations under the baseline and the four regulatory options. Finally, the EPA estimated the change in bromide concentrations in each reach as the difference between each regulatory option and the baseline. This change is not dependent on bromide contributions from other sources (*i.e.*, receiving waterbody background levels).

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

4.3.2.1 Affected Public Water Systems

The population potentially exposed to trihalomethanes deriving from bromide discharges from steam electric power plants includes individuals served by PWS whose source waters receive steam electric power plant discharges.

The EPA's Safe Drinking Water Information System (SDWIS) database[28] provides the latitude and longitude of surface water facilities[29], 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. [30] *Appendix E* describes the methodology the EPA used to determine 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,

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

[28] The EPA used intake locations as of January 2018 and PWS data as of June 2018, which reflects the second quarter report for 2018. 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/.

[29] Surface water facilities include any part of a public water system 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.

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

among other attributes. For this analysis, the EPA used the subset of facilities that identify surface water as their primary water source (specifically surface water intakes and reservoirs) and were 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 TTHM exposures and associated health effects due to the regulatory options.

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.[31] 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. The 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 both directly and indirectly affected systems.

Table 4-1 summarizes the intakes, PWS, and populations potentially affected by steam electric power plant discharges. Fourteen PWS are both directly and indirectly affected in that they both have intakes downstream from steam electric power plants and purchase water from another directly affected PWS. In this analysis, the average distance from the steam electric discharge point to the drinking water treatment plant intake is approximately 40 miles.

Table 4-1: Estimated Reaches, Surface Water Intakes, Public Water Systems, and Populations Potentially Affected by Bromide Discharges from Steam Electric Power Plants

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)
Direct[a]	278	348	294	20.2
Indirect	Not applicable	Not applicable	721	11.2
Total	**278**	**348**	**1,015**	**31.4**

a. Includes 14 systems that are both directly and indirectly affected by steam electric power plant discharges.

Source: U.S. EPA analysis, 2019

4.3.2.2 System-Level Changes in Bromide Concentrations in Source Water

The EPA estimated the changes in TTHM concentrations to which populations served by affected PWS are exposed by first estimating the change in bromide concentrations in the source water for each public water system that would result from the regulatory options, and then estimating the resulting changes in TTHM concentration in the treated water. In this discussion, the term "system" refers to public water systems and

31 To identify potentially affected PWS, the 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.

their associated drinking water 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, the EPA obtained the number of active permanent surface water sources used by each PWS based on SDWIS data. SDWIS does not provide any 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, the 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, the 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, the EPA assumed zero change in bromide concentration. Because SDWIS does not provide information on source flows contributed by intake facilities used by a given PWS, the 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 ($[\Delta Br + 0 + 0]/3$).

The 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, the EPA assumed zero change in bromide concentrations for any other unaffected source facility associated with the buyer. The EPA also assumed that each permanent source facility contributes an equal share of the total volume of water distributed by the buyer. For the 14 intakes classified as both directly and indirectly affected by steam electric power plant bromide discharges, the EPA assessed the total change in bromide concentration as a blended average of the change in concentration from both directly-drawn and purchased water.

Table 4-2 summarizes the distribution of changes in bromide concentrations under the four regulatory options. The direction of the changes depends on the option, source water reach, and PWS. Overall, Option 1 would result in an increase in bromide concentrations. Options 2, 3, and 4 would result in both increases and a decreases in bromide concentrations. Option 4 has a higher frequency and magnitude of reduction in bromide concentrations than the other regulatory options. All modeled changes to PWS bromide concentrations are small. Refer to Table 3-3 for a summary of changes in bromide loadings associated with FGD and bottom ash transport wastewaters under each regulatory option.

Table 4-2: Estimated Distribution of Changes in Source Water and PWS-level Bromide Concentrations by Regulatory Option

ΔBr range (µg/L)	Number of source water reaches			Number of PWS[a]		
	Positive[b] ΔBr	Negative[b] ΔBr	No ΔBr (ΔBr = 0)	Positive[b] ΔBr	Negative[b] ΔBr	No ΔBr (ΔBr = 0)
Option 1						
0 to 10	212	0	66	699	0	316
10 to 30	0	0	0	0	0	0
30 to 50	0	0	0	0	0	0
50 to 75	0	0	0	0	0	0
>75	0	0	0	0	0	0
Option 2						
0 to 10	154	33	38	502	168	125
10 to 30	0	47	0	0	193	0
30 to 50	0	3	0	0	8	0
50 to 75	0	0	0	0	0	0
>75	0	3	0	0	19	0
Option 3						
0 to 10	110	72	39	374	274	143
10 to 30	0	50	0	0	196	0
30 to 50	0	3	0	0	8	0
50 to 75	0	1	0	0	1	0
>75	0	3	0	0	19	0
Option 4						
0 to 10	66	94	9	243	383	46
10 to 30	0	89	0	0	280	0
30 to 50	0	10	0	0	24	0
50 to 75	0	2	0	0	10	0
>75	0	8	0	0	29	0

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

b. Positive values indicate higher estimated bromide concentrations under the regulatory option as compared to the baseline, whereas negatives values indicate lower bromide concentrations under the regulatory option.

Source: U.S. EPA Analysis, 2019.

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 4-3 summarizes the results from the Regli et al. (2015) analysis.

Table 4-3: 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

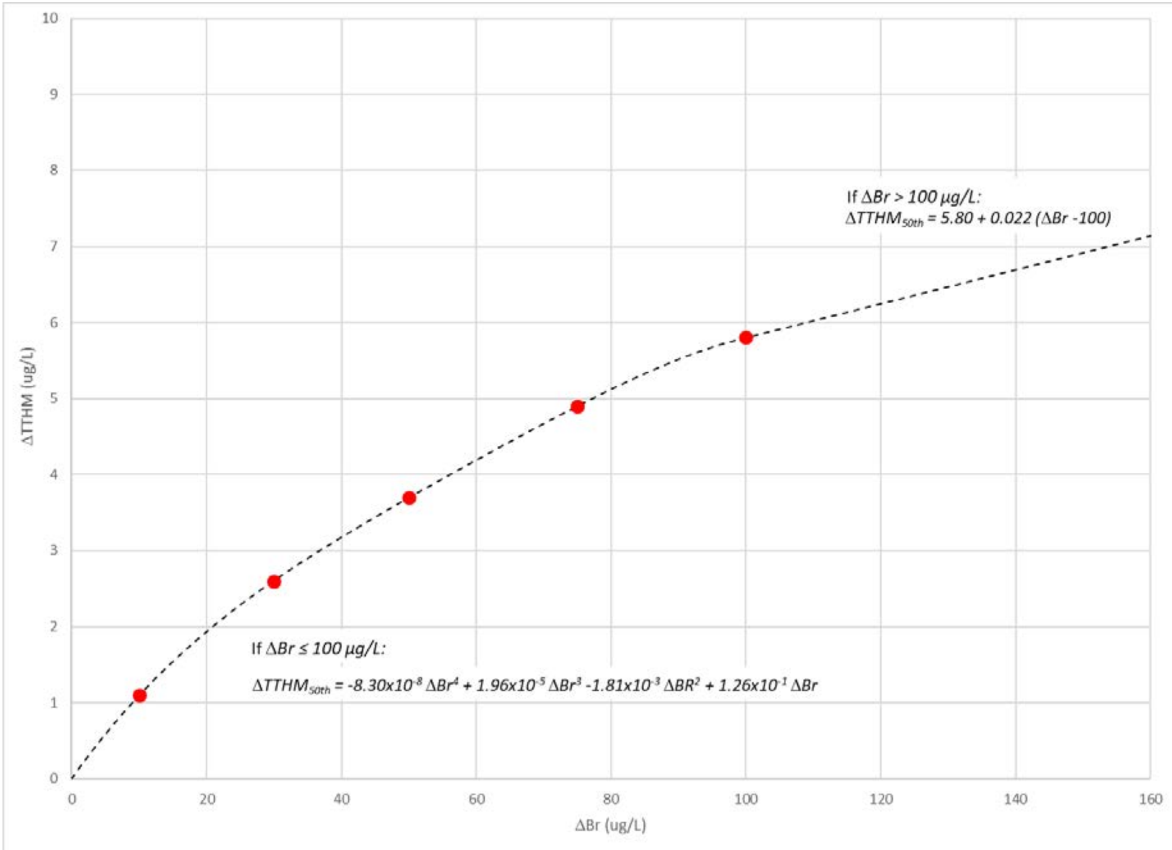
Source: Regli et al (2015), Table 2.

For this analysis, the 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 4-3 (circular markers). The EPA used the equation of the best-fit curve[32] 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). For changes in bromide greater than 100 µg/L, the EPA extrapolated values by continuing the slope of the best-fit curve for a 100 µg/L change in bromide concentration (equivalent to 0.022 µg/L ΔTTHM per 1 µg/L ΔBr). Estimates of TTHM concentration changes presented in the remainder of this section reflect median changes from Regli et al. (2015).[33] The EPA developed similar relationships for the 5th and 95th percentile estimates in Table 4-3 to evaluate the sensitivity of the benefits estimates to the relationship between changes in bromide and changes in TTHM. *Appendix C* summarizes the results of this sensitivity analysis.

32 The polynomial curve fits observations in Table 4-3 with residuals of zero over the range of observations.

33 While Regli et al. (2015) show similar mean and median changes in TTHM concentrations across the range of changes in bromide concentrations, the EPA used the median to minimize potential influence of outlier values or skew in the distribution.

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, 2019, based on Regli et al. (2015).

Table 4-4 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, Option 1 is estimated to increase TTHM concentrations in treated water. Options 2, 3, and 4 are estimated to increase TTHM concentrations at some PWS and decrease them at the majority of PWS.

Table 4-4: 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 1			
>0 to 10	0.000103 to 0.0844	699	25.27
10 to 30	--	--	--
30 to 50	--	--	--
50 to 75	--	--	--
>75	--	--	--

Table 4-4: 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 2			
>0 to 10	0.000114 to 1.07	670	24.76
10 to 30	1.10 to 2.25	193	1.46
30 to 50	2.86 to 3.43	8	0.02
50 to 75	No data	No data	No data
>75	5.87 to 9.88	19	0.67
Option 3			
>0 to 10	0.000114 to 1.07	648	24.62
10 to 30	1.11 to 2.46	196	1.54
30 to 50	2.87 to 3.43	8	0.02
50 to 75	3.96 to 3.96	1	0.01
>75	5.87 to 9.88	19	0.67
Option 4			
>0 to 10	0.000114 to 1.09	626	24.53
10 to 30	1.11 to 2.60	280	5.08
30 to 50	2.61 to 3.61	24	0.15
50 to 75	3.78 to 4.55	10	0.60
>75	4.93 to 10.2	29	0.93

a. Shows only non-zero absolute changesΔΔ. Modeled PWS-level changes under individual options may be zero, positive, or negative.

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

c. Approximately 0.3 percent to 20 percent (depending on the regulatory option) of the total population served by PWS potentially affected by bromide discharges from steam electric power plants are served by PWS with no change in source water bromide concentrations.

Source: U.S. EPA analysis, 2019.

4.3.3 Step 3: Quantifying Population Exposure and Health Effects

The 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

SDWIS provides the total population served by each PWS and identifies the counties constituting the PWS service area. For this analysis, the 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.

The EPA used county-level data from the 2017 American Community Survey (ACS, U.S. Census Bureau, 2018) to distribute the total exposed population for each PWS by age group to model health effects as described in *Section 4.3.3.3*.[34]

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, 2016; 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 the EPA's Stage 2 DBP Rule[35] which specifically aimed to reduce the potential health risks from DBPs (U.S. EPA, 2005a).

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, 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. 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.

The 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. $$O(x) = O(0) \cdot \exp\,(0.00427 * x),$$

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 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.

34 The EPA used 2012 to 2016 Census county-level data to distribute the exposed population by racial/ethnic group and poverty status to support analysis of environmental justice (EJ) considerations in baseline exposure to pollutants in steam electric power plant discharges and to evaluate how regulatory options may mitigate EJ concerns (see *Chapter 14* for details).

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

4.3.3.3 Health Risk Model and Data Sources

The 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 of health impacts during a defined period (Miller and Hurley, 2003; Rockett, 2010).[36] 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, the 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 2021 – and to alternative TTHM levels from 2021 through 2047. 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 (2028). 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 cost-benefit framework of the regulatory options, the EPA modeled changes in health outcomes resulting from changes in exposure in 2021-2047. To capture long term benefits of reduced exposure to TTHM from 2021 to 2047, EPA modeled associated changes in cancer incidence through 2121.

Lifetime health risk model data sources, detailed in Table 4-5 (next page), include EPA SDWIS, ACS 2017 (U.S. Census Bureau, 2018), the Surveillance, Epidemiology, and End Results (SEER) program database (National Cancer Institute), and the Center for Disease Control (CDC) National Center for Health Statistics.

[36] The 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 and Puskin, 2004; Munns and Mitro, 2006; National Research Council, 2011).

Table 4-5: 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 2021	Age: 1-year groups (ages 0 to 100) Sex: males, females Location: county for PWS service area from SDWIS[a]	2017 American Community Survey (ACS) (data on age- and sex-specific county-level population [U.S. Census Bureau, 2017b]). Location-specific number of exposed persons as described in *Appendix C*.	ACS data were in 5-year age groups. The EPA assumed uniform distribution within each age interval to represent data as 1-year age groups. The EPA then computed relevant age- and sex- population shares and used them to distribute location-specific affected population within each county.
Bladder cancer incidence rate (IR) per 100,000 persons	Age at diagnosis: 1-year groups (ages 0 to 100) Sex: males, females	Surveillance, Epidemiology, and End Results (SEER)[b] 18 bladder cancer incidence rates by age and sex at diagnosis	Distinct SEER 18 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+. The 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, 2014	The EPA extracted 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 18 distribution of bladder cancer incidence over stages by age and sex at diagnosis	Distinct SEER 18 data were available for ages 0-44, 45-54, 55-64, 65-74, 75+. The EPA assumed that the same cancer incidence shares by stage apply to all ages within each age group.
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, distant, unstaged	SEER 18 relative bladder cancer survival by age at diagnosis, sex, cancer stage and duration with diagnosis	For males, distinct SEER 18 data were available for ages at diagnosis 0-44, 45-54, 55-64, 65-74, 75+. For females, data were available for ages at diagnosis 0-49, 50-54, 55-64, 65-74, 75+. The 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 years. For disease durations >5 years the EPA applied 5-year relative survival rates.

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

b. SEER program, National Cancer Institute, National Institute of Health

Source: U.S. EPA Analysis, 2019.

Table 4-6 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 C* 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, the EPA then 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 small estimated changes in annual average bromide discharges and associated TTHM exposure under the regulatory options compared to the baseline.

Table 4-6: 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	0s	0.1296	80.5565	0.0225
Male	10s	0.1305	39.8300	0.0615
Male	20s	0.1425	131.3614	0.4104
Male	30s	0.1399	171.6144	1.5856
Male	40s	0.1266	314.4912	7.6596
Male	50s	0.1356	762.5491	31.6385
Male	60s	0.1095	1522.7546	96.5131
Male	70s	0.0577	3355.4487	215.9884
Male	80s	0.0188	8252.4234	333.1737
Male	90s	0.0094	31453.2483	366.5350
Female	0s	0.1177	66.5815	0.0000
Female	10s	0.1190	18.9204	0.0290
Female	20s	0.1350	51.6802	0.1986
Female	30s	0.1355	91.9849	0.6450
Female	40s	0.1248	202.5000	2.5795
Female	50s	0.1366	468.1672	9.2859
Female	60s	0.1170	951.2290	25.2908
Female	70s	0.0681	2357.4268	50.1267
Female	80s	0.0285	6420.9784	74.3698
Female	90s	0.0177	27743.8548	78.1720

a. Shares calculated for the total population served by potentially affected PWS, based on county-level 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 (2019) of 2017 ACS Data.

4.3.3.4 Model Implementation

The 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, the EPA models TTHM changes (ΔTTHM) due to the regulatory options as being in effect for the years 2021 through 2047. After 2047, the EPA does not attribute costs or changes in bromide loadings to the rule, and therefore does not model incremental changes in exposures to TTHM.[37]

To estimate changes in bladder cancer incidence, the EPA defined and quantified a set of 102,414 unique combinations[38] of the following parameters:

- *Location and TTHM changes*: 507 PWS groups;[39]
- *Age*: age of the population at the start of the evaluation period (2021), ranging from 0 to 100;
- *Sex*: population sex (male or female).

4.3.4 Step 4: Quantifying the Monetary Value of Benefits

The 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 3 percent and 7 percent discount rates for each of the four regulatory options.[40]

- *Morbidity*: To value changes in the economic burden associated with cancer morbidity the EPA used estimates of annual medical expenses for bladder cancer treatment from Greco et al. (2018) and the estimated life years with cancer morbidity (differentiating between first and subsequent years after cancer diagnosis). For invasive cancer, the medical treatment costs are $42,750 and $2,850 per case for the first and subsequent years respectively. For non-invasive cancer, medical treatment costs are $15,618 and $1,026 per case for the first and subsequent years, respectively.

- *Mortality*: To value changes in excess mortality from bladder cancer the EPA used a default central tendency VSL estimate of $11.021 million per death (U.S. EPA 2010a). 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 the 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

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37 In other words, costs after 2047 = $0 and Δbromide after 2047 is zero (hence ΔTTHM after 2047 is zero).

38 The set of 102,414 combinations was determined by multiplying the number of PWS groups by the number of ages and sexes considered (507 x 101 x 2).

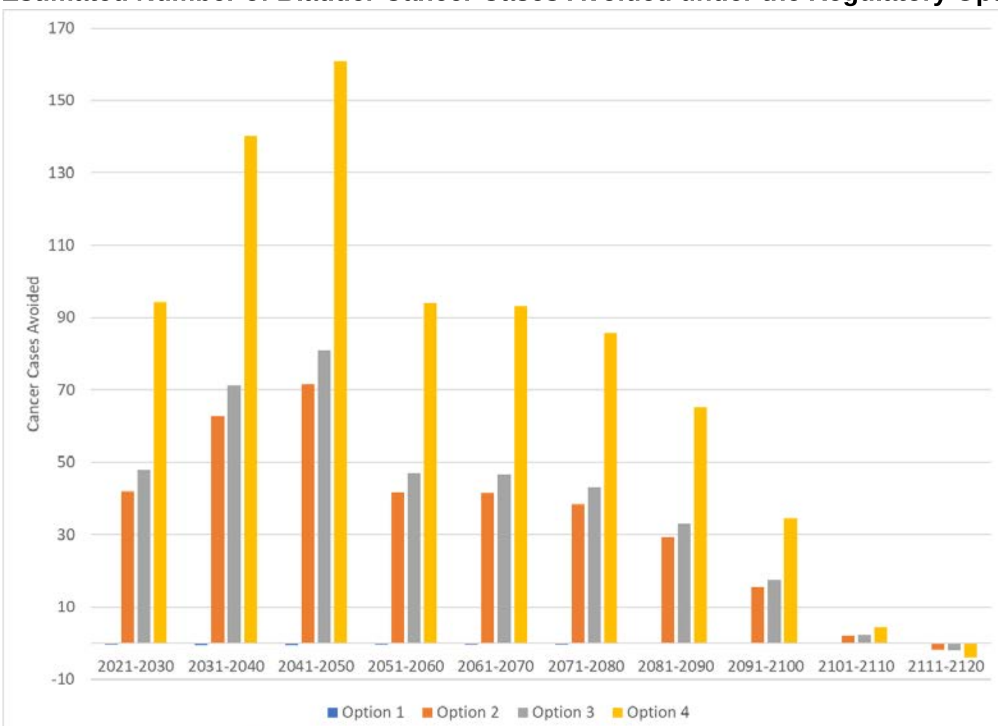
39 The PWS groups represent unique combinations of location (county) and ΔTTHM values and typically consist of a directly affected PWS and other PWSs serving populations located in the same county and purchasing water from the directly affected PWS. The number of PWS in each PWS group ranges from 1 to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

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

number of bladder cancer cases and premature deaths avoided, respectively, under the four regulatory options by decade.

Consistent with the small increase in bromide loadings for Option 1 in Table 3-3, this option would result in a small increase in cancer incidence as compared to the baseline. Options 2, 3, and 4 generally show decreases in cancer incidence over the period of analysis. More than 50 percent of the modeled avoided bladder cancer incidence associated with Options 2, 3, and 4 occurs between 2021 and 2050. This pattern is consistent with existing cancer cessation lag models (*e.g.*, Hrubec and McLaughlin 1997, Hartge et al. 1987, and Chen and Gibbs 2003) that show between 61 and 94 percent reduction in cancer risk in the first 25 years after exposure cessation (see *Appendix C* for detail). After 2050, the benefits attributable to exposures incurred under the regulatory options in 2021-2047 decline due to comparably fewer people surviving to mature ages.[41] In the years after 2080, the avoided cases decline considerably and in the last decade considered in the analysis, the cancer incidences increase relative to baseline incidences.[42]

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

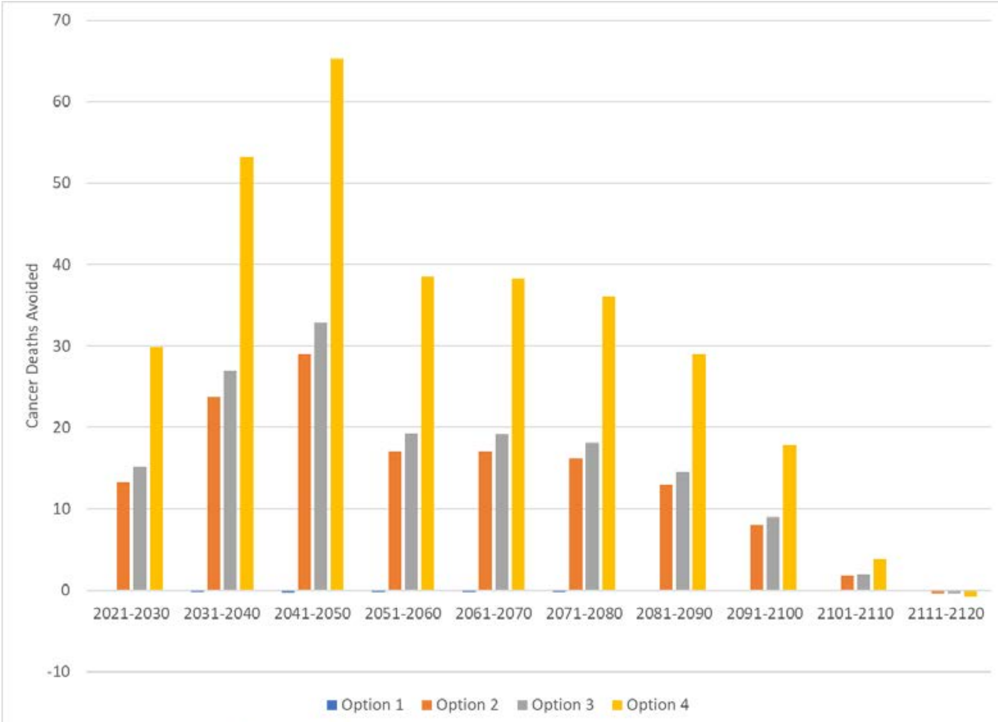


Source: U.S. EPA Analysis, 2019.

41 In the period between 2051 and 2080, 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 (ACS, 2019).

42 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 4-4: Estimated Number of Cancer Deaths Avoided under the Regulatory Options.



Source: U.S. EPA Analysis, 2019.

Table 4-7 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.

Table 4-7: Estimated Bromide-related Bladder Cancer Mortality and Morbidity Monetized Benefits

Regulatory Option	Changes in cancer cases from changes in TTHM exposure 2021-2047[a]		Benefits (million 2018$, discounted to 2020)					
	Total bladder cancer cases avoided	Total cancer deaths avoided	Annualized[b] benefits from avoided mortality		Annualized[b] benefits from morbidity avoided		Total annualized[b] benefits	
			3%	7%	3%	7%	3%	7%
1	-3	-1	-$0.36	-$0.23	$0.00	$0.00	-$0.36	-$0.23
2	343	139	$37.42	$24.08	$0.19	$0.12	$37.61	$24.21
3	387	157	$42.36	$27.34	$0.21	$0.14	$42.57	$27.48
4	769	311	$83.90	$54.03	$0.42	$0.28	$84.32	$54.30

a. The analysis accounts for the persisting health effects (up until 2121) from changes in TTHM exposure during the period of analysis (2021-2047).

b. Benefits are annualized over 27 years.

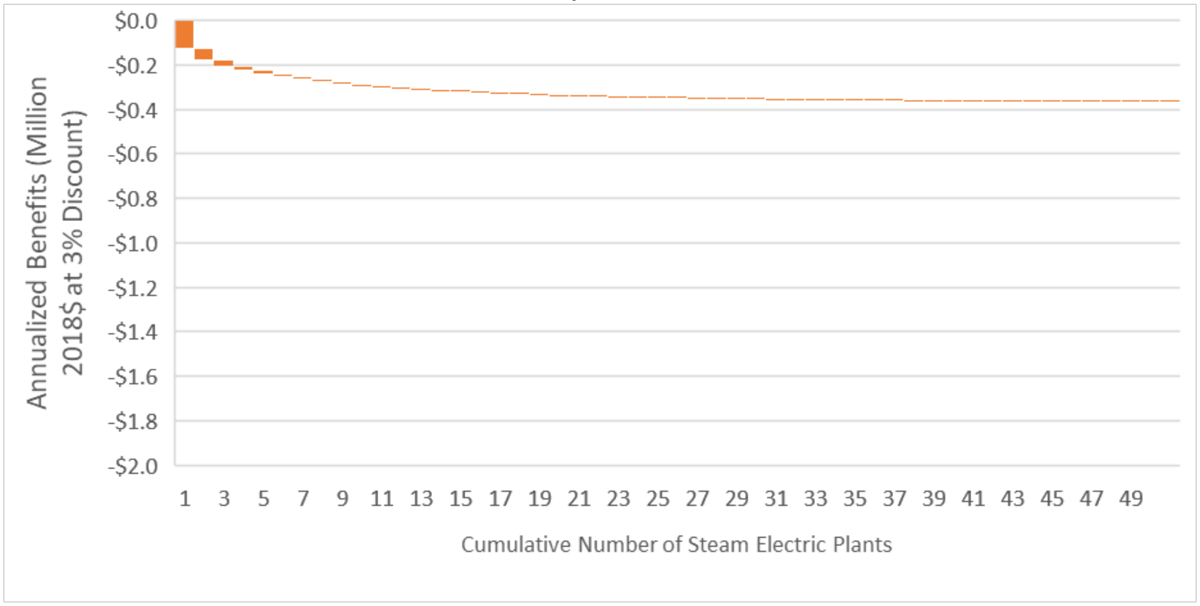
Source: U.S. EPA Analysis, 2019

These estimated total benefits are not uniformly distributed across plants that discharge bromide. For example, out of the 104 steam electric power plants included in this analysis, under Option 2 more than

85 percent of total benefits are attributable to discharge changes at only five steam electric power plants. Similarly, approximately 78 percent of the benefits of Option 4 come from changes at ten steam electric power plants. Figure 4-5 illustrates the plant-level contributions to total annualized benefits for each of the four regulatory options. Orange and blue bars show negative and positive benefits, respectively.

Figure 4-5: Contributions of Individual Steam Electric Power Plants to Total Annualized Benefits of Changes in Bromide Discharges under the Regulatory Options (3 Percent Discount Rate)

Option 1



Option 2

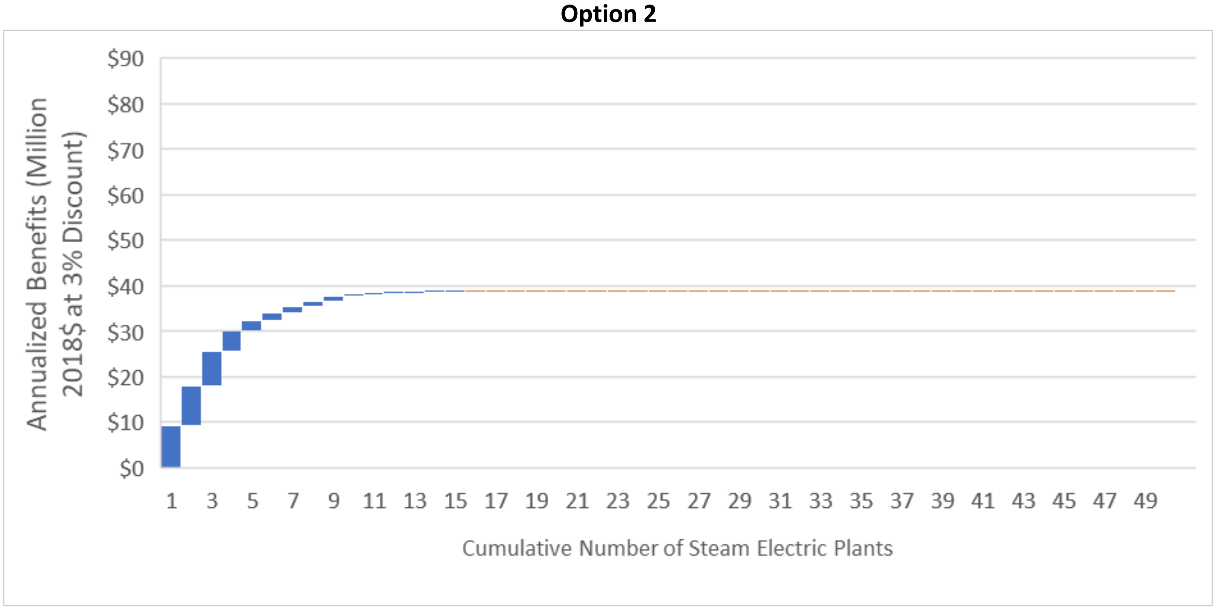
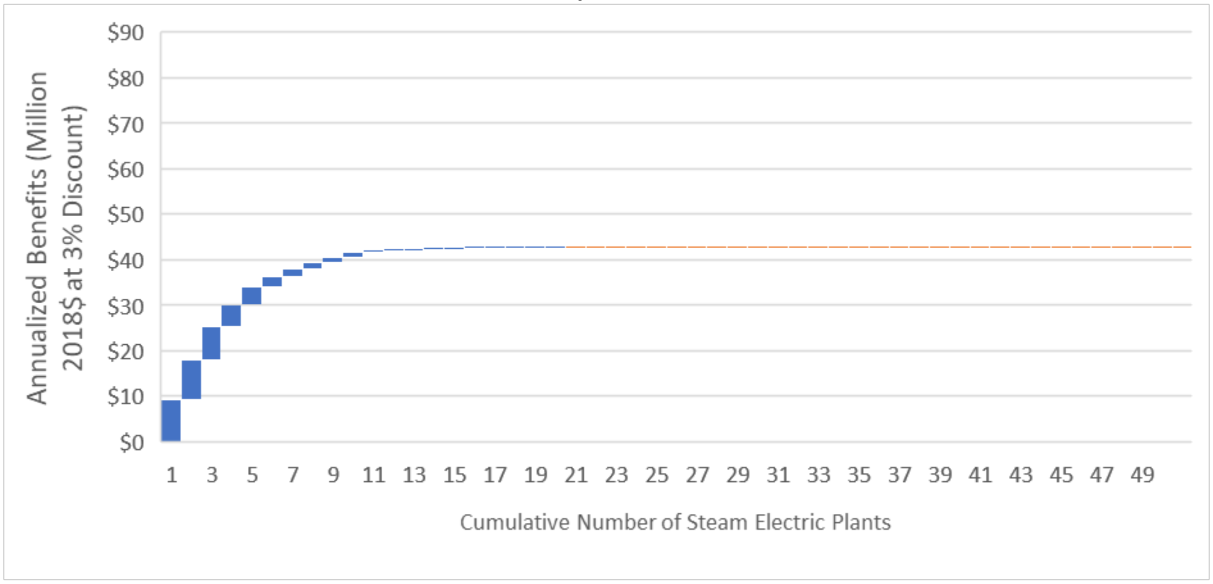
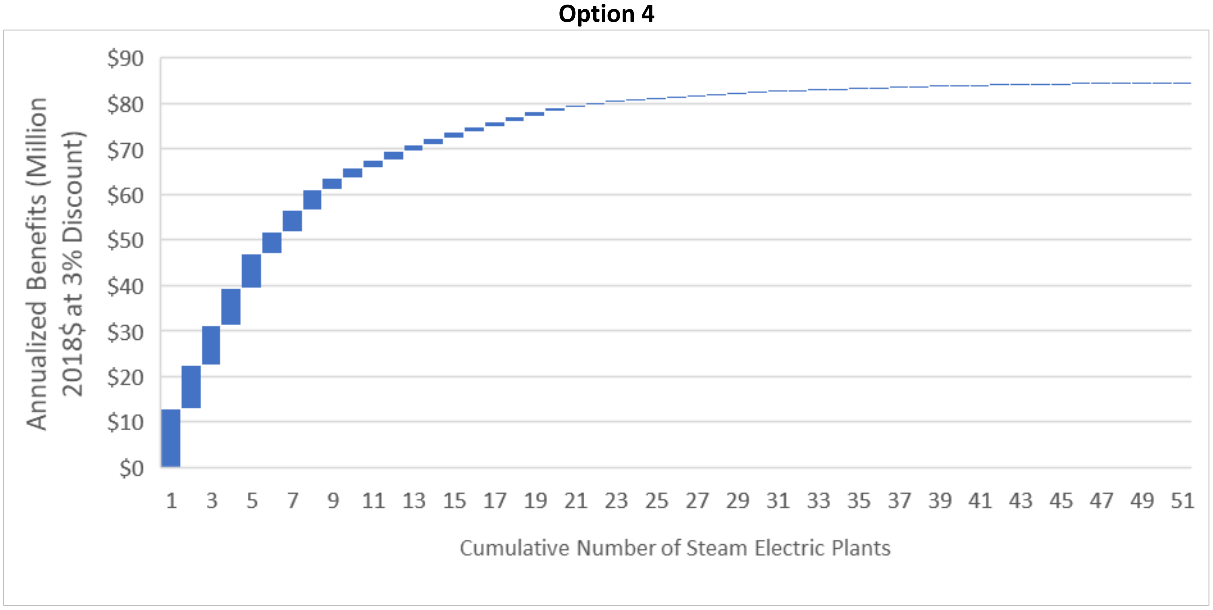


Figure 4-5: Contributions of Individual Steam Electric Power Plants to Total Annualized Benefits of Changes in Bromide Discharges under the Regulatory Options (3 Percent Discount Rate)

Option 3



Option 4



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

The regulatory options may result in 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.[43]

To assess potential additional drinking water-related health benefits of the regulatory options for pollutants found in steam electric power plant discharges, the EPA estimated the expected changes in the number of receiving reaches with drinking water intakes that have modeled pollutant concentrations in excess of MCLs. The EPA did this analysis for all of the pollutants listed in Table 2-2, except bromate and TTHM.[44] This analysis showed no changes in the number of MCL exceedances under the regulatory options, when compared to the baseline. Furthermore, the EPA found no reaches with drinking water intakes that had modeled lead or arsenic concentrations in excess of MCLs under either the baseline or the regulatory options.[45] The Agency concluded, based on these screening analyses, that any additional benefits from changes in exposure to other pollutants via the drinking water pathway would be minimal.

4.6 Limitations and Uncertainties

Table 4-8 summarizes principal limitations and sources of uncertainties associated with the estimated changes in incidences of bladder cancer cases from exposure to TTHM in drinking water affected by steam electric power plant discharges. Additional limitations and uncertainties are associated with the estimation of bromide discharges (see U.S. EPA, 2019a) and derivation of other analysis inputs such as cancer incidence and mortality rates. 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).

Table 4-8: Limitations and Uncertainties in the Analysis of Human Health Benefits from Changes in Bromide Discharges

Uncertainty/Assumption	Effect on Benefits Estimate	Notes
Characterizing the exposed population		
Analysis does not account for births and migration within the exposed population.	Underestimate	The analysis does not account for people born after 2021, nor does it account for people leaving or moving into the service area. The analysis does account for mortality. To the extent that population growth exceeds migration out of the area, omitting those additional individuals understates the affected population and benefits.

43 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. EPA, 2013c).

44 Only reaches designated as fishable (*i.e.*, Strahler Stream Order larger than 1) were included in the human health ambient water quality criteria exceedances analysis.

45 The EPA also found that there are no reaches with drinking water intakes that have pollutant concentrations in excess of human health ambient water quality criteria for either the consumption of water and organism or the consumption of organism only.

Table 4-8: Limitations and Uncertainties in the Analysis of Human Health Benefits from Changes in Bromide Discharges

Uncertainty/Assumption	Effect on Benefits Estimate	Notes
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, 2005c) although certain modes of action and health effects may be associated with exposure to TTHM during childhood (U.S. EPA, 2016). Because bladder cancer incidence in children is very small, the EPA assesses any bias to be negligible.
Modeling changes in TTHM in publicly supplied water		
The analysis does not consider bromide sources beyond those associated with steam electric power plants.	Uncertain	The approach to modeling bromide concentrations in source water excludes other bromide sources such as oil and gas production, active and abandoned coal mines, and certain types of chemical manufacturing. To the degree that the relationship between changes in bromide levels and changes in TTHM formation is non-linear and depends on absolute bromide concentrations in source waters, this analysis uses a linear model and therefore may overstate or understate the impacts of changes in bromide levels.
For PWS with multiple sources of water, the analysis assumes equal contributions from each source.	Uncertain	Data on the flow rates of individual source facilities are not available and the EPA therefore assumed 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.
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 assumption 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. The 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	The 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. Actual changes in TTHM concentrations for a given change in bromide concentrations at any specific drinking water treatment system could be higher or lower than that estimated using the national relationship.

Table 4-8: Limitations and Uncertainties in the Analysis of Human Health Benefits from Changes in Bromide Discharges

Uncertainty/Assumption	Effect on Benefits Estimate	Notes
Modeling changes in health risks		
Change in risk is based on changes in exposure to TTHMs rather than to brominated trihalomethanes specifically.	Underestimate	As noted in *Section 4.3.3.2*, 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 changes in risk could be greater than that which the EPA estimated in this analysis. See U.S. EPA (2016) for additional information about health effects of DBPs.
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).
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	There is literature suggesting that TTHM effects could be possibly 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 the 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	While there is greater uncertainty for smaller changes in TTHM concentrations, the EPA assesses that it is appropriate to include these predicted changes when estimating benefits rather than assuming zero benefits by omitting the results. The 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.

Table 4-8: Limitations and Uncertainties in the Analysis of Human Health Benefits from Changes in Bromide Discharges

Uncertainty/Assumption	Effect on Benefits Estimate	Notes
Potential health effects other than bladder cancer are not quantified in this analysis.	Uncertain	U.S. EPA (2016) 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 to fully evaluate these endpoints.

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

The 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 EPA's *Supplemental EA* (U.S. EPA, 2019a) provides details on the health effects of steam electric pollutants. Recreational anglers and subsistence fishers (and their household members) who consume fish caught in the reaches receiving steam electric power plant discharges could benefit from reduced pollutant concentrations in fish tissue. This chapter presents the EPA's analysis of human health effects resulting from changes in exposure to pollutants in bottom ash transport water and FGD wastewater 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 the cost of compensatory education for children with learning delays.
- Changes in exposure to mercury: Changes in neurological and cognitive damages in infants from exposure to mercury *in-utero*.
- Changes in exposure to arsenic: Changes in incidence of cancer cases.

The total quantified human health effects included in this analysis represent only a subset of the potential health benefits expected to result from the regulatory options. While additional adverse health effects are also 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[46] between ingestion rates and these effects precluded EPA from quantifying the associated health effects.

The EPA's analysis of the monetary value of human health effects utilizes data and methodologies described in Chapter *3* and in the *Supplemental EA* (U.S. EPA, 2019a). The relevant data include COMIDs[47] for receiving waters, estimated baseline and regulatory options annual plant-level loadings of each discharged pollutant, estimated ambient pollutant concentrations in receiving reaches, and estimated fish consumption rates among different age and ethnic cohorts for affected recreational anglers and subsistence fishers.

Section 5.1 describes how the 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. *Sections 5.3* to *5.5* describe EPA's analysis of various human health endpoints potentially affected by the regulatory options. *Section 5.7* provides additional measures of human health benefits. *Section 5.8* describes these assumptions, limitations, and uncertainties.

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

47 A COMID is a unique numeric identifier for a given waterbody, assigned by a joint effort of the United States Geological Survey, EPA, and Horizon Systems, Inc.

In general, the estimated human health effects of the proposed regulatory option, Option 2, are small compared to those estimated in 2015 (see U.S. EPA, 2015a).

5.1 Affected Population

The affected population (*i.e.*, individuals potentially exposed to steam electric pollutants via consumption of contaminated fish tissue) includes recreational anglers and subsistence fishers who fish reaches affected by steam electric power plant discharges (including receiving and downstream reaches), as well as their household members. The 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. The EPA notes that the universe of sites potentially visited by recreational anglers includes reaches subject to fish consumption advisories (FCA).[48] Angler's response to FCA's presence is assumed to be reflected in their catch and release practice, as discussed below. Since fish consumption rates vary across different age, racial and ethnic groups, and fishing mode (recreational versus subsistence fishing), the EPA estimated potential health effects separately for a number of age-, ethnicity-, and mode-specific cohorts.

First, for each Census Block Group (CBG) within 50 miles of an affected reach, the EPA assembled 2016 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 or higher), and then subdivided each group according to 7 racial/ethnic categories:[49] 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[50]. Within each racial/ethnic group, the EPA further subdivided the population according to recreational and subsistence groups. The Agency assumed that the 95th percentile of the general population consumption rate is representative of the subsistence fisher consumption rate. Accordingly, the Agency assumed that 5 percent of the angler population practices subsistence fishing.[51] Finally, the EPA also subdivided the affected population by income into poverty and non-poverty groups, based on the share of people below the federal poverty line.[52] After subdividing population groups by age, race, fishing mode, and the poverty indicator, each CBG has 196 unique population cohorts (7 age groups × 7 ethnic/racial groups × 2 fishing modes [recreational vs. subsistence fishing] × 2 poverty status designations).

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[48] Based on the EPA's review of studies documenting anglers' awareness of FCA and their behavioral responses to FCAs, 57.0 percent to 61.2 percent of anglers are aware of FCAs, and 71.6 percent to 76.1 percent of those who are aware ignore FCAs (Burger, 2004, Jakus et al., 1997; Jakus et al., 2002; Williams et al., 2000). Therefore, only 17.4 percent of anglers may adjust their behavior in response to FCA (U.S. EPA 2015a). As noted above, we assumed the angler's response to FCA is reflected in their catch and release practice.

[49] 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.

[50] 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.

[51] Data are not available on the share of the fishing population that practices subsistence fishing. The 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 the EPA's Exposure Factors Handbook (see U.S. EPA, 2011).

[52] 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.

The EPA distinguished the exposed population by racial/ethnic group and poverty status to support analysis of potential EJ considerations in 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 *Chapter 14* for details of the EJ analysis. As noted below, distinguishing the exposed population in this manner also allows the Agency to account for differences in exposure among demographic groups, where supported by available data.

Equation 5-1 shows how the EPA estimated the affected population, ExPop(i)(s)(c), for CBG *i* in state *s* for cohort *c*.

Equation 5-1. $$\boldsymbol{ExPop}(\boldsymbol{i})(\boldsymbol{s})(\mathbf{c}) = \boldsymbol{Pop}(\boldsymbol{i})(\mathbf{c}) \times \%\boldsymbol{Fish}(\boldsymbol{s}) \times \boldsymbol{CaR}(\boldsymbol{c})$$

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 2016 American Community Survey, which provides population numbers for each CBG broken out by age and racial/ethnic group separately. To estimate the population in each age- and ethnicity/race-specific group, the 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 anglers. To determine what percentage of the total population participates in fishing, the EPA used region-specific U.S. Fish and Wildlife Service (U.S. FWS, 2016) estimates of the population 16 and older who fish.[53] The EPA assumed that the share of households that includes anglers is equal to the fraction of people over 16 who are anglers.

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

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 the EPA's estimate of the population potentially exposed to the pollutants via consumption of subsistence- and recreationally-caught fish (based on 2016 population data and not adjusted for population growth during the analysis period). Of the total population, 16.0 percent live within 50 miles of an affected reach and participate in recreational and/or subsistence fishing, and 12.4 percent are potentially exposed to fish contaminated by steam electric pollutants in bottom ash transport water and/or FGD wastewater discharges.

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[53] The share of the population who fishes ranges from 8 percent in the Pacific region to 20 percent in the East South Central region. Other regions include the Middle Atlantic (10 percent), New England (11 percent), South Atlantic (15 percent), Mountain (15 percent), West South Central (17 percent), East North Central (17 percent), and West North Central (18 percent).

Table 5-1: Summary of Potentially Affected Population Living within 50 Miles of Affected Reaches (baseline, as of 2016)

Total population	123,829,132
Total angler population[a]	19,772,063
Population potentially exposed to contaminated fish[b, c]	15,395,517

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 (2016; between 8 percent and 20 percent, depending on the state).

b. Total angler population adjusted to reflect lower consumption rates from catch-and-release practices.

c. Analysis accounts for projected population growth so that the average affected population over the period of 2021 through 2047 is 12 percent higher than the population in 2016 presented in the table, or 17.2 million people. The analysis further assumes that the fraction of the U.S. population engaged in recreational and subsistence fishing remains constant from 2021 through 2047.

Source: U.S. EPA Analysis, 2019

5.2 Pollutant Exposure from Fish Consumption

The 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. For each combination of pollutant, cohort and CBG, the EPA calculated the average daily dose (ADD) and lifetime average daily dose (LADD) consumed via the fish consumption pathway.

5.2.1 Fish Tissue Pollutant Concentrations

The set of reaches that may represent a source of contaminated fish for recreational anglers and subsistence fishers in each CBG depends on the typical travel distance anglers travel to fish. The EPA assumed that anglers typically travel up to 50 miles to fish[54], using this distance to estimate the relevant fishing sites for the population of anglers in each CBG.

Anglers may have several fishable sites to choose from within 50 miles of travel. To account for the effect of substitute sites, the EPA assumed that anglers are uniformly distributed among all the available fishing sites within 50 miles from the CBG (travel zone) and alternate their travels across all the sites. For each CBG, the EPA identified all fishable COMIDs within 50 miles (where distance was determined based on the Euclidian distance between the centroid of the CBG and the midpoint of the COMID) and the COMID length in miles.

The EPA then calculated, for each CBG within the 50-mile buffer, the fish tissue concentration of As, Hg, and lead (Pb). *Appendix D* 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, the EPA then calculated the reach length ($Length_i$) weighted fish fillet concentration ($C_{Fish\_Fillet}(CBG)$) based on all fishable COMIDS within the 50 mile radius according to Equation 5-2:

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

54 Studies of angler behavior and practices have made similar assumptions (*e.g.*, Sohngen et al., 2015 and Sea Grant, Illinois-Indiana, 2018).

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 the EPA's Exposure Factors Handbook (U.S. EPA, 2011). For more details on these fish consumption rates, see U.S. EPA (2019a) and the uncertainty discussion in Section 5.8.

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

Race/ Ethnicity[a]	EA Cohort[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. U.S. EPA (2019a).

Source: U.S. EPA Analysis, 2019

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 from U.S. EPA (2019a), as shown below.

Equation 5-3. $$ADD(c)(i) = \frac{C_{Fish\_Fillet}(i) \times CR_{Fish}(c) \times F_{Fish}}{1000}$$

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; assumed 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; assumed value of 350)

AT = averaging time (years; assumed value of 70)

The 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

The EPA estimated changes in lead exposure as a result of the regulatory options are small compared to those estimated in the 2015 analysis (see U.S. EPA, 2015a).

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[55], and motor skill deficits (see National Toxicology Program 2012, U.S. EPA 2013b, U.S. EPA, 2019a, and U.S. EPA 2019h). Elevated blood lead (PbB) concentrations in children may also result in slowed postnatal growth in children ages one to 16, delayed puberty in 8- to 17-year-olds, decreased hearing and motor function (National Toxicology Program 2012, U.S. EPA 2019h). 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 (National Toxicology Program 2012; U.S. EPA 2019h; Zhu et al., 2010). Because of data limitations, the EPA estimated only the effects of changes in neurological and cognitive damages to pre-school (ages 0 to 7) children using the dose-response relationship for IQ decrements (Crump et al. 2013).

The EPA estimated health effects from changes in exposure to lead to preschool children using PbB as a biomarker of lead exposure. The EPA first modeled PbB under the baseline and post-compliance scenarios, and then used a concentration-response relationship between PbB and IQ loss to estimate avoided 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). The 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 and the cost of compensatory education for children with learning disabilities (including children with IQ less than 70 and PbB levels above 20 μg/dL).

The EPA used the methodology described in *Section 5.1* to estimate the population of children from birth to age seven who live in recreational angler and subsistence fisher households and are potentially exposed to lead via consumption of contaminated fish tissue. The 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. The 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, the EPA restricted the analysis to the relevant age cohorts of angler household members.

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

5.3.1 Methods

This analysis considers children who are born after implementation of the regulatory options and live in recreational angler and subsistence fisher households. It relies on the EPA's Integrated Exposure, Uptake, and Biokinetics (IEUBK) Model for Lead in Children (U.S. EPA, 2009c), 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 this total exposure, the model generates a predicted geometric mean PbB for a population of children exposed to similar lead levels (See the 2013 BCA report (U.S. EPA, 2013a) for more detail).

For each CBG, the EPA used the cohort-specific ADD based on Equation 5-3. The EPA then multiplied the cohort-specific ADD by the average body weight for each age group[56] to calculate the "alternative source" input for the IEUBK model. Lead bioavailability and uptake after consumption varies 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, the EPA used the default media-specific bioavailability factor for the "alternative source" provided in the IEUBK model, which is 50 percent for oral ingestion.

The EPA used the IEUBK model to generate the geometric mean PbB for each cohort in each CBG under the baseline and post-compliance scenarios. Note 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 missed by using the model (*i.e.*, it does not capture very small changes), since the estimated changes in health effects are driven by very small changes across large populations. This aspect of the model contributes to potential underestimation of the actual monetary value of lead-related health effects in children arising from the regulatory options.

5.3.1.1 Estimating Changes in IQ Point Losses

The EPA used the Crump et al. (2013) dose-response function to estimate changes in IQ losses between the baseline and post-compliance scenarios. Comparing the baseline and post-compliance 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 PbB. Equation 5-5 shows an exposure-response function that represents this non-linearity:

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

Where:

β_1 = -3.315 (log-linear regression coefficient on the lifetime blood lead level[57])

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.

56 The average body weight values are 11.4 kg for ages 0 to 2, 13.8 kg for ages 2 to <3, 18.6 kg for ages 3 to <6, and 31.8 kg for ages 6 to 7.

57 The lifetime blood lead level in children ages 0 to 7 is defined as a mean from six months of age to present (Crump et al. 2013).

The IEUBK model estimates the mean of the PbB distribution in children, assuming a continuous exposure pattern for children from birth through the seventh birthday. The 2016 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, the EPA divided the estimated number of affected pre-school children by 7. This division adjusts the equation to apply only to children age 0 to 1. The estimated changes in IQ loss is thus an annual value (*i.e.*, it would apply to the cohort of children born each year after implementation).[58] Equation 5-6 shows this calculation for the annual increase in total IQ points.

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

Where:

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

$Ln(\Delta GM(i)(c))$ = the log-linear change in the average PbB in affected population of children (µg/dL) in cohort *c* in CBG *i*

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

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

The available economic literature provides little empirical data on society’s overall WTP to avoid a decrease in children’s IQ. To determine the value of avoided IQ losses, the EPA used estimates of the changes in a child’s future expected lifetime earnings per one IQ point reduction and the cost of compensatory education for children with learning disabilities.

The EPA monetized the value of an IQ point based on the methodology from Salkever (1995). The EPA estimated the value of an IQ point using the methodology presented in Salkever’s (1995) analysis but with more recent data from the 1997 National Longitudinal Survey of Youth (U.S. EPA, 2019e). 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 3 percent and 7 percent discount rates. These values are discounted to the third year of life to represent the midpoint of the exposed children population. The EPA also used an alternative value of an IQ point from Lin et al. (2018) in a sensitivity analysis (*Appendix G*).

[58] 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 lead exposure.

Table 5-3: Value of an IQ Point (2018$) based on Expected Reductions in Lifetime Earnings

Discount Rate	Value of an IQ Point[a,b] (2018$)
3 percent	$20,832
7 percent	$4,358

a. Values are adjusted for the cost of education.

b. The EPA adjusted the value of an IQ point to 2018 dollars using the GDP deflator.

Source: U.S. EPA (2019e) re-analysis of data from Salkever (1995)

5.3.1.2 Reduced Expenditures on Compensatory Education

Children whose PbB exceeds 20 µg/dL are more likely to have IQs less than 70, which means that they would require compensatory education tailored to their specific needs. Costs of compensatory education and special education are not reflected in the IQ point dollar value. Reducing exposure to lead at an early age is expected to reduce the incidence of children requiring compensatory and/or special education, which would in turn lower associated costs. Though these costs are not a substantial component of the overall benefits, they do represent a potential benefit of reducing lead exposure. While the EPA quantitatively assessed this benefit category using the methodology from the 2015 BCA (U.S. EPA, 2015a), the estimated cost savings from the expected changes in the need of compensatory education are negligible and are not included in the total monetized benefits.

5.3.2 Results

Table 5-4 shows the social welfare effects associated with changes in IQ losses from lead exposure via fish consumption. The EPA estimated that regulatory options 1 and 2 lead to slight increases in lead exposure and, as a result, forgone benefits, whereas Options 3 and 4 result in slight reductions. The total net change in IQ points over the entire population of children with changes in lead exposure ranges from -11.1 points to 0.9 points. Annualized monetary values of increased IQ losses range from -$9,140 (Option 2) to $740 (Option 4) using a 3 percent discount, and -2,070 (Option 2) to $170 (Option 4) using a 7 percent discount.

Table 5-4: Estimated Monetary Value of Changes in IQ Points for Children Exposed to Lead

Regulatory Option	Average Annual Number of Affected Children 0 to 7[c]	Total Change in IQ Points, 2021 to 2047 in All Affected Children 0 to 7	Annualized Value of Changes in IQ Points[a,b] (Thousands 2018$)	
			3% Discount Rate	7% Discount Rate
Option 1	1,521,036	-3.58	-$2.96	-$0.67
Option 2	1,521,036	-11.07	-$9.14	-$2.07
Option 3	1,521,036	0.35	$0.29	$0.07
Option 4	1,521,036	0.90	$0.74	$0.17

a. Assumes 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 (2019e)).

b. Negative values represent forgone benefits.

c. The number of affected children is based on reaches analyzed across the four options. Some of the children included in this count see no changes in exposure under some options.

Source: U.S. EPA Analysis, 2019

5.4 Heath Effects in Children from Changes in Mercury Exposure

The EPA estimated small changes in mercury exposure as a result of the regulatory options, compared to those estimated in the 2015 analysis (see U.S. EPA, 2015a).

Mercury can have a variety of adverse health effects on adults and children (see U.S. EPA, 2019a). 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 effects. Due to data limitations, however, the 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.

The EPA identified the population of children exposed *in-utero* starting from the CBG-specific affected population described in *Section 5.1*. Because this analysis focuses only on infants born after implementation of the regulatory options, the EPA further limited the affected 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.[59] 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 2015 in the National Vital Statistics Report (Martin et al., 2017). 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 71.7, followed by African Americans at 64.1, Caucasians at 59.3, Asian or Pacific Islanders at 58.5, and Tribal/Other at 43.9.

5.4.1 Methods

The EPA used the same 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. In this analysis, the 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*), the 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 5-7 shows the EPA's calculation of the total annual IQ changes for a given receiving reach.

Equation 5-7. $$\boldsymbol{IQL(i)(c) = InExPop(i) * MADD(i)(c) * (\frac{1}{Conv}) * DRF}$$

Where:

IQL(i) = 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) = affected population of infants in CBG *i* (the number of births)

59 The 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.

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 lost between the baseline and modeled post-compliance 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 determine the value of avoided IQ losses, the EPA used estimates of the changes in a child's future expected lifetime earnings per one IQ point reduction and the cost of additional education. The values of an IQ point presented in *Section 5.3.1* are discounted to the third year of life to represent the midpoint of the exposed children population. EPA further discounted the present value of lifetime income differentials three additional years to reflect the value of an IQ point at birth and better align the benefits of reducing exposure to mercury with in-utero exposure (U.S. EPA, 2019i). The IQ values discounted to birth range from $3,704 to $19,064. The EPA also used an alternative value of an IQ point from Lin et al. (2018) in a sensitivity analysis (*Appendix G*).

5.4.2 Results

Table 5-5 shows the estimated changes in IQ point losses for infants exposed to mercury in-utero and the corresponding monetary values, using a 3 percent and 7 percent discount rates. All regulatory options result in a small net increase in IQ losses and, as a result, in forgone benefits to society. Using a 3 percent discount rate, monetary values of an increased IQ losses range from -$2.85 million (Option 3) to -$0.31 million (Option 1). Using a 7 percent discount rate, estimates range from -$0.58 million (Option 3) to -$0.06 million (Option 1).

Table 5-5: Estimated Monetary Values from Changes in IQ Points for Infants from Mercury Exposure

Regulatory Option	Number of Affected Infants per Year[c]	Total Change in IQ Points, 2021 to 2047 in All Affected Infants	Annualized Value of Changes in IQ Points[a,b] (Millions 2018$)	
			3% Discount Rate	7% Discount Rate
Option 1	225,272	-411	-$0.31	-$0.06
Option 2	225,272	-3,785	-$2.84	-$0.57
Option 3	225,272	-3,777	-$2.85	-$0.58
Option 4	225,272	-2,021	-$1.49	-$0.30

a. Assumes 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 (2019i)).

b. Negative values represent forgone benefits.

c. The number of affected infants is based on reaches analyzed across the four options. Some of the children included in this count see no changes in exposure under some options.

Source: U.S. EPA Analysis, 2019

5.5 Estimated Changes in Cancer Cases from Arsenic Exposure

Among steam electric pollutants that can contaminate fish tissue and are analyzed in the *Supplemental EA*, arsenic is the only confirmed carcinogen with a published dose response function (see U.S. EPA, 2010b).[60] The EPA used the methodology presented in *Section 3.6* of the 2015 BCA document (U.S. EPA 2015a) to estimate the number of annual 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. Based on the EPA's analysis, no changes in cancer cases from exposure to arsenic via fish consumption are expected under the regulatory options. Accordingly, the expected social welfare effects are zero under all regulatory options.

5.6 Total Monetary Values of Estimated Changes in Human Health Effects

Table 5-6 presents the estimated monetary value of changes in adverse human health outcomes under the regulatory options. Using a 3 percent discount rate, the estimated monetary values range from -$2.85 million to -$0.31 million. Using a 7 percent discount rate, the estimated monetary values range from -$0.58 million to -$0.06 million. Negative values reflect forgone benefits. Changes in mercury exposure for children account for the majority of total monetary values from increases in adverse health outcomes.

Table 5-6: Total Monetary Values of Changes in Human Health Outcomes Associated with Fish Consumption for Regulatory Options (millions of 2018$)

Discount Rate	Regulatory Option	Reduced Lead Exposure for Children[a,b,c]	Reduced Mercury Exposure for Children[a,b]	Reduced Cancer Cases from Arsenic	Total[a,b]
3%	1	<$0.00	-$0.31	$0.00	-$0.31
	2	-$0.01	-$2.84	$0.00	-$2.85
	3	<$0.00	-$2.85	$0.00	-$2.85
	4	<$0.00	-$1.49	$0.00	-$1.49
7%	1	<$0.00	-$0.06	$0.00	-$0.06
	2	<$0.00	-$0.57	$0.00	-$0.57
	3	<$0.00	-$0.58	$0.00	-$0.58
	4	<$0.00	-$0.30	$0.00	-$0.30

a. Negative values represent forgone benefits and positive values represent realized benefits.

b. Assumes 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 (2019e)).

c. "<$0.00" indicates that monetary values are greater than -$0.01 million but less than $0.00 million. Benefits to children from changes in exposure to lead range from -$9.1 to $0.7 thousands per year, using a 3 percent discount rate, and from -$2.1 to $0.2 thousands, using a 7 percent discount rate.

Source: U.S. EPA Analysis, 2019

5.7 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. The EPA compared immediate receiving water concentrations to human health-based NRWQC in U.S. EPA (2019a). To provide an additional measure of the

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

potential health effects of the regulatory options, the EPA also estimated the expected changes in the number of receiving and downstream reaches with pollutant concentrations in excess of human health-based NRWQC. 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. This analysis compares in-stream pollutant concentrations estimated for the baseline and each analyzed regulatory option in receiving reaches and downstream reaches to criteria established by the EPA for protection of human health. The 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 national recommended water quality criteria protective of human health used by states and tribes (U.S. EPA, 2018b).[61] Estimated pollutant concentrations in excess of these values indicate potential risks to human health.

Table 5-7 shows the results of this analysis.[62] The EPA estimates that with baseline steam electric pollutant discharges, in-stream concentrations of steam electric pollutants exceed human health criteria for at least one pollutant in 141 reaches based on the "consumption of water and organism" criteria, and 37 reaches based on the "consumption of organism only" criteria nationwide. The EPA estimates that the total number of reaches with exceedances to increase under Options 1, 2, and 3 and decrease under Option 4. Table 5-7 presents the estimated number of stream reaches that may change for each regulatory option.

Table 5-7: 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 Higher Number of Exceedances, Relative to Baseline		Number of Reaches with Lower Number of Exceedances, Relative to Baseline	
	Consumption of Water + Organism	Consumption of Organism Only	Consumption of Water + Organism	Consumption of Organism Only	Consumption of Water + Organism	Consumption of Organism Only
Baseline	141	37	--	--	--	--
Option 1	165	37	30	3	0	0
Option 2	222	71	85	37	12	5
Option 3	171	38	34	4	12	5
Option 4	110	27	16	4	66	21

a. Pollutants for which there was at least one exceedance include antimony, arsenic, cyanide, lead, manganese, nitrate-nitrite as N, selenium, and thallium.

Source: U.S. EPA Analysis, 2019

5.8 Limitations and Uncertainties

The analysis presented in this chapter does not include all possible human health effects associated with post-compliance 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

[61] For pollutants that do not have national recommended water quality criteria protective of human health, EPA used MCLs. These pollutants include cadmium, chromium, lead, and mercury.

[62] Only reaches designated as fishable (*i.e.*, Strahler Stream Order larger than 1) were included in the human health ambient water quality criteria exceedances analysis.

included in this analysis represent only a subset of the potential health effects expected to result from the regulatory options.

Additionally, the methodologies and data used in the analysis of health effects associated with changes in incidences of adverse health outcomes due to consumption of fish contaminated with steam electric pollutants involve limitations and uncertainties. Table 5-8 summarizes the limitations and uncertainties and indicates the direction of the potential bias. 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). Additional limitations and uncertainties associated with the EA analysis and data are discussed in the *Supplemental EA* (see U.S. EPA, 2019a).

Table 5-8: Limitations and Uncertainties in the Analysis of Human Health Effects

Uncertainty/Assumption	Effect on Benefits Estimate	Notes
The EPA estimated the annual average loadings during the period of analysis and estimated annual average concentrations to which individuals or environmental receptors are exposed over the period of analysis.	Uncertain	The timing of changes in pollutant levels is an important factor for analyzing the benefits of the regulatory options. However, the approach for estimating the benefits of changes in pollutant concentration cannot readily incorporate a complex temporal profile of pollutant loadings, nor would the analysis necessarily gain by doing so for benefits depend on long-term processes such as adverse health effects from lifetime exposures to toxic pollutants.
The EPA's analysis uses annual average values for stream flows.	Uncertain	The EPA recognizes that low-flow periods may coincide with higher pollutant loadings and result in higher pollutant concentrations, and vice versa. There may be human health effects from short-duration exposure to higher steam electric pollutant levels. The Agency's analysis focused on long-term exposure only given that concentrations are not likely to reach levels of concern for acute exposure, and adverse health effects for non-acute short-duration exposures are generally not well understood.
Anglers are assumed to be distributed evenly (over the reach miles) over all available fishing sites within the 50-mile travel distance.	Uncertain	The EPA assumed that all anglers travel up to 50 miles and distribute their visits over all fishable sites within the area. In fact, recreational anglers 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 the EPA does not have data to support a more detailed analysis of fishing visits. The impact of the assumption on monetary estimates is uncertain since fewer/more anglers may be exposed to higher/lower fish tissue concentrations than assumed by the EPA in the analysis.
The exposed population is estimated based on households in proximity to affected reaches and the fraction of the general population who fish.	Uncertain	The EPA assumed that the share of households that includes anglers is equal to the fraction of people over 16 who are anglers. On the one hand, this may double-count households with two anglers over 16. On the other hand, the exposed population may also include non-household members who also consume the catch.

Table 5-8: Limitations and Uncertainties in the Analysis of Human Health Effects

Uncertainty/Assumption	Effect on Benefits Estimate	Notes
Fish intake rates used in estimating exposure are based on recommended values for the entire consuming population and include all fish sources.	Overestimate	The fish consumption rates used in the analysis account for all fish sources, i.e., store-bought or recreationally-caught fish. This assumption may overestimate exposure from recreationally-caught fish. The degree of the overestimate is unknown as the fish consumption rates for the general consuming population are within the range of freshwater recreational fish intake rates reported in EPA's Exposure Factors Handbook (U.S. EPA, 2011).
The number of subsistence fishers was assumed to equal 5 percent of the total number of anglers fishing the affected reaches.	Uncertain	The magnitude of subsistence fishing in the United States or individual states is not known. Assuming 5 percent may understate or overstate the number of potentially affected subsistence fishers (and their households) overall, and ignores potential variability in subsistence rates across racial/ethnic groups.
There is a linear 0.18 point IQ loss for each 1 ppm increase in maternal hair mercury.	Uncertain	This dose-response function may over- or underestimate IQ impacts arising from mercury exposure if a linear function is not the best representation of the relationship between maternal body burden and IQ losses.
For the mercury- and lead-related health impact analyses, the EPA assumed that IQ losses are 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 acquisition and retention of information presented verbally and many motor skills (U.S. EPA, 2005b). To the extent that these impacts create disadvantages for children exposed to mercury at current exposure levels or result in the absence of (or independent from) measurable IQ losses, this analysis may underestimate the social welfare effects of the regulatory options of increased 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).
The EPA did not quantify 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; if measurable effects are occurring at current exposure levels, excluding the effects of increased adult exposure results in an underestimate of forgone benefits.

6 Nonmarket Benefits from Water Quality Changes

As discussed in the *Supplemental EA* (U.S. EPA, 2019a), heavy metals, nutrients, and other pollutants discharged by steam electric power plants can have a wide range of effects on water resources located in the vicinity and 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) cannot be bought or sold directly and thus do not have observable market values. These second types of environmental goods and services are classified as "nonmarket". The expected changes in the nonmarket values of the water resources affected by the regulatory options (hereafter nonmarket benefits) are additive to the market benefits (*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 the EPA used in the analysis of the 2015 rule (U.S. EPA, 2015a). This approach, which is briefly summarized below, involves:

- characterizing the change in water quality for 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 6.1*),
- monetizing changes in the nonmarket value of affected water resources attributable to 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 6.2*).

The analysis accounts for changes 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.

In general, the analysis shows that the estimated effects of the proposed regulatory option, Option 2, on the nonmarket value of water quality are small compared to those estimated in 2015 (see U.S. EPA, 2015a).

6.1 Linking Changes in Water Quality to Valuation

Once an overall WQI value is calculated (see *Section 3.4* for detail), it 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 of zero to 10 instead of the WQI scale of zero to 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. See Table 3-5 (in *Chapter 3*) for the correspondence between WQI scores and use classifications.

6.2 Total WTP for Water Quality Changes

The EPA estimated economic values of water quality changes at the CBG level using results of a meta-analysis of 140 estimates of total WTP (including both use and nonuse values) for water quality improvements, provided by 51 original studies conducted between 1981 and 2011.[63] 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 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 the EPA's central estimate of non-market benefits and Model 2 develops a range of estimates that account for uncertainty in the WTP estimates. *Appendix H* provides details on how the EPA used the meta-analysis to predict household WTP for each CBG and year as well as the estimated regression equation intercept, variable coefficients for the two models used in this analysis, and the corresponding independent variable names and assigned values.

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

Equation 6-1. $$HWTP_{Y,B} = MWTP_{Y,B} \times \Delta WQI_B$$

where:

$HWTP_{Y,B}$	=	Annual household WTP in 2018$ in year *Y* for households located in the CBG (*B*),
$MWTP_{Y,B}$	=	Marginal WTP for water quality 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*).

As summarized in Table 6-1, average annual household WTP estimates for the regulatory options range from -$0.11 under Option 1 to $1.04 under Option 4, for the four regulatory options the EPA analyzed.

[63] Although the potential limitations and challenges of benefit transfer are well established (Desvousges et al., 1998), benefit transfers are a nearly universal component of benefit cost analyses conducted by and for government agencies. As noted by Smith et al. (2002; p. 134), "nearly all benefit cost analyses rely on benefit transfers, whether they acknowledge it or not."

Table 6-1: Estimated Household Willingness-to-Pay for Water Quality Changes

Regulatory Option	Number of Affected Households (Millions)	Average Annual WTP Per Household (2018$)[a,b]		
		Low	Central	High
Option 1	85.24	-$0.11	-$0.14	-$0.62
Option 2	86.86	$0.10	$0.14	$0.56
Option 3	84.64	$0.16	$0.22	$0.87
Option 4	86.51	$0.19	$0.26	$1.04

a. Negative values represent forgone benefits and positive values represent realized benefits

b. Model 2 provides low and high estimates for each option, while Model 1 provides central estimates. We note that the central estimate does not fall at the midpoint of the range, but instead represents the value from Model 1 which falls between the low and high bound estimates provided by Model 2.

Source: U.S. EPA Analysis, 2019

To estimate total WTP (TWTP) for water quality changes for each CBG, the EPA multiplied the per-household WTP values for the estimated water quality change by the number of households within each block group in a given year. The EPA then calculated annualized total WTP values for each CBG with both a 3 percent and 7 percent discount rate as shown below in Equation 6-2. As discussed in *Chapter 1*, monetary values of water quality changes are estimated for all years between 2021 and 2047.

Equation 6-2.

$$TWTP_B = \left(\sum_{T=2021}^{2047} \frac{HWTP_{Y,B} \times HH_{Y,B}}{(1+i)^{Y-2018}} \right) \times \left(\frac{i \times (1+i)^n}{(1+i)^{n+1} - 1} \right)$$

where:

$TWTP_B$	=	Total household WTP in 2018$ for households located in the CBG (*B*),
$HWTP_{Y,B}$	=	Annual household WTP in 2018$ 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 (3 or 7 percent)
n	=	Duration of the analysis (27 years)[64]

The 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 6-2 presents the results for the 3 percent and 7 percent discount rates.

[64] See *Section 1.3.3* for detail on the period of analysis.

Table 6-2: Estimated Total Annualized Willingness-to-Pay for Water Quality Changes Compared to Baseline (Millions 2018$)

Regulatory Option	Number of Affected Households (Millions)	3% Discount Rate[a]			7% Discount Rate[a]		
		Low	Central	High	Low	Central	High
Option 1	85.2	-$10.0	-$12.5	-$55.5	-$8.6	-$10.9	-$48.1
Option 2	86.9	$11.8	$16.7	$65.6	$10.1	$14.3	$56.1
Option 3	84.6	$16.3	$22.5	$90.7	$14.0	$19.4	$77.8
Option 4	86.5	$19.8	$27.3	$110.2	$17.0	$23.6	$94.6

a. Negative values represent forgone benefits and positive benefits represent realized benefits.

Source: U.S. EPA Analysis, 2019

The total annualized benefits of water quality changes resulting from reduced toxics, nutrient and sediment discharges in these reaches range from -$55.5 million under Option 1 (3 percent discount rate) to $110.2 million under Option 4 (3 percent discount rate). The negative values under Option 1 represent forgone benefits, while the positive values for Option 2, 3, and 4 represent realized benefits. *Appendix H* provides a detailed description of the results in Table 6-2.

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. 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).

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

Issue	Effect on Benefits Estimate	Notes
Limitations inherent to the meta-analysis model and benefit transfer		
Use of 100-mile buffer for calculating water quality benefits for each CBG	Underestimate	The distance between the surveyed households and the affected waterbodies is not well measured by any of the explanatory variables in the meta-regression model. The EPA would expect values for water quality changes to diminish with distance (all else equal) between the home and affected waterbody. The choice of 100 miles is based on typical driving distance to recreational sites (*i.e.*, 2 hours or 100 miles). Therefore, the EPA used 100 miles to approximate the distance decay effect on WTP values. The analysis effectively assumes that people living farther than 100 miles place *no* value on water quality improvements for these waterbodies despite literature that shows that while WTP tends to decline with distance from the waterbody, people place value on the quality of waters outside their region.
Selection of the WQI parameter value for estimating low and high WTP values	Uncertain	The EPA set ΔWQI to 5 and 50 units to estimate high and low benefit values based on Model 2. These values were based on the lowest and highest water quality changes included in the meta-data. To the extent that ΔWQI = 50 is significantly larger than the change in water quality expected from the regulatory options, it is likely to significantly understate the estimated WTP value. ΔWQI = 5 is more consistent with the magnitude of water quality changes resulting from the regulatory options.

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

Issue	Effect on Benefits Estimate	Notes
Whether potential hypothetical bias is present 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 et al. 2007; Rosenberger and Phipps 2007). To minimize potential hypothetical bias underlying stated preference studies included in meta-data, the EPA set independent variable values to reflect best benefit transfer practices.
Use of different water quality measures in the underlying meta-data	Uncertain	The estimation of WTP may be sensitive to differences in the environmental water quality measures 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. In preliminary model runs, the EPA tested a dummy variable (WQI) that captures the effect of a study using (WQI=1) or not using (WQI=0) the WQI. The variable coefficient was not statistically different from zero, indicating no evidence of systematic bias in the mapping of studies that did not use 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. While meta-analysis is fairly accurate when estimating benefit function, transfer error may be a problem in cases where the sample size is small. Meta-analyses have been shown to outperform other function-based transfer methods in many cases, but this result is not universal (Shrestha et al. 2007). This notwithstanding, results reviewed by Rosenberger and Phipps (2007) are "very promising" for the performance of meta-analytic benefit transfers relative to alternative transfer methods.
Use of the WQI to link water quality changes to human uses and support for aquatic and terrestrial species		
Omission of Great Lakes and estuaries from analysis of benefits from water quality changes	Underestimate	Eight out of 112 (7 percent) steam electric power generating 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 is likely to underestimate benefits of water quality changes from the regulatory options.
Changes in WQI reflect only reductions in toxics, nutrient, and total suspended sediment concentrations	Uncertain	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. If the omitted water quality parameters also change, then the analysis underestimates the expected water quality changes.

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

Issue	Effect on Benefits Estimate	Notes
In-stream toxics concentrations are based only on loadings from steam electric power generating plants and other TRI dischargers	Uncertain	In-stream concentrations for toxics were estimated based on loadings from steam electric power plant and other TRI dischargers only and, as a result, do not account for background concentrations of these pollutants from other sources, such as contaminated 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 overall impact of this limitation on the estimated WTP for water quality changes is uncertain but is expected to be small since the WTP function used in this analysis is most sensitive to the change in water quality.

7 Impacts and Benefits to Threatened and Endangered Species

7.1 Introduction

Threatened and endangered (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. In many cases, T&E species are given special protection due to inherent vulnerabilities to habitat modification, disturbance, or other human impacts. This chapter examines the change in environmental impacts of steam electric power plant discharges on T&E species and the benefits associated with changes resulting from the regulatory options.

As described in the *Supplemental EA* (U.S. EPA, 2019a), the untreated chemical constituents of steam electric power plant waste streams 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 psychological alterations in aquatic organisms (U.S. EPA, 2015a; Appendix I). 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 (Williams et al., 2001). 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 effects of the regulatory options compared to baseline, the EPA identified the inhabited waterbodies that see changes in achievement of wildlife NRWQC, relative to the baseline, as a consequence of the regulatory options and used these data to estimate the number of the geographic locations where the options are likely to affect T&E species recovery. Because NRWQC are set at levels to protect aquatic organisms, reducing the frequency at which aquatic life-based NRWQC are exceeded is likely to translate into reduced risk to T&E species and potential improvement in species population. Conversely, increasing the frequency of exceedances may increase risk to T&E species and jeopardize their survival or recovery.

In this chapter, the EPA explores the current conservation status of major freshwater taxa and identifies the extent to which the regulatory options can be expected to benefit species protected by the Endangered Species Act (ESA).

In general, the analysis shows the estimated effects of the proposed regulatory option, Option 2, on T&E species to be small compared to those estimated in 2015 for the baseline.

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 are disproportionately imperiled relative to terrestrial species. For example, while 39 percent of freshwater and diadromous fish species (Jelks et al., 2008) are classified as T&E, a similar status review found that only 7 percent of North American bird and mammal species are currently imperiled (Wilcove and Master, 2005).

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 have 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 recent conservation efforts, including the listing of several species under the 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 strikingly 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 ranged 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 Affected by the Regulatory Options

To assess the potential effects of the regulatory options on T&E species, the EPA constructed databases to determine which species are found in waters expected to improve or degrade due to changes in pollutant discharge from steam electric power plants. Notably, these databases exclude all species considered threatened or endangered by scientific organizations (*e.g.*, the American Fisheries Society [Williams et al., 1993; Taylor et al., 2007; Jelks et al., 2008]) but not protected by the ESA.[65] These databases allowed EPA to estimate the changes in potential impacts of steam electric power plant discharges on surface waters overlapping critical habitat of T&E species, a quantitative, but unmonetized proxy of the benefits associated with the regulatory options.

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

To estimate the effects of the regulatory options on surface waters overlapping with critical habitat of T&E species, all affected species must first be identified. The EPA identified all species currently listed or in consideration for listing under the ESA using the U.S. FWS Environmental Conservation Online System (U.S. FWS, 2014a). Whenever possible, the EPA obtained the geographical distribution of T&E species in geographic information system (GIS) format as polygon (shape) files, line files (for inhabitants of small creeks and rivers) and as a subset of geodatabase files. Data sources include U.S. FWS (2014b), the National Oceanic and Atmospheric Administration's (NOAA's) Office of Response and Restoration (NOAA, 2010), NatureServe (NatureServe, 2014), and NOAA National Marine Fisheries Service (NMFS, 2014a; NMFS, 2014b; NMFS, 2014c). For several freshwater species, geographic ranges were available only as 8-digit HUCs (NatureServe, 2014; U.S. FWS, 2014b). For these species, the EPA compared 8-digit HUCs for T&E species to 8-digit HUCs associated with affected reaches.

[65] The EPA chose to limit its analysis to the species protected by the ESA due to limitations of the data provided by other scientific organizations as well as time and resource constraints.

To determine the probability that an individual T&E species has critical habitat overlapping with surface waters which could benefit from the regulatory options, the EPA compiled data on locations of steam electric power plants and receiving waterbodies. See *Supplemental EA* for details on approach used to determine outfall locations (U.S. EPA, 2019a). The result of this analysis consists of the NHDPlus reaches that receive bottom ash transport water or FGD wastewater discharges from steam electric power plants and indicators of water quality under the baseline and each analyzed regulatory option based on comparison of modeled concentrations to aquatic life criteria (see *Section 3.4.1.1*). The EPA queried these data to identify "affected areas" as those habitats where 1) receiving waters do not meet water quality benchmark values for pollutants recognized to cause harm in organisms under baseline conditions but meet the benchmarks under one or more of the regulatory options; and 2) receiving waters meet the benchmarks under baseline conditions but do not meet the benchmarks under one or more of the regulatory options. The EPA used these data in ArcGIS to determine the T&E species with habitat extents overlapping the affected areas.

The EPA identified T&E species living in aquatic habitats for several life history stages and/or species that obtain a majority of their food from aquatic sources. Life history data used to classify species were obtained from a wide variety of sources (Froese and Pauly, 2009; NatureServe, 2014; Alaska Fisheries Science Center (AFSC), 2010; Atlantic States Marine Fisheries Commission (ASMFC), 2010; Northeast Fisheries Science Center (NEFSC), 2010; Pacific Islands Fisheries Science Center (PIFSC), 2010a; PIFSC, 2010b; Southeast Fisheries Science Center (SEFSC), 2010; Southwest Fisheries Science Center (SWFSC), 2010; U.S. FWS, 2010). For these species, the EPA conducted further analyses to remove from further consideration:

- Species presumed to be extinct, including those not collected for a minimum of 30 years.
- Endemic species living in waterbodies (*e.g.*, isolated headwaters, natural springs) unlikely to be affected by steam electric power plant discharges.
- Species protected by the ESA whose recovery plans i) do not include pollution or water quality issues as factors preventing recovery, and ii) identify habitat destruction (due to damming, stream channelization, water impoundments, wetland drainage, etc.) as a primary factor preventing recovery.
- Listings due to non-native species introductions and/or hybridization with native or non-native congeners .
- Listings where water quality issues are identified as the primary issue preventing recovery, but where a specific industry or entity not within the scope of the regulatory options is identified as the culprit..
- Species about which very little is known, including geographic distribution.

After eliminating the T&E species meeting these criteria, the EPA identified a total of 24 species, listed in Table 7-1, whose known critical habitat overlaps with surface waters which may be affected by the regulatory options.

Table 7-1: T&E Species with High Vulnerability Habitat Occurring within Waterbodies Affected by Steam Electric Power Plants

Species Group	Species Count	Species	Common Name
Amphibians	1	*Cryptobranchus alleganiensis*	Hellbender salamander
Birds	1	*Sterna antillarum*	Least tern
Clams and Mussels	17	*Cyprogenia stegaria*	Fanshell
		Dromus dromas	Dromedary pearlymussel
		Epioblasma obliquata obliquata	Purple cat's paw
		Epioblasma obliquata perobliqua	White cat's paw
		Fusconaia cor	Shiny pigtoe
		Fusconaia cuneolus	Finerayed pigtoe
		Hemistena lata	Cracking pearlymussel
		Lampsilis abrupta	Pink mucket
		Lampsilis virescens	Alabama lampmussel
		Lemiox rimosus	Birdwing pearlymussel
		Obovaria retusa	Ring pink
		Plethobasus cicatricosus	White wartyback
		Plethobasus cooperianus	Orangefoot pimpleback
		Plethobasus cyphyus	Sheepnose mussel
		Pleurobema clava	Clubshell
		Pleurobema plenum	Rough pigtoe
		Quadrula fragosa	Winged mapleleaf
Fishes	3	*Acipenser brevirostrum*	Shortnose sturgeon
		Acipenser oxyrinchus oxyrinchus	Atlantic sturgeon
		Etheostoma trisella	Trispot darter
Reptiles	1	*Clemmys muhlenbergii*	Bog turtle
Snails	1	*Athearnia anthonyi*	Anthony's riversnail
Total	**24**		

Source: U.S. EPA Analysis, 2019.

7.3.2 Estimating Effects of the Proposed Rule on T&E Species

The regulatory options, if implemented, have the potential to positively affect surface waters overlapping known critical habitat for six T&E species. To assess effects of the regulatory options on these surface waters, the EPA compared the estimated pollutant concentrations under the baseline and each regulatory option to NRWQC for wildlife. For each of the six species considered in this analysis, the EPA estimated the magnitude of potential benefits by identifying inhabited waterbodies likely to meet or fail to meet NRWQC for aquatic life as a consequence of the regulatory options and comparing these areas to the overall area of habitat occupied by T&E species.

First, for each T&E species affected by steam electric power plant discharges, the EPA estimated water quality in each of the waterbodies inhabited by each T&E species under baseline conditions, and under regulatory options conditions. Then, the EPA identified waterbodies that 1) do not meet NRWQC for wildlife under baseline conditions, but have no wildlife NRWQC exceedances following implementation of the regulatory options and 2) do meet NRWQC for wildlife under baseline conditions, but have wildlife NRWQC exceedances following implementation of the regulatory options.

As shown in Table 7-2, six T&E species under Option 4 and two species (Atlantic sturgeon and Trispot darter) under Options 2 and 3 have known critical habitat which overlaps with surface waters that may benefit from habitat improvements.

Table 7-2: T&E Species Whose Habitat May Benefit from the Regulatory Options

Species Common Name[a]	State(s)	Number of Reaches with NRWQC Exceedances for at Least One Pollutant				
		Baseline	Option 1	Option 2	Option 3	Option 4
Atlantic sturgeon	GA	1	1	0	0	0
Clubshell	PA	1	1	1	1	0
Hellbender salamander	PA	1	1	1	1	0
Least tern	KS	1	1	1	1	0
Trispot darter	GA	1	1	0	0	0
Winged mapleleaf	KS	1	1	1	1	0
Total number of reaches with NRWQC exceedances		**6**	**6**	**4**	**4**	**0**

a. Species Latin names are listed in Table 7-1

Source: U.S. EPA Analysis, 2019.

The EPA's analysis also shows that 23 T&E species have known critical habitat which overlaps with surface waters which may be adversely affected by water degradation under one or more of the regulatory options (see Table 7-3 for detail). Note that there are five species listed in both Table 7-2 and Table 7-3 (Atlantic sturgeon, Clubshell, Hellbender salamander, Least tern, and Trispot darter); two of these species (Atlantic sturgeon and Trispot darter) inhabit the same reach that is expected to experience both improvement and degradation, depending on the pollutants considered. Specifically, this reach meets NRWQC in the baseline for selenium and shows degradation under all four regulatory options. However, the reach does not meet NRWQC in the baseline for cadmium and shows improvements under the regulatory options for Options 2, 3, and 4. The remaining three species have known critical habitat that overlaps surface waters which may be affected by the options differently based on the state in which they reside (*i.e.*, the Clubshell critical habitat overlaps surface waters which would experience water quality improvement under Option 4 in Pennsylvania but would experience degradation under Option 4 in Ohio). The actual effect of the regulatory options on these surface waters would depend on the effects of improvements in ambient concentrations of some pollutants outweigh the effects of water quality degradation associated with other pollutants.

Table 7-3: T&E Species Whose Habitat May be Adversely Affected by the Regulatory Options

Species Common Name	State(s)	Number of Reaches with Ambient Water Quality Criteria Exceedances for at Least One Pollutant				
		Baseline	Option 1	Option 2	Option 3	Option 4
Alabama lampmussel	TN	0	0	0	1	0
Anthony's riversnail	TN	0	0	0	1	0
Atlantic sturgeon	GA	0	3	3	3	3
Birdwing pearlymussel	TN	0	0	0	1	0
Bog turtle	NY	0	2	2	0	0

Table 7-3: T&E Species Whose Habitat May be Adversely Affected by the Regulatory Options

Species Common Name	State(s)	Number of Reaches with Ambient Water Quality Criteria Exceedances for at Least One Pollutant				
		Baseline	Option 1	Option 2	Option 3	Option 4
Clubshell	OH	0	1	0	0	0
Cracking pearlymussel	KY, OH, TN, WV	0	3	0	1	0
Dromedary pearlymussel	TN	0	0	0	1	0
Fanshell	KY, OH, TN, WV	0	7	4	5	4
Finerayed pigtoe	TN	0	0	0	1	0
Hellbender salamander	KY	0	1	1	1	1
Least tern	KY	0	1	1	1	1
Orangefoot pimpleback	IL, KY, OH, TN, WV	0	3	1	2	1
Pink mucket	OH, TN	0	1	0	1	0
Purple cat's paw	KY	0	6	5	5	5
Ring pink	IL, KY, OH, TN, WV	0	4	1	2	1
Rough pigtoe	KY, OH, TN, WV	0	7	4	5	4
Sheepnose mussel	TN	0	0	0	1	0
Shiny pigtoe	TN	0	0	0	1	0
Shortnose sturgeon	SC	0	1	1	1	1
Trispot darter	GA, TN	0	3	3	4	3
White cat's paw	KY	0	1	1	1	1
White wartyback	OH, TN	0	1	0	1	0
Total number of reaches with NRWQC exceedances		**0**	**45**	**27**	**40**	**25**

a. Species Latin names are listed in Table 7-1.

Source: U.S. EPA Analysis*, 2019.*

7.4 Limitations and Uncertainties

The main limitation of the EPA's analysis of the regulatory options' impacts on T&E species habitat is the lack of data necessary to quantitively estimate population changes of T&E species and to monetize these effects. First, data required to estimate the response of T&E populations to improved habitats are rarely available. Second, the contribution of T&E species to ecosystem stability, ecosystem function, and life history remains relatively unknown. Third, there is a paucity of economic data focused on the benefits of preserving habitat for T&E species because nonuse values comprise the principal source of benefit estimates for most T&E species. Additional caveats, omissions, biases, and uncertainties known to affect the EPA's assessment of ELG's impacts on T&E species are summarized in Table 7-4.

Table 7-4: Limitations and Uncertainties in the Analysis of T&E Species Benefits

Issue	Effect on Benefits Estimate	Notes
Change in T&E populations due to the effect of revised ELGs is uncertain	Uncertain	Data necessary to quantitatively estimate population changes are unavailable. Therefore, the EPA used the methodology described in *Section 7.3.1* to assess whether the regulatory options is likely to contribute to recovery of T&E populations.
Only those T&E species listed as threatened or endangered on the Endangered Species Act are included in the analysis	Underestimate	The databases used to estimate benefits to T&E species exclude all species considered threatened or endangered by scientific organizations but not protected by the ESA. The magnitude of the underestimate is likely to be significant, since the proportion of imperiled fish and mussel species is high (*e.g.*, Jelks et al 2008, Taylor et al 2007).

Table 7-4: Limitations and Uncertainties in the Analysis of T&E Species Benefits

Issue	Effect on Benefits Estimate	Notes
Lack of available and/or precise spatial data for T&E habitats	Uncertain	For several freshwater T&E species, geographic ranges were available only as 8-digit HUCs. Because of this, the exact location of T&E habitats was estimated based on correspondence with the geographic range 8-digit HUC.

8 Air-Related Benefits

The regulatory options may affect air quality through three main mechanisms: 1) changes in energy use by steam electric power plants to operate wastewater treatment, ash handling, and other systems needed to comply with the regulatory options; 2) transportation-related emissions due to the changes in trucking of coal combustion residuals and other waste to on-site or off-site landfills; and 3) electricity generation profile changes due to changes in the cost to generate electricity at plants incurring compliance costs for the regulatory options. The different profile of generation can result in lower or higher air pollutant emissions due to differences in emission factors. Thus, small increases in coal-based electricity generation as a result of the regulatory options are compensated by reductions in generation using other fuels or energy sources – natural gas, nuclear, solar, wind, hydro, and biomass. For example, as detailed in *Chapter 5* of the RIA (U.S. EPA, 2019c), the Integrated Planning Model (IPM) projects a 0.7 percent increase in electricity generation from coal (6,278 GWh), under Option 2; this increase is partially offset by a 0.2 percent decline in natural gas generation (3,171 GWh) and additional declines in electricity generation from nuclear, wind, and hydro sources.[66] The changes in air emissions reflect the differences in emissions factors for these other fuels or sources of energy, as compared to coal.

In this analysis, which follows the same general methodology the EPA used in the analysis of the 2015 rule (U.S. EPA, 2015a), the EPA estimated the human health and other benefits resulting from net changes in emissions of three pollutants: NO_X, SO_2, and CO_2.

NO_X and SO_X (which include SO_2 emissions quantified in this analysis) are known precursors to fine particles ($PM_{2.5}$) air pollution, a criteria air pollutant that has been associated with a variety of adverse health effects — most notably, premature mortality.[67] In addition, in the presence of sunlight, NO_X and volatile organic compounds (VOCs) can undergo a chemical reaction in the atmosphere to form ozone. Depending on localized concentrations of VOCs, reducing NO_X emissions would also reduce human exposure to ozone and the incidence of ozone-related health effects. Reducing emissions of SO_2 and NO_X would also reduce ambient exposure to SO_2 and NO_2, respectively. For the purpose of this analysis, the EPA quantified only those health effects and associated benefits from associated reductions $PM_{2.5}$.[68]

CO_2 is the most prevalent of the greenhouse gases, which are air pollutants that the EPA has determined endangers public health and welfare through their contribution to climate change. The EPA used estimates of the domestic social cost of carbon (SC-CO_2) to monetize the benefits of changes in CO_2 emissions as a result of this proposal. The SC-CO_2 is a metric that estimates the monetary value of projected impacts associated with marginal changes in CO_2 emissions in a given year. It includes a wide range of anticipated climate

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66 These projections are based on the IPM sensitivity analysis scenario that includes the Affordable Clean Energy (ACE) rule in the baseline.

67 Sulfur oxides (SOx) include sulfur monoxide (SO), sulfur dioxide (SO_2), sulfur trioxide (SO_3) and other sulfur oxides. In this analysis, the EPA analyzed changes in emissions of SO_2 only.

68 The Integrated Science Assessment for Particulate Matter (PM ISA) (U.S. EPA, 2009b) identified the human health effects associated with ambient $PM_{2.5}$ exposure, which include premature morality and a variety of morbidity effects associated with acute and chronic exposures. Similarly, the Integrated Science Assessment for Ozone and Related Photochemical Oxidants (Ozone ISA) (U.S. EPA, 2013b) identified the human health effects associated with ambient ozone exposure, which include premature morality and a variety of morbidity effects associated with acute and chronic exposures.

impacts, such as net changes in agricultural productivity and human health, property damage from increased flood risk, and changes in energy system costs, such as reduced costs for heating and increased costs for air conditioning.

8.1 Data and Methodology

8.1.1 Changes in Air Emissions

As discussed in the *RIA (Chapter 5: Electricity Market Analyses)*, the EPA used IPM to estimate the electricity market-level effects of two of the four regulatory options (Options 2 and 4; see *Chapter 5* in *RIA* (U.S. EPA, 2019c)). IPM outputs include NO_X, SO_2, and CO_2 emissions to air from electricity generating units (EGU). Comparing these emissions to those projected for the baseline scenario provides an assessment of the changes in air emissions resulting from changes in the profile of electricity generation under the regulatory options. The EPA used seven run years, shown in Table 8-1, to represent the 2021-2047 period of analysis (for a more detailed discussion of the IPM analysis, refer to *Chapter 5* in *RIA*).

Table 8-1: IPM Run Years

Run Year	Years Represented
2021	2021
2023	2022-2023
2025	2024-2027
2030	2028-2032
2035	2033-2037
2040	2038-2042
2045	2043-2047

Source: U.S. EPA, 2018f

The EPA used the IPM sensitivity scenario that includes the ACE rule in the baseline (IPM-ACE) as the basis for estimating changes in emissions for proposed Option 2 and the IPM analysis scenario that does not include the ACE rule in the baseline as the basis for estimating changes in emissions for proposed Option 4.

As part of its analysis of non-water quality environmental impacts, the EPA developed separate estimates of changes in energy requirements for operating wastewater treatment systems and ash handling systems, and changes in transportation needed to landfill solid waste and combustion residuals (see *Supplemental TDD* for details; U.S. EPA, 2019b). The EPA estimated NO_X, SO_2, and CO_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 each analysis year. The EPA estimated air emissions associated with changes in transportation by multiplying the number of miles by average emission factors.

Table 8-2 and Table 8-3 summarize the estimated changes in emissions for the three mechanisms, the three pollutants, and the two regulatory options covered in this analysis. As shown in the tables, the EPA estimates that changes in power requirements and transportation (Table 8-2) would result in a decrease in emissions under Option 2 and an increase in emissions under Option 4. These values reflect full compliance with the regulatory options, which is projected to occur no later than by the end of 2028. For the purpose of this analysis, however, the EPA used these same values for the years 2021-2028.[69]

As shown in Table 8-3, projected changes in the profile of electricity generation generally lead to increased CO_2, SO_2 and NO_X emissions, with the exception of a decline in CO_2 and NO_X emissions during 2033-2042 under Option 4. Table 8-4 presents the net emissions changes across the three mechanisms.

The largest effect on projected air emissions is due to the change in the emissions profile of electricity generation at the market level. As presented in the *RIA* (U.S. EPA, 2019c; see *Section 5.2*), IPM projects increases in electricity generation coming from coal as a result of the either of the two regulatory options analyzed (about 0.6 percent for Option 2; 0.2 percent for Option 4), while decreases are projected for generation from other fuels or energy sources – natural gas and renewables, including biomass, wind, and solar. The changes in air emissions reflect the differences in emissions factors for these other fuels, as compared to coal.

Table 8-2: Estimated Changes in Air Pollutant Emissions due to Increase in Power Requirements and Trucking at Steam Electric Power Plants 2021-2047, Relative to Baseline

Source	CO_2 (Metric Tonnes/Year)[a]	NOx (Tons/Year)[a]	SO_2 (Tons/Year)[a]
Option 2			
Power requirements[b]	-44,084.2	-32.2	-54.3
Trucking	-490.0	-0.5	0.0
Option 4			
Power requirements[c]	59,320.0	31.3	20.4
Trucking	1,440.0	1.4	0.0

a. Negative values indicate a reduction in emissions; positive values indicate increased emissions

b. Estimates are based on the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE).

c. Estimates are based on IPM analysis scenario that does not include the ACE rule in the baseline.

Source: U.S. EPA Analysis, 2019

Table 8-3: Estimated Changes in Annual Air Pollutant Emissions due to Changes in Electricity Generation Profile, Relative to Baseline

Regulatory Option	Year	CO_2 (Metric Tonnes/Year)[a]	NOx (Tons/Year)[a]	SO_2 (Tons/Year)[a]
Option 2[b]	2021	502,249	2,932	1,701
	2022-2023	2,724,221	5,081	3,659
	2024-2027	3,516,021	6,083	6,654
	2028-2032	5,655,615	4,654	4,928
	2033-2037	4,530,351	3,214	3,846
	2038-2042	3,739,662	2,190	3,417
	2043-2047	3,256,567	2,172	2,063

69 The EPA estimated transportation emissions for the aggregate industry to avoid the disclosure of Confidential Business Information, preventing precise allocation of these emissions to individual years within the period of 2021 to 2028. These emissions are small when compared to emissions from changes in the electricity generation profile. Assuming that the changes occur in the first year of the analysis (2021) does not materially affect benefit estimates.

Table 8-3: Estimated Changes in Annual Air Pollutant Emissions due to Changes in Electricity Generation Profile, Relative to Baseline

Regulatory Option	Year	CO_2 (Metric Tonnes/Year)[a]	NOx (Tons/Year)[a]	SO_2 (Tons/Year)[a]
Option 4[c]	2021	773,369	3,055	5,424
	2022-2023	2,184,188	4,241	4,699
	2024-2027	296,007	2,928	1,748
	2028-2032	1,183,400	999	1,870
	2033-2037	-685,296	-276	1,204
	2038-2042	-353,497	-143	3,679
	2043-2047	1,354,002	1,807	3,290

a. Negative values indicate a reduction in emissions; positive values increase increased emissions.

b. Estimates are based on the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE).

c. Estimates are based on IPM analysis scenario that does not include the ACE rule in the baseline.

Source: U.S. EPA Analysis, 2019; See Chapter 5 in RIA for details on IPM (U.S. EPA, 2019c).

Table 8-4: Estimated Net Changes in Air Pollutant Emissions due to Changes in Power Requirements, Trucking, and Electricity Generation Profile, Relative to Baseline

Regulatory Option	Year	CO_2 (Metric Tonnes/Year)[a]	NOx (Tons/Year)[a]	SO_2 (Tons/Year)[a]
Option 2[b]	2021	457,675	2,899	1,646
	2022-2023	2,679,647	5,048	3,605
	2024-2027	3,471,447	6,050	6,599
	2028-2032	5,611,041	4,621	4,874
	2033-2037	4,485,777	3,181	3,791
	2038-2042	3,695,087	2,157	3,362
	2043-2047	3,211,993	2,140	2,009
Option 4[c]	2021	834,033	3,088	5,445
	2022-2023	2,244,852	4,274	4,720
	2024-2027	356,671	2,961	1,768
	2028-2032	1,244,064	1,032	1,890
	2033-2037	-624,632	-244	1,224
	2038-2042	-292,833	-110	3,699
	2043-2047	1,414,666	1,840	3,310

a. Negative values indicate a reduction in emissions; positive values increase increased emissions.

b. Estimates are based on the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE).

c. Estimates are based on IPM analysis scenario that does not include the ACE rule in the baseline.

Source: U.S. EPA Analysis, 2019

8.1.2 NO_X and SO_2

NO_X and SO_2 are known precursors to $PM_{2.5.}$ Several adverse health effects have been associated with $PM_{2.5,}$ including premature mortality, non-fatal heart attacks, hospital admissions, emergency department visits, upper and lower respiratory symptoms, acute bronchitis, aggravated asthma, lost work days and acute respiratory symptoms. For the analysis of the 2015 rule, the EPA relied on estimates of national monetized benefits per ton of emissions avoided, which represented the total monetized human health benefits from changes in the adverse outcomes mentioned above (U.S. EPA, 2015a)). Table 8-5 presents EPA's estimates of benefits per ton for NO_X and SO_2 for the years 2016, 2020, 2025, and 2030. The estimates vary based on the epidemiology study used as the basis for premature mortality estimates (Krewski et al. (2009) or Lepeule et al. (2012)), the discount rate (3 percent or 7 percent), and the emissions source (EGUs or on-road mobile sources).[70]

Table 8-5: National Benefits per Ton Estimates for NOx and SO_2 Emissions (2018$/ton) from the Benefits per Ton Analysis Reported by U.S. EPA (2018d)

Discount Rate	Year	EGU [a]				Mobile Source (On-road) [a]			
		Krewski et al. (2009)		Lepeule et al. (2012)		Krewski et al. (2009)		Lepeule et al. (2012)	
		SO_2	NOx	SO_2	NOx	SO_2	NOx	SO_2	NOx
3 percent	2016	$41,718	$6,258	$95,950	$14,601	$21,902	$8,656	$50,061	$19,816
	2020	$43,803	$6,466	$100,122	$14,601	$23,988	$9,074	$54,233	$20,859
	2025	$47,975	$6,988	$104,294	$15,644	$26,073	$9,804	$59,448	$21,902
	2030	$51,104	$7,509	$114,723	$16,687	$29,202	$10,429	$66,748	$23,988
7 percent	2016	$37,546	$5,632	$86,564	$12,515	$19,816	$7,822	$44,846	$17,730
	2020	$39,632	$5,840	$89,693	$13,558	$21,902	$8,135	$49,018	$18,773
	2025	$42,761	$6,258	$96,993	$14,601	$23,988	$8,865	$54,233	$19,816
	2030	$46,932	$6,779	$104,294	$15,644	$26,073	$9,595	$59,448	$21,902

a. Estimation of benefits per ton for 2016, 2020, 2025, and 2030 were based on year 2016 emissions modeling. Values were updated from 2015 dollars to 2018 dollars using the GDP deflator (1.043).

Source: U.S. EPA Analysis, 2019 based on U.S. EPA (2018d)

For this proposed rule, the Agency quantified, but did not monetize, changes in emissions of $PM_{2.5}$ precursors NO_X and SO_2. To map those emission changes to air quality changes across the country, full scale air quality modeling is needed. Prior to this proposal, the EPA's modeling capacity was fully allocated to supporting other regulatory and policy efforts and as a result we did not do an air quality impact assessment and quantify the air disbenefits of this proposal, were it to become a final regulation. Full scale air quality modeling provides spatially explicit estimates of concentration changes, which is required for characterizing uncertainty in mortality risk from changes in $PM_{2.5}$ concentrations at different levels of baseline $PM_{2.5}$ exposure. If the EPA estimates $PM_{2.5}$ concentration changes and monetizes these effects for the final rule, it will do so consistent with methods current at that time.

8.1.3 CO_2

The EPA estimated the monetary value of CO_2 emission changes using a measure of the domestic social cost of carbon (SC-CO_2). The SC-CO_2 is a metric that estimates the monetary value of projected impacts associated with marginal changes in CO_2 emissions in a given year. It includes a wide range of anticipated climate impacts, such as net changes in agricultural productivity and human health, property damage from increased flood risk, and changes in energy system costs, such as reduced costs for heating and increased costs for air conditioning. It is used to assess the avoided damages as a result of regulatory actions (*i.e.*, benefits of rulemakings that lead to an incremental reduction in cumulative global CO_2 emissions). The SC-

[70] While all of the health effects enumerated in the paragraph above are included in the estimation of benefits per ton values in U.S. EPA (2018d, a very large percentage, 98 percent, of the total monetized benefits of changes in $PM_{2.5}$ concentrations are attributable to premature mortality. U.S. EPA (2018d) presents two benefit per ton estimates for valuing changes in premature mortality based on the change in the incidence of premature mortality associated with a given change in exposure to $PM_{2.5}$: Krewski et al. (2009) and Lepeule et al. (2012).

CO_2 estimates used in this analysis focus on the projected impacts of climate change that are anticipated to directly occur within U.S. borders.

The SC-CO_2 estimates used in this analysis are interim values developed under E.O. 13783 for use in regulatory analyses until an improved estimate of the impacts of climate change to the U.S. can be developed based on the best available science and economics. E.O. 13783 directed agencies to ensure that estimates of the social cost of greenhouse gases used in regulatory analyses "are based on the best available science and economics" and are consistent with the guidance contained in OMB Circular A-4, "including with respect to the consideration of domestic versus international impacts and the consideration of appropriate discount rates" (E.O. 13783, Section 5(c)). In addition, E.O. 13783 withdrew the technical support documents (TSDs) used in the benefits analysis of the 2015 ELG for describing the global social cost of greenhouse gas estimates developed under the prior Administration as no longer representative of government policy.

Regarding the two analytical considerations highlighted in E.O. 13783 – how best to consider domestic versus international impacts and appropriate discount rates – current guidance in OMB Circular A-4 is as follows. Circular A-4 states that analysis of economically significant proposed and final regulations "should focus on benefits and costs that accrue to citizens and residents of the United States." (OMB, 2003) We follow this guidance by adopting a domestic perspective in our central analysis. Regarding discount rates, Circular A-4 states that regulatory analyses "should provide estimates of net benefits using both 3 percent and 7 percent." (OMB, 2003) The 7 percent rate is intended to represent the average before-tax rate of return to private capital in the U.S. economy. The 3 percent rate is intended to reflect the rate at which society discounts future consumption, which is particularly relevant if a regulation is expected to affect private consumption directly. The EPA follows this guidance below by presenting estimates based on both 3 and 7 percent discount rates in the main analysis. See *Appendix I* for a discussion the modeling steps involved in estimating the domestic SC-CO_2 estimates based on these discount rates. These SC-CO_2 estimates developed under E.O. 13783 presented below will be used in regulatory analysis until more comprehensive domestic estimates can be developed, which would take into consideration recent recommendations from the National Academies of Sciences, Engineering, and Medicine (2017) to further update the current methodology to ensure that the SC-CO_2 estimates reflect the best available science.[71]

Table 8-6 presents the average domestic SC-CO_2 estimate across all of the integrated assessment model runs used to estimate the SC-CO_2 for each discount rate for the years 2015 to 2050.[72] As with the global SC-CO_2 estimates, the domestic SC-CO_2 increases over time because future emissions are expected to produce larger incremental damages as economies grow and physical and economic systems become more stressed in response to greater climate change.

The EPA estimates the dollar value of the CO_2-related effects for each analysis year between 2021 and 2047 by applying the SC-CO_2 estimates, shown in Table 8-6, to the estimated changes in CO_2 emissions in the

[71] See National Academies of Sciences, Engineering, and Medicine, Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide, Washington, D.C., January 2017. http://www.nap.edu/catalog/24651/valuingclimate-changes-updating-estimation-of-the-social-cost-of

[72] The SC-CO_2 estimates rely on an ensemble of three integrated assessment models (IAMs): Dynamic Integrated Climate and Economy (DICE) 2010; Climate Framework for Uncertainty, Negotiation, and Distribution (FUND) 3.8; and Policy Analysis of the Greenhouse Gas Effect (PAGE) 2009.

corresponding year under the regulatory options. The EPA then calculates the present value and annualized benefits from the perspective of 2020 by discounting each year-specific values to the year 2020 using the same 3 percent and 7 percent discount rates.

Table 8-6: Interim Domestic Social Cost of Carbon Values (2018$/metric tonne CO_2)

Year	3% Discount Rate, Average	7% Discount Rate, Average
2015	$6	$1
2020	$7	$1
2025	$7	$1
2030	$8	$1
2035	$9	$2
2040	$10	$2
2045	$10	$2
2050	$11	$2

Note: These SC-CO_2 values are stated in $/metric ton CO_2 and rounded to the nearest dollar. The estimates vary depending on the year of CO_2 emissions and are defined in real terms, i.e., adjusted for inflation using the GDP implicit price deflator. Values updated from 2016 dollars to 2018 dollars using GDP deflator (1.030). The EPA interpolated annual values for intermediate years.

Source: U.S. EPA Analysis, 2019 based on U.S. EPA (2019f)

The limitations and uncertainties associated with the SC-CO_2 analysis, which were discussed in the 2015 BCA (U.S. EPA, 2015a), likewise apply to the domestic SC-CO_2 estimates presented in this Chapter. Some uncertainties are captured within the analysis, as discussed in detail in *Appendix I*, while other areas of uncertainty have not yet been quantified in a way that can be modeled. For example, limitations include the incomplete way in which the integrated assessment models capture catastrophic and non-catastrophic impacts, their incomplete treatment of adaptation and technological change, the incomplete way in which inter-regional and intersectoral linkages are modeled, uncertainty in the extrapolation of damages to high temperatures, and inadequate representation of the relationship between the discount rate and uncertainty in economic growth over long time horizons. The science incorporated into these models understandably lags behind the most recent research, and the limited amount of research linking climate impacts to economic damages makes this comprehensive global modeling exercise even more difficult. These individual limitations and uncertainties do not all work in the same direction in terms of their influence on the SC-CO_2 estimates. In accordance with guidance in OMB Circular A-4 on the treatment of uncertainty, *Appendix I* provides a detailed discussion of the ways in which the modeling underlying the development of the SC-CO_2 estimates used in this RIA addressed quantified sources of uncertainty and presents a sensitivity analysis to show consideration of the uncertainty surrounding discount rates over long time horizons.

Recognizing the limitations and uncertainties associated with estimating the SC-CO_2, the research community has continued to explore opportunities to improve SC-CO_2 estimates. Notably, the National Academies of Sciences, Engineering, and Medicine conducted a multidiscipline, multi-year assessment to examine potential approaches, along with their relative merits and challenges, for a comprehensive update to the current methodology. The task was to ensure that the SC-CO_2 estimates that are used in Federal analyses reflect the best available science, focusing on issues related to the choice of models and damage functions, climate science modeling assumptions, socioeconomic and emissions scenarios, presentation of uncertainty, and discounting. In January 2017, the Academies released their final report, "Assessing Approaches to Updating the Social Cost of Carbon," and recommended 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 Academies' 2017 report also discussed the challenges in developing domestic SC-CO_2 estimates, noting that current integrated assessment models do not model all relevant regional interactions – *i.e.*, how climate change impacts in other regions of the world could affect the United States, through pathways such as global migration, economic destabilization, and political destabilization. The Academies concluded that it "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. More thoroughly estimating a domestic SC-CO_2 would therefore need to consider the potential implications of climate impacts on, and actions by, other countries, which also have impacts on the United States." (National Academies, 2017, pg. 12-13). In addition to requiring reporting of impacts at a domestic level, Circular A-4 states that when an agency "evaluate[s] a regulation that is likely to have effects beyond the borders of the United States, these effects should be reported separately" (OMB, 2003; page 15). This guidance is relevant to the valuation of damages from CO_2 and other greenhouse gases (GHGs), given that GHGs contribute to damages around the world independent of the country in which they are emitted. Therefore, in accordance with this guidance in OMB Circular A-4, *Appendix I* presents the global climate benefits from this proposed rulemaking using global SC-CO_2 estimates based on both 3 and 7 percent discount rates. The EPA did not quantitatively project the full impact of the ELG on international trade and the location of production, so it is not possible to present analogous estimates of international costs resulting from the regulatory options. However, to the extent that the electricity market analysis endogenously models international electricity and natural gas trade (see Chapter 5 in *RIA*; U.S. EPA, 2019c), and to the extent that affected firms have some foreign ownership, some of the costs accruing to entities outside U.S. borders is captured in the compliance costs presented in the *RIA* (U.S. EPA, 2019c).

8.2 Results

Table 8-7 shows the estimated monetary value of the estimated changes in CO_2 emissions in each of several selected years for the two regulatory options the EPA analyzed. Negative values indicate forgone benefits of the proposed regulatory option as compared to the baseline.

Table 8-7: Estimated Domestic Climate Benefits from Changes in CO_2 Emissions for Selected Years (millions; 2018$)

Regulatory Option	Year	3% Discount Rate	7% Discount Rate
Option 2[a]	2021	-$3.0	-$0.4
	2025	-$22.2	-$3.0
	2030	-$33.7	-$4.0
	2035	-$25.3	-$2.7
	2040	-$19.4	-$1.8
	2045	-$15.7	-$1.3
	2047	-$15.2	-$1.2

Table 8-7: Estimated Domestic Climate Benefits from Changes in CO_2 Emissions for Selected Years (millions; 2018$)

Regulatory Option	Year	3% Discount Rate	7% Discount Rate
Option 4[b]	2021	-$5.6	-$0.8
	2025	-$2.3	-$0.3
	2030	-$7.5	-$0.9
	2035	$3.5	$0.4
	2040	$1.5	$0.1
	2045	-$6.9	-$0.6
	2047	-$6.7	-$0.5

a. Estimates are based on the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE).

b. Estimates are based on IPM analysis scenario that does not include the ACE rule in the baseline.

Source: U.S. EPA Analysis, 2019

Table 8-8 shows the total annualized monetary values associated with changes in CO_2 emissions for the two regulatory options the EPA analyzed and by category of emissions. The EPA annualized monetary value estimates to enable consistent reporting across benefit categories (*e.g.*, benefits from improvement in water quality). All monetary values are negative, indicating that the regulatory options result in forgone benefits when compared to the baseline. The annualized values for Options 2 are -$31.6 million and -$5.2 million, using discount rates of 3 and 7 percent, respectively. For Option 4, the estimated benefits are -$4.8 million and -$0.9 million, using discount rates of 3 and 7 percent, respectively. The vast majority of the forgone benefits arise from changes in the profile of electricity generation.

Table 8-8: Estimated Total Annualized Domestic Climate Benefits from Changes in CO_2 Emissions (Millions; 2018$)

Regulatory Option	Category of Air Emissions	3% Discount Rate	7% Discount Rate
Option 2[a]	Electricity Generation	-$32.0	-$5.2
	Trucking	$0.0	$0.0
	Energy use	$0.4	$0.1
	Total	**-$31.6**	**-$5.2**
Option 4[b]	Electricity Generation	-$4.3	-$0.8
	Trucking	$0.0	$0.0
	Energy use	-$0.5	-$0.1
	Total	**-$4.8**	**-$0.9**

a. Estimates are based on the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE).

b. Estimates are based on IPM analysis scenario that does not include the ACE rule in the baseline.

Source: U.S. EPA Analysis, 2019

The EPA did not analyze domestic climate benefits for Options 1 and 3 but extrapolated values to enable comparison of total benefits of the four options. To estimate domestic climate benefits for Options 1 and 3, the EPA scaled Option 2 benefits in proportion to the social costs of the respective options (see *Section 12.2*) since changes in the profile of electricity generation accounts for the majority of changes in air emissions and this generation profile is affected most directly by the incremental compliance costs. Specifically, the EPA calculated the ratio of the domestic climate benefits to total social costs for Option 2,[73] then multiplied total social costs for Options 1 and 3 by this ratio. Table 8-9 presents extrapolated annualized benefits for changes in air emissions for Options 1 and 3. Extrapolated domestic climate benefits are -$30.3 million to -$4.8 million for Option 1 and from -$20.9 million to -$3.7 million for Option 3, depending on the discount rate.

Table 8-9: Extrapolated Annualized Domestic Climate Benefits from Changes in CO_2 Emissions (Millions; 2018$)

Regulatory Option[a, b]	3% Discount Rate	7% Discount Rate
Option 1	-$30.3	-$4.8
Option 3	-$20.9	-$3.7

a. The EPA estimated air-related benefits for Options 1 and 3 by multiplying the total social costs for each option (see Table 12-1) by the ratio of [air-related benefits / total social costs] for Option 2.

b. Results are based on the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE).

Source: U.S. EPA Analysis, 2019

As discussed above, the EPA used different baselines for estimating the air-related benefits of proposed Options 2 and 4. Estimates for proposed Option 2 are based on an IPM sensitivity scenario that includes the ACE rule in the baseline (IPM-ACE), whereas proposed Option 4 estimates are based on an IPM scenario that does not include the ACE rule in the baseline. The EPA did not extrapolate air-related benefits estimated for Option 2 using the IPM-ACE scenario outputs to corresponding values for Option 4 due to anticipated inaccuracies such extrapolation would introduce in benefit estimates for Option 4 (e.g., suggesting positive benefits where they may be negative). As discussed in the preamble for the proposed rule, the EPA solicits comments on the significance of using two different IPM baselines for estimating benefits of Options 1 through 3 (with the ACE rule) and Option 4 (without the ACE rule) and intends to include the ACE rule in the baseline for IPM analyses for the final rulemaking.

8.3 Limitations and Uncertainties

Table 8-10 summarizes the limitations and uncertainties associated with the analysis of the air-related benefits. 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). The analysis also inherits uncertainties associated with IPM modeling, which are discussed in Chapter 5 in the *RIA* (U.S. EPA, 2019c).

73 The ratios are 0.23 for the 3 percent discount rate estimates, and 0.03 for the 7 percent discount rate estimates.

Table 8-10: Limitations and Uncertainties in Analysis of Air-related Benefits

Issue	Effect on Benefits Estimate	Notes
Domestic SC-CO_2 estimates do not capture the full range of impacts from climate change	Underestimate	Current integrated assessment models (IAMs) used in developing the SC-CO_2 do not model all relevant regional interactions – *i.e.*, how climate change impacts in other regions of the world could affect the United States, through pathways such as global migration, economic destabilization, and political destabilization.
The EPA did not monetize air-related benefits of changes in NO_X, SO_2, and other pollutants emitted by electricity generating units	Underestimate	NO_X and SO_2 are precursors to $PM_{2.5}$, which causes a variety of adverse health effects including premature death, non-fatal heart attacks, hospital admissions, emergency department visits, upper and lower respiratory symptoms, acute bronchitis, aggravated asthma, lost work days, and acute respiratory symptoms. There are additional direct benefits from changes in levels of NO_X, SO_2 and other air pollutants emitted by electricity generating units. As described in U.S. EPA (2019f), 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.
The EPA used predicted changes in air emissions from an IPM run that does not include the ACE rule in the baseline to estimate air-related benefits for proposed Option 4	Uncertain	Effects of the ACE rule on predicted changes in emissions for proposed Option 4 are unknown. The EPA assessed that the air-related benefits for Option 4 estimated using the IPM scenario without the ACE rule provide an approximate representation of the benefits of this option.

9 Changes in Water Withdrawals

Steam electric power plants use water for ash transport and for operating wet FGD scrubbers. The regulatory options are estimated to change water withdrawal from surface waterbodies and aquifers by affecting sluicing operations or incentives to recycle water within the plants. The change in water use depends on the regulatory option, but are small compared to those estimated in 2015 (see U.S. EPA, 2015a).

Table 9-1 shows estimated changes in water withdrawals for each evaluated regulatory option.

Table 9-1: Industry-level Total Changes in Water Withdrawals (Surface Water and Aquifers)

Regulatory Option	Change in water withdrawals (billion gallons per year)
Option 1	1.2
Option 2	7.7
Option 3	0.2
Option 4	-3.4

Source: U.S. EPA Analysis, 2019

The sections below discuss the benefits resulting specifically from estimated changes in groundwater withdrawals. Benefits associated with surface water withdrawals are discussed qualitatively in *Chapter 2*.

9.1 Methods

The analysis follows the same general methodology the EPA used in the analysis of the 2015 rule (U.S. EPA, 2015a). Changes in water withdrawal from groundwater sources by steam electric power plants may affect availability of groundwater for local municipalities that rely on groundwater aquifers for drinking water supplies. These municipalities may incur incremental costs for supplementing drinking water supplies through alternative means, such as bulk drinking water purchases as water withdrawals by steam electric power plants change. The EPA estimated the monetary value of changes in groundwater withdrawals based on costs of purchasing drinking water during periods of shortages in groundwater supply.

9.2 Results

The EPA's analysis of the regulatory options indicates that one plant would increase the volume of groundwater withdrawn under Option 2. No changes in groundwater withdrawal are estimated under Options 1, 3, and 4. See details in the *Supplemental TDD* (U.S. EPA, 2019b).

The EPA estimated that the plant would increase withdrawals by a total of 21,971 gallons per day (8 million gallons per year) under Option 2. To estimate the value of reduced groundwater supply, the EPA used state-specific prices of bulk drinking water supplies, based on the assumption that municipalities may need to purchase supplementary supplies in response to any change in groundwater availability arising from additional withdrawals. While this is an approximate assumption, the analysis provides screening-level indication of the potential forgone benefits.

To estimate the monetary value of the specific reduced groundwater withdrawal due to the one facility's increase in groundwater use, the EPA relied on the current state-specific drinking water prices of $1,192 per acre/foot for the affected location. The EPA multiplied the increase in groundwater withdrawal (in gallons per year) by the estimated price of drinking water per gallon.[74]

Table 9-2 shows estimated annual forgone benefits from increased groundwater withdrawals under Option 2. The annual forgone benefits from Option 2 are $0.02 million using a 3 percent discount rate ($0.02 million using a 7 percent discount rate). As described above, there are no changes in groundwater withdrawals associated with any of the other regulatory options and, therefore, no change in monetary benefits under those options.

Table 9-2: Estimated Annualized Benefits from Increased Groundwater Withdrawals (Millions; 2018$)

Regulatory Option	Increase in Groundwater Intakes (million gallons per year)	3% Discount Rate	7% Discount Rate
Option 1	0.0	$0.00	$0.00
Option 2	8.0	-$0.02	-$0.02
Option 3	0.0	$0.00	$0.00
Option 4	0.0	$0.00	$0.00

a Reflects changes after full compliance with requirements for Option 2 in 2023.

Source: U.S. EPA Analysis, 2019

9.3 Limitations and Uncertainties

Table 9-3 summarizes the limitations and uncertainties in the analysis of benefits associated with changes in groundwater withdrawals.

Table 9-3: Limitations and Uncertainties in Analysis of Changes in Groundwater Withdrawals

Uncertainty/Assumption	Effect on Benefits Estimate	Notes
The EPA assumed that municipalities would need to replace lost groundwater supplies with bulk drinking water purchases.	Uncertain See below.	Municipalities may not need to replace groundwater withdrawn by steam electric power plants (in which case the benefits of the ELG may be overstated), or they may choose to replace the groundwater through other means.
The EPA assumed a direct relationship between groundwater withdrawals in water-stressed states and groundwater shortages, *i.e.*, that reducing demand for limited groundwater supplies would result in avoided costs for purchased water.	Overestimate	The EPA assumed that demand for additional water supply exists in the affected areas due to potential drought. However, the extent of this demand is uncertain.

74 The EPA used a conversion factor of 325,851 to convert acre foot to gallons.

Table 9-3: Limitations and Uncertainties in Analysis of Changes in Groundwater Withdrawals

Uncertainty/Assumption	Effect on Benefits Estimate	Notes
The EPA estimated cost of bulk water purchases based on state-wide averages	Uncertain	Costs of water may vary within a state and assuming the average value may result in under- or overstating of the cost for any given location. This uncertainty is more significant in cases where there are few affected locations, as is the case for this analysis which shows only one plant with changes in groundwater withdrawals.
Data on the characteristics of affected aquifers are not available	Uncertain	If the affected aquifers are used for private wells only, the estimated benefits of improved groundwater recharge could be under- or overstated, depending on households WTP for protecting groundwater quantity.

10 Estimated Changes in Dredging Costs

As summarized in Table 3-3, the regulatory options could result in small changes to total suspended solid (TSS) discharged by steam electric power plants, which could have an impact on the rate of sediment deposition to affected waterbodies, 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 et al., 1985). 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 storage of drinking and irrigation water supplies, flood control, hydropower supply, and recreation. Streams and rivers carry sediment into reservoirs, where it can settle and cause buildup of silt layers 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 et al., 1985).

The EPA estimated that the proposed regulatory option, Option 2, would have a small effect on dredging costs when compared to those estimated in 2015 (see U.S. EPA, 2015a).

10.1 Methods

In this analysis, the EPA followed the same general methodology for estimating changes in costs associated with changes in sediment depositions in navigational waterways and reservoirs that the EPA used in the 2015 rule (U.S. EPA 2015a; see Appendix K). 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 sediment deposition and removal in dredged waterways and reservoirs under the regulatory options. Benefits are equal to avoided costs, calculated as the difference in total annualized dredging costs at baseline and under each regulatory option. Negative values represent cost increases (*i.e.*, forgone benefits to society).

10.1.1 Estimated Changes in Navigational Dredging Costs

The EPA identified 22 unique dredging jobs and 91 dredging occurrences[75] within the affected reaches equivalent to 0.8 percent of the dredging occurrences with coordinates reported in the Dredging Information System (USACE, 2013). The recurrence interval for dredging jobs ranged from 1 to 15 years across all affected reaches and averaged 9.6 years. Costs vary considerably across affected reaches, from approximately $1.72 per cubic yard at Establishment Bar in North Carolina to $30.30 per cubic yard at Bonum Creek in Virginia. The average unit cost of dredging for the entire conterminous United States is $6.00 per cubic yard.

[75] Dredging jobs refer to unique sites/locations defined by USACE where dredging was conducted, whereas dredging occurrences are unique instances when dredging was conducted and may include successive dredging at the same location.

Table 10-1 presents estimates of baseline sediment dredging in navigational waterways that may be affected by bottom ash transport water and FGD wastewater discharges from 2021 to 2047 and low, mean, and high cost estimates. The EPA generated low, medium, and high estimates for navigational dredging by varying assumptions for 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 detail). Estimated total baseline navigational dredging costs range from $49.4 to $58.5 million per year, using a 3 percent discount rate, and from $43.4 to $55.6 million using a 7 percent discount rate.

Table 10-1: Estimated Annualized Dredging Costs at Affected Reaches under the Baseline (Millions of 2018$)

Total Sediment Dredged (millions cubic yards)			Costs at 3% discount rate (millions of 2018$ per year)			Costs at 7% discount rate (millions of 2018$ per year)		
Low	Mean	High	Low	Mean	High	Low	Mean	High
118.5	118.7	129.1	$49.4	$49.6	$58.5	$43.4	$43.5	$55.6

Source: U.S. EPA analysis, 2019.

The difference between the estimated dredging costs under the baseline and a particular regulatory option represents the avoided costs (or forgone benefits) of that regulatory option. Table 10-2 presents estimated cost changes for navigational dredging for the four regulatory options.

Table 10-2: Estimated Annualized Changes in Navigational Dredging Costs (Thousands of 2018$)

Regulatory Option	Total Reduction in Sediment Dredged (millions cubic yards)			3% discount rate (millions of 2018$ per year)[a]			7% discount rate (millions of 2018$ per year)[a]		
	Low	Mean	High	Low	Mean	High	Low	Mean	High
Option 1	-0.1	-0.1	-0.1	-$0.04	-$0.04	-$0.05	-$0.03	-$0.03	-$0.05
Option 2	-0.1	-0.1	-0.1	-$0.04	-$0.04	-$0.07	-$0.03	-$0.03	-$0.07
Option 3	-0.1	-0.1	-0.1	-$0.04	-$0.04	-$0.05	-$0.03	-$0.03	-$0.05
Option 4	1.1	1.1	1.3	$0.49	$0.49	$0.62	$0.42	$0.42	$0.60

a. Positive values represent cost savings; negative values represent cost increases.

Source: U.S. EPA analysis, 2019.

10.1.2 Estimated Changes in Reservoir Dredging Costs

The EPA identified 217 reservoirs within the affected reaches with changes in sediment loads under at least one of the regulatory options, equivalent to 0.3 percent of the reservoirs included in the E2RF1 file (USGS, 2002). Table 10-3 presents the total amount of sediment that is estimated to be dredged in 2021 to 2047 from these reservoirs, and the estimated annualized cost of dredging under the baseline scenario, including low, mean, and high estimates. Estimated dredging costs for the reservoirs range between $460.4 million and $624.8 million with a 3 percent discount rate and $385.4 million and $574.2 million with a 7 percent discount rate under the baseline scenario.

Table 10-3: Estimated Annualized Reservoir Dredging Costs under Baseline (Millions 2018$)

Total Sediment Dredged (millions cubic yards)			Costs at 3% Discount Rate (millions of 2018$ per year)			Costs at 7% Discount Rate (millions of 2018$ per year)		
Low	Mean	High	Low	Mean	High	Low	Mean	High
2,090.2	2,508.2	2,717.2	$460.4	$557.2	$624.8	$385.4	$483.5	$574.2

Source: U.S. EPA analysis, 2019.

The difference between the estimated dredging costs under the baseline and a particular regulatory option represents the avoided costs of that regulatory option. Table 10-4 presents estimated cost changes for reservoir dredging under the four regulatory options, including low, mean, and high estimates.

Table 10-4: Estimated Total Annualized Changes in Reservoir Dredging Costs (2018$)

Regulatory Option	Total Reduction in Sediment Dredged (millions cubic yards)			Costs at 3% Discount Rate[a] (millions of 2018$ per year)			Costs at 7% Discount Rate[a] (millions of 2018$ per year)		
	Low	Mean	High	Low	Mean	High	Low	Mean	High
Option 1	-0.1	-0.2	-0.2	-$0.03	-$0.04	-$0.04	-$0.02	-$0.03	-$0.04
Option 2	-0.5	-0.6	-0.6	-$0.10	-$0.13	-$0.14	-$0.09	-$0.11	-$0.13
Option 3	-0.1	-0.1	-0.1	-$0.02	-$0.02	-$0.02	-$0.01	-$0.02	-$0.02
Option 4	0.3	0.4	0.4	$0.08	$0.09	$0.10	$0.06	$0.08	$0.10

a. Positive values represent cost savings; negative values represent cost increases.

Source: U.S. EPA analysis, 2019.

10.2 Limitation and Uncertainty

Key uncertainties and limitations in the analysis of sediment dredging benefits are summarized in Table 10-5. Detailed description is provided in Appendix K of the 2015 BCA document (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). Uncertainties and limitations associated with SPARROW model estimates of sediment deposition are discussed in U.S. EPA (2009a).

Table 10-5: Limitations and Uncertainties in Analysis of Changes in Dredging Costs

Uncertainty/Assumption	Effect on Benefits Estimate	Notes
The analysis of navigational waterways is restricted to jobs reported in USACE Database for 1998 to 2012 (USACE, 2013).	Underestimate	Because some dredging jobs included in the USACE Database lack latitude and longitude and the database does not use standardized job names the EPA was only able to map about 71 percent of all dredging occurrences with records in the data. This may lead to potential underestimation of baseline and changes in dredging costs under the regulatory options.
The EPA's analysis for modeled watersheds explicitly omits any reservoirs that are not located on the E2RF1 network.	Underestimate	The omission of other reservoirs would understate the magnitude of estimated baseline and changes in reservoir dredging benefits in cases where there are additional reservoirs located downstream from steam electric power plants that discharge bottom ash transport water or FGD wastewater.

11 Summary of Estimated Total Monetized Benefits

Table 11-1 and Table 11-2, on the next two pages, summarize the total annualized monetary value of social welfare changes using 3 percent and 7 percent discount rates, respectively.

The monetary value of social welfare changes does not account for all effects of the regulatory options, including changes in certain non-cancer health risk (*e.g.*, effects of cadmium on kidney functions and bone density), impacts of pollutant load changes on threatened and endangered species habitat, and ash marketing changes. See *Chapter 2* for a discussion of categories of social welfare effects the EPA did not monetize. *Chapter 4* through *Chapter 10* provide more detail on the estimation methodologies for each benefit category.

Table 11-1: Summary of Estimated Total Annualized Benefits at 3 Percent (Millions; 2018$)

Benefit Category	Option 1[a]			Option 2[a]			Option 3[a]			Option 4[a]		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Human Health		**-$0.7**			**$34.8**			**$39.7**			**$82.8**	
Changes in IQ losses in children from exposure to lead[b]		<$0.0			<$0.0			<$0.0			<$0.0	
Changes in IQ losses in children from exposure to mercury		-$0.3			-$2.8			-$2.9			-$1.5	
Changes in cancer risk from DBPs in drinking water		-$0.4			$37.6			$42.6			$84.3	
Ecological Conditions and Recreational Uses Changes	**-$10.0**	**-$12.5**	**-$55.5**	**$11.8**	**$16.7**	**$65.6**	**$16.3**	**$22.5**	**$90.7**	**$19.8**	**$27.3**	**$110.2**
Use and nonuse values for water quality changes	-$10.0	-$12.5	-$55.5	$11.8	$16.7	$65.6	$16.3	$22.5	$90.7	$19.8	$27.3	$110.2
Market and Productivity	**-$0.1**	**-$0.1**	**-$0.1**	**-$0.2**	**-$0.2**	**-$0.2**	**-$0.1**	**-$0.1**	**-$0.1**	**$0.6**	**$0.6**	**$0.7**
Changes in dredging costs	-$0.1	-$0.1	-$0.1	-$0.1	-$0.2	-$0.2	-$0.1	-$0.1	-$0.1	$0.6	$0.6	$0.7
Reduced water withdrawals[b]		$0.0			<$0.0			$0.0			$0.0	
Air-related effects		**-$30.3**			**-$31.6**			**-$20.9**			**-$4.8**	
Changes in CO_2 air emissions[c]		-$30.3			-$31.6			-$20.9			-$4.8	
Total[d]	**-$41.0**	**-$43.6**	**-$86.6**	**$14.8**	**$19.6**	**$68.5**	**$35.1**	**$41.3**	**$109.4**	**$98.4**	**$105.9**	**$188.9**

a. Negative values represent forgone benefits and positive values represent realized benefits.

b. "<$0.0" indicates that monetary values are greater than -$0.1 million but less than $0.00 million.

c. The EPA estimated the air-related benefits for Option 2 using the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE). EPA extrapolated estimates for Options 1 and 3 air-related benefits from the estimate for Option 2 that is based on IPM-ACE outputs. The values for Option 4 air-related benefits were estimated using the IPM analysis scenario that does not include the ACE rule in the baseline. See *Chapter 8* for details.

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

Source: U.S. EPA Analysis, 2019

Table 11-2: Summary of Estimated Total Annualized Benefits at 7 Percent (Millions; 2018$)

Benefit Category	Option 1[a]			Option 2[a]			Option 3[a]			Option 4[a]		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Human Health		**-$0.3**			**$23.6**			**$26.9**			**$54.0**	
Changes in IQ losses in children from exposure to lead[b]		<$0.0			<$0.0			<$0.0			<$0.0	
Changes in IQ losses in children from exposure to mercury[b]		-$0.1			-$0.6			-$0.6			-$0.3	
Changes in cancer risk from DBPs in drinking water		-$0.2			$24.2			$27.5			$54.3	
Ecological Conditions and Recreational Uses Changes	**-$8.6**	**-$10.9**	**-$48.1**	**$10.1**	**$14.3**	**$56.1**	**$14.0**	**$19.4**	**$77.8**	**$17.0**	**$23.6**	**$94.6**
Use and nonuse values for water quality Changes	-$8.6	-$10.9	-$48.1	$10.1	$14.3	$56.1	$14.0	$19.4	$77.8	$17.0	$23.6	$94.6
Market and Productivity	**-$0.1**	**-$0.1**	**-$0.1**	**-$0.1**	**-$0.2**	**-$0.2**	**$0.0**	**-$0.1**	**-$0.1**	**$0.5**	**$0.5**	**$0.7**
Changes in dredging costs	-$0.1	-$0.1	-$0.1	-$0.1	-$0.1	-$0.2	$0.0	-$0.1	-$0.1	$0.5	$0.5	$0.7
Reduced water withdrawals[b]		$0.0			<$0.0			$0.0			$0.0	
Air-related Effects		**-$4.8**			**-$5.2**			**-$3.7**			**-$0.9**	
Changes in CO_2 air emissions[c]		-$4.8			-$5.2			-$3.7			-$0.9	
Total[d]	**-$13.7**	**-$16.0**	**-$53.3**	**$28.4**	**$32.6**	**$74.4**	**$37.1**	**$42.5**	**$100.9**	**$70.6**	**$77.2**	**$148.4**

a. Negative values represent forgone benefits and positive values represent realized benefits.

b. "<$0.0" indicates that monetary values are greater than -$0.1 million but less than $0.00 million.

c. The EPA estimated the air-related benefits for Option 2 using the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE). EPA extrapolated estimates for Options 1 and 3 air-related benefits from the estimate for Option 2 that is based on IPM-ACE outputs. The values for Option 4 air-related benefits were estimated using the IPM analysis scenario that does not include the ACE rule in the baseline. See *Chapter 8* for details.

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

Source: U.S. EPA Analysis, 2019

12 Summary of Total Social Costs

This chapter discusses the 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, 2019c), the EPA did not evaluate incremental cost to state governments to evaluate and incorporate best professional judgment into National Pollutant Discharge Elimination System (NPDES) permits. Consequently, the only category of costs used to calculate social costs are estimated compliance costs for steam electric power plants. As discussed below, these costs may be positive or negative, with the latter occurring when a regulatory option provides savings as compared to the baseline.

12.1 Overview of Costs Analysis Framework

RIA Chapter 3: Compliance Costs presents the EPA's development of costs to the 951 steam electric power plants subject to the regulatory options (U.S. EPA, 2019c). These costs (pre-tax) are used as the basis of the social cost analysis.

As described in *Chapter 1*, the EPA assumed that steam electric power plants, in the aggregate, would implement control technologies between 2021 and 2028, with the compliance schedule varying across wastestreams and regulatory options. For the analysis of social costs, the EPA estimated a plant- and year-explicit schedule of compliance cost outlays over the period of 2021 through 2047.[76] After creating a cost-incurrence schedule for each cost component, the 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. Following the approach used for the 2015 ELG analysis (U.S. EPA, 2015a), after compliance costs were assigned to the year of occurrence, the Agency adjusted these costs for change between their stated year 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 2027; after these years, the EPA assumed that the real change in prices is zero – that is, costs are expected to change in line with general inflation. The EPA judges this to be a reasonable assumption, given the fact that capital expenditures would occur by 2028 and 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, the EPA calculated the present value of these cost outlays as of the rule promulgation year by discounting the cost in each year back to 2020, using both 3 percent and 7 percent discount rates. These discount rate values reflect guidance from the OMB regulatory analysis guidance document, Circular

[76] The period of analysis extends to 2047 to capture a substantive portion of the life of the compliance technology at any steam electric power plant (20 or more years), and the last year of technology implementation (2028).

A-4 (U.S. OMB, 2003). The EPA calculated the constant annual equivalent value (annualized value), again using the two values of the discount rate, 3 percent and 7 percent, over a 27-year social cost analysis period. The EPA assumed no re-installation of compliance technology during the period covered by the social cost analysis.

To assess the economic costs of the regulatory options to society, the 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 (2019b) for detail). 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. The EPA assumed in its social cost analysis that the regulatory options do not affect the aggregate quantity of electricity that would be sold to consumers and, thus, that the rule's social cost would 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, this assumption 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: Electricity Market Analyses*). 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 promulgation and technology implementation years.[77]

Finally, as discussed in Chapter 10 of the RIA document (U.S. EPA, 2019c; see Section 10.7: Paperwork Reduction Act of 1995), the regulatory options would not result in additional administrative costs for plants to implement, and state and federal National Pollutant Discharge Elimination System (NPDES) permitting authorities to administer, the revised ELGs, once promulgated. As a result, the social cost analysis focuses on the resource cost of compliance as the only direct cost incurred by society as a result of the regulatory options.

12.2 Key Findings for Regulatory Options

Table 12-1 presents annualized costs for the baseline and each of the four regulatory options. The table also provides the incremental costs attributable to the regulatory options, calculated as the difference between each option and the baseline. As shown in the table, the regulatory options generally result in cost savings across the four options and discount rates, with the exception of Option 4 which results in incremental costs at 3 percent discount rate. Thus, incremental costs range from -$136.3 million to $11.9 million at a 3 percent discount rate, and from -$166.2 million to -$27.3 million at a 7 percent discount rate.

Table 12-1: Summary of Estimated Annualized Costs (Millions; $2018)

Regulatory Option	Annualized Costs		Incremental Costs	
	3% Discount Rate	7% Discount Rate	3% Discount Rate	7% Discount Rate
Baseline	$364.9	$417.0		
Option 1	$234.3	$263.0	-$130.6	-$154.0
Option 2	$228.6	$250.8	-$136.3	-$166.2
Option 3	$274.8	$297.5	-$90.1	-$119.5
Option 4	$376.8	$389.7	$11.9	-$27.3

Source: U.S. EPA Analysis, 2019.

77 The specific assumptions of when each cost component is incurred can be found in *Chapter 3: Compliance Costs* of the *RIA*.

Table 12-2 provides additional detail on the social cost calculations. The table compiles, for the baseline and each of the four regulatory options, the time profiles of compliance costs incurred. The table also reports the estimated annualized values of costs at 3 percent and 7 percent discount rates. The maximum compliance outlays differ across the options but are incurred over the years 2021 through 2028, *i.e.*, during the estimated window when steam electric power plants are expected to implement compliance technologies.

Table 12-2: Time Profile of Costs to Society (Millions; $2018)

Year	Compliance Costs					Incremental Costs			
	Baseline	Option 1	Option 2	Option 3	Option 4	Option 1	Option 2	Option 3	Option 4
2020	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0	$0.0
2021	$1,211.9	$673.5	$635.9	$683.3	$554.9	-$538.4	-$576.0	-$528.6	-$657.0
2022	$746.5	$487.0	$375.9	$475.2	$405.3	-$259.5	-$370.6	-$271.3	-$341.1
2023	$2,070.8	$1,231.1	$907.4	$996.0	$870.9	-$839.7	-$1,163.4	-$1,074.8	-$1,200.0
2024	$192.8	$135.2	$178.8	$203.1	$321.3	-$57.6	-$14.0	$10.3	$128.5
2025	$195.1	$136.6	$181.8	$222.8	$460.0	-$58.4	-$13.3	$27.7	$265.0
2026	$190.7	$131.4	$109.4	$134.7	$647.0	-$59.3	-$81.3	-$56.1	$456.2
2027	$201.5	$141.2	$115.1	$141.0	$456.4	-$60.3	-$86.3	-$60.4	$255.0
2028	$189.6	$129.4	$445.2	$575.0	$657.8	-$60.3	$255.5	$385.3	$468.2
2029	$204.8	$144.6	$146.5	$185.2	$287.0	-$60.3	-$58.4	-$19.6	$82.2
2030	$201.8	$141.6	$144.7	$183.7	$285.1	-$60.3	-$57.1	-$18.1	$83.3
2031	$205.1	$144.9	$149.8	$190.1	$288.4	-$60.3	-$55.3	-$15.0	$83.3
2032	$207.0	$146.8	$149.9	$191.2	$294.1	-$60.3	-$57.1	-$15.8	$87.1
2033	$214.7	$154.4	$148.1	$188.8	$299.5	-$60.3	-$66.6	-$25.9	$84.8
2034	$201.7	$141.4	$146.7	$185.6	$289.3	-$60.3	-$55.0	-$16.1	$87.6
2035	$204.8	$144.6	$147.6	$186.3	$289.7	-$60.3	-$57.3	-$18.5	$84.9
2036	$193.9	$133.6	$142.8	$181.8	$286.9	-$60.3	-$51.1	-$12.1	$93.0
2037	$199.5	$139.2	$146.2	$185.0	$288.7	-$60.3	-$53.3	-$14.5	$89.2
2038	$189.5	$129.3	$140.8	$182.9	$287.5	-$60.3	-$48.7	-$6.6	$97.9
2039	$203.1	$142.8	$146.1	$185.5	$287.6	-$60.3	-$57.0	-$17.6	$84.5
2040	$201.7	$141.4	$145.0	$183.5	$285.4	-$60.3	-$56.7	-$18.2	$83.7
2041	$208.8	$148.6	$150.4	$190.3	$290.3	-$60.3	-$58.4	-$18.5	$81.5
2042	$207.3	$147.0	$150.4	$191.9	$294.8	-$60.3	-$56.9	-$15.4	$87.5
2043	$212.7	$152.4	$151.4	$192.9	$299.7	-$60.3	-$61.3	-$19.8	$87.1
2044	$201.6	$141.3	$146.4	$185.8	$289.7	-$60.3	-$55.2	-$15.8	$88.1
2045	$202.5	$142.2	$146.7	$186.2	$290.0	-$60.3	-$55.7	-$16.2	$87.6
2046	$200.5	$140.3	$146.3	$185.3	$289.5	-$60.3	-$54.3	-$15.3	$88.9
2047	$202.2	$141.9	$146.9	$186.0	$289.9	-$60.3	-$55.3	-$16.2	$87.7
Annualized Costs, 3%	**$364.9**	**$234.3**	**$228.6**	**$274.8**	**$376.8**	**-$130.6**	**-$136.3**	**-$90.1**	**$11.9**
Annualized Costs, 7%	**$417.0**	**$263.0**	**$250.8**	**$297.5**	**$389.7**	**-$154.0**	**-$166.2**	**-$119.5**	**-$27.3**

Source: U.S. EPA Analysis, 2019.

13 Benefits and Social Costs

This chapter compares total monetized benefits and costs for the four regulatory options analyzed. 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 Executive Order 12866: Regulatory Planning and Review and Executive Order 13563: Improving Regulation and Regulatory Review (see *Chapter 9: Other Administrative Requirements* of the *RIA*; U.S. EPA, 2019c).

13.1 Comparison of Benefits and Costs by Option

Chapter 11 and *Chapter 12* present estimates of the benefits and costs, respectively, for the regulatory options as compared to the baseline.

Table 13-1 presents the EPA's estimates of benefits and costs of the regulatory options, at 3 percent and 7 percent discount rates, and annualized over 27 years. These values are all in 2018 dollars and are based on the discounting of costs and benefits to 2020, the rule promulgation year.

Table 13-1: Total Estimated Annualized Benefits and Costs by Regulatory Option and Discount Rate (Millions; 2018$)

Regulatory Option	Total Monetized Benefits[a]			Total Costs
	Low	Mid	High	
3% Discount Rate				
Option 1	-$41.0	-$43.6	-$86.6	-$130.6
Option 2	$14.8	$19.6	$68.5	-$136.3
Option 3	$35.1	$41.3	$109.4	-$90.1
Option 4	$98.4	$105.9	$188.9	$11.9
7% Discount Rate				
Option 1	-$13.7	-$16.0	-$53.3	-$154.0
Option 2	$28.4	$32.6	$74.4	-$166.2
Option 3	$37.1	$42.5	$100.9	-$119.5
Option 4	$70.6	$77.2	$148.4	-$27.3

a. The EPA estimated the air-related benefits for Option 2 using the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE). EPA extrapolated estimates for Options 1 and 3 air-related benefits from the estimate for Option 2 that is based on IPM-ACE outputs. The values for Option 4 air-related benefits were estimated using the IPM analysis scenario that does not include the ACE rule in the baseline. See *Chapter 8* for details.

Source: U.S. EPA Analysis, 2019.

13.2 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, the 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.

The EPA conducted the incremental net benefit analysis by calculating, for the four regulatory options, 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 that would implement the technologies and of the receiving waterbodies.

As reported in Table 13-2, the EPA estimated that cost savings exceed forgone monetized benefits under Option 1, with mid-range net annual monetized benefits of $87.0 million using a 3 percent discount rate. Options 2 and 3 have positive benefits and cost savings, with mid-range net annual monetized benefits ranging from $131.4 million under Option 3 to $155.9 million under Option 2 (3 percent discount rate). Option 4 has both positive benefits and costs, with mid-range net annual monetized benefits of $94.0 million using a 3 percent discount rate. Among the regulatory options, the proposed option (Option 2) results in the highest net annual monetized benefits.

Using a 3 percent discount rate, the incremental net annual monetized benefits of moving from Option 1 to Option 2 is $68.9 million. The positive value indicates that net annual monetized benefits are higher for Option 2 than for Option 1. Moving from Option 2 to Option 3, the change is negative, at -$24.6 million, which indicates that the increase in costs is greater than the increase in benefits. The change of moving from Option 3 to Option 4 is also negative, at -$37.3 million, again indicating that the increase in costs is larger than the increase in benefits.

Table 13-2: Estimated Incremental Net Benefit Analysis (Millions; 2018$)

Regulatory Option	Net Annual Monetized Benefits[a,b]			Incremental Net Annual Monetized Benefits[c]		
	Low	Mid	High	Low	Mid	High
3% Discount Rate						
Option 1	$89.6	$87.0	$44.0	NA	NA	NA
Option 2	$151.1	$155.9	$204.8	$61.5	$68.9	$160.8
Option 3	$125.2	$131.4	$199.5	-$25.9	-$24.6	-$5.3
Option 4	$86.5	$94.0	$177.0	-$38.7	-$37.3	-$22.5
7% Discount Rate						
Option 1	$140.3	$138.0	$100.7	NA	NA	NA
Option 2	$194.6	$198.8	$240.6	$54.4	$60.9	$139.8
Option 3	$156.6	$162.0	$220.4	-$38.0	-$36.8	-$20.1
Option 4	$97.9	$104.5	$175.7	-$58.8	-$57.5	-$44.7

Table 13-2: Estimated Incremental Net Benefit Analysis (Millions; 2018$)

Regulatory Option	Net Annual Monetized Benefits[a,b]			Incremental Net Annual Monetized Benefits[c]		
	Low	Mid	High	Low	Mid	High

NA: Not applicable for Option 1

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. The EPA estimated the air-related benefits for Option 2 using the IPM sensitivity analysis scenario that includes the ACE rule in the baseline (IPM-ACE). EPA extrapolated estimates for Options 1 and 3 air-related benefits from the estimate for Option 2 that is based on IPM-ACE outputs. The values for Option 4 air-related benefits were estimated using the IPM analysis scenario that does not include the ACE rule in the baseline. 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, 2019.

14 Environmental Justice

Executive Order (E.O.) 12898 (59 FR 7629, February 11, 1994) requires that, to the greatest extent practicable and permitted by law, each Federal agency must make the achievement of EJ part of its mission. E.O. 12898 provides that each Federal agency must conduct its programs, policies, and activities that substantially affect human health or the environment in a manner that ensures such programs, policies, and activities do not have the effect of (1) excluding persons (including populations) from participation in, or (2) denying persons (including populations) the benefits of, or (3) subjecting persons (including populations) to discrimination under such programs, policies, and activities because of their race, color, or national origin.

To meet the objectives of E.O. 12898, the EPA examined whether the change in benefits from the regulatory options may be differentially distributed among population subgroups in the affected areas. The EPA considered the following factors in this analysis: population characteristics, proximity to affected waters, exposure pathways, cumulative risk exposure, and susceptibility to environmental risk. For example, subsistence fishers rely on self-caught fish for a larger share of their food intake than do recreational fishermen, and as such may incur a larger share of effects arising from the regulatory options.

As described in the following sections, the EPA conducted two types of analyses to evaluate the EJ implications of the regulatory options: (1) summarizing the demographic characteristics of the households living in proximity to steam electric power plant discharges; (2) analyzing the distribution of human health impacts among minority and/or low-income populations from changes in exposure to pollutants via the consumption of self-caught fish and drinking water. The first analysis provides insight on the distribution of regulatory options effects (*e.g.*, changes in air emissions and effects of water quality changes) on communities in close proximity to steam electric power plants. The second analysis seeks to provide more specific insight on the distribution of changes in adverse health effects and benefits and to assess whether minority and/or low-income populations incur disproportionally high environmental impacts and/or are disproportionally excluded from realizing the benefits of this regulatory options.

The following two sections describe (1) a comparison of the socio-economic characteristics of the populations that live in proximity to steam electric power plants to state and national averages, and (2) the evaluation of human health effects and benefits that accrue to populations in different socio-economic cohorts.

14.1 Socio-economic Characteristics of Populations Residing in Proximity to Steam Electric Power Plants

For the first analysis, the EPA assessed the demographic characteristics of the populations within specified distances of steam electric power plants. The analysis is analogous to the profile the EPA developed to support the 2015 rule (U.S. EPA, 2015a).

The EPA collected population-specific the U.S. Census Bureau's ACS data on:

- the percent of the population below the poverty threshold,[78] and
- the population categorized in various racial/ethnic groups, from which EPA calculated the percent of the total population that belongs to a minority racial/ethnic group.[79]

The EPA compiled these data for CBGs located within specified distances (*e.g.*, one mile, three miles, 15 miles, 30 miles, and 50 miles) of steam electric power plants. The EPA compared demographic metrics to state and national averages to identify communities where EJ concerns may exist. EJ concerns may exist in areas where the percent of the population living below the poverty threshold or that is minority is higher than the respective state or national averages.

This first analysis considers the spatial distribution of low-income and minority groups to determine whether these groups are more or less represented in the populations in proximity to steam electric power plants that discharge bottom ash transport water or FGD wastewater. The specified distance buffers from the reaches are denoted below as the "benefit region." Populations within the regions included in the analysis may be affected by steam electric power plant discharges and other environmental impacts in the baseline and would be affected by environmental changes resulting from the regulatory options, whether those changes are beneficial or detrimental. If the population within a given region has a larger proportion of minority or low-income families than the state average, it may indicate that the regulatory options may affect communities that have been historically exposed to a disproportionate share of environmental impacts and the proposal may thus contribute to redressing or exacerbating existing EJ concerns, depending on the direction of the changes.

The EPA used the U.S. Census Bureau's ACS data for 2012 to 2016 to identify poverty and minority status at the state and CBG levels. The EPA overlaid the data with GIS data of buffer zones of specified distances from steam electric power plants to characterize the communities living in proximity to the affected reaches. Table 14-1 summarizes the socio-economic characteristics of the regions defined using radial distances of one, three, 10, 15, 30 and 50 miles from the steam electric power plants.

[78] 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.

[79] 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. Minority groups include: African American (non-Hispanic); Asian (non-Hispanic); Native Hawaiian/Pacific Islander (non-Hispanic); American Indian/Alaska Native (non-Hispanic); Other non-Hispanic; Hispanic/Latino.

Table 14-1: Socio-economic Characteristics of Communities Living in Proximity to Steam Electric Power Plants, Compared to National Average

Distance from receiving reach	Total population (millions)	Percent minority	Percent below poverty level	Demographic Index[a]
1 mile	0.49	16.7%	12.9%	14.8%
3 miles	1.56	19.9%	14.0%	17.0%
15 miles	18.49	31.2%	14.9%	23.1%
30 miles	56.56	33.0%	14.4%	23.7%
50 miles	107.84	33.2%	14.6%	23.9%
United States	**318.6**	**26.7%**	**15.1%**	**20.9%**

a. The demographic index is an average of the two demographic indicators explicitly named in EO 12898: low-income and minority.

b. Communities are based on Census Block Groups within the specified distance of one or more steam electric power plants.

Source: U.S. EPA analysis, 2019

As shown in Table 14-1 approximately 490,000 people live within one mile of steam electric power plants currently discharging bottom ash transport water or FGD wastewater to surface waters, over 1.5 million live within three miles, and nearly 56.6 million people live within 30 miles. The statistics also show that a greater fraction of the communities living between 15 to 50 miles from steam electric power plants is minority, when compared to the national average. Approximately 31 to 33 percent of households in communities within 15 to 50 miles from steam electric power plants belong to minority racial or ethnic groups as compared to a national average of 27 percent. Communities between one to three miles from steam electric power plants have a smaller fraction of their population belonging to minority groups compared to the national average. A smaller fraction of the population within all analyzed radial distances from the plants have income below the poverty level compared to the national average (15 percent), but the difference is generally small. As one moves farther away from the steam electric power plants, the fraction of the community that is below the poverty threshold fluctuates below the national average while the percent minority increases, so that the overall demographic index approaches and then exceeds that of the U.S. population overall.

The simple comparison to the national average may not account for important differences, however, between states, particularly given the non-uniform geographical distribution of steam electric power plants across the country. The EPA therefore also compared the demographic profile of affected communities within the state where plants are located. Table 14-2 summarizes the results of this comparison. For this analysis, the demographic profile of each affected community (defined at the CBG level) located within a given distance of a steam electric power plant is compared to the average profile within the relevant state. Although the results in Table 14-1 show that poverty and some minority percentages within the various radial distances from steam electric facilities are below the national average, the comparison to state averages show affected communities within the various distance buffers with greater poverty or minority percentages than the state average. This pattern derives, in part, from variances of state average poverty and minority levels from national levels. For example, of the 346 communities within one mile of steam electric power plants, 120 (35 percent) have a higher percentage of households living below the poverty threshold than their state average, 62 (18 percent) have a higher percent of the population that is minority, and 38 (11 percent) have a higher proportion of households that are both living below the poverty level *and* minority. Details of this analysis are included in the docket for this proposed rule (DCN SE07640). These results highlight the potential for localized differences indicative of potential EJ concern, but the overall comparison shows no indication that any communities with EJ concern would be precluded from the benefits of the regulatory options, or conversely, would be disproportionally affected by the resulting environmental changes.

Table 14-2: Socio-economic Characteristics of Affected Communities, Compared to State Average

Distance from plant	Number of Affected Communities[a]	Number of Communities that…		
		are Poorer	have a Higher Proportion of Minority Population	are Poorer and have a Higher Proportion of Minority Population
		… than the State Average		
1 mile	346	120	62	38
3 miles	1,105	432	266	172
15 miles	13,032	5,604	5,001	3,345
30 miles	38,811	15,584	14,872	9,277
50 miles	73,628	29,896	27,975	17,585

a. "Affected communities" are Census Block Groups within the specified distance of one or more steam electric power plants.

Source: U.S. EPA analysis, 2019

14.2 Distribution of Human Health Impacts and Benefits

The second type of analysis looks at the distribution of environmental effects and benefits to further inform understanding of the potential EJ concerns and the extent to which the regulatory options may mitigate or exacerbate them.

A significant share of the benefits of the regulatory options comes from the small estimated changes in the discharges of harmful pollutants to surface waters and associated changes in fish tissue contamination and drinking water quality. The sections below discuss the distribution of health effects for these two pathways. This analysis allows the Agency to report the distribution of benefits or forgone benefits across population subgroups, including subgroups who may have been historically exposed to a disproportionate share of environmental impacts.

The EPA did not analyze the potential EJ concerns associated with changes in air emissions since the approach used to estimate air-related benefits from changes in EGU emissions does not provide explicit airsheds to overlay with population data, nor does it break out effects for sensitive subgroups. See *Chapter 8* for details.

14.2.1 Socio-economic Characteristics of Populations Impacted by Changes in Exposure to Pollutants via Drinking Water Pathway

The EPA quantified the human health benefits resulting from the small estimated changes in exposure to TTHM in drinking water in individuals served by PWS either directly or indirectly affected by steam electric power plants' bromide discharges. The analysis relied on county-level and tribal area data to estimate the number and characteristics of individuals exposed to steam electric pollutants through the consumption of drinking water, and race and ethnicity-specific assumptions to estimate exposure. The EPA did not quantify or monetize health effects associated with exposure to other pollutants in drinking water (see *Chapter 2* for a qualitative discussion).

This section presents estimates for populations affected by changes in exposure to TTHM associated with bromide in drinking water in two types of geographic areas: tribal areas and counties. *Chapter 4* discusses the approach used to identify the affected population, estimate exposure levels, quantify health effects, and monetize benefits.

Table 14-3 summarizes the estimated affected population exposed to TTHM through consumption of drinking water in the general population and in population subgroups that may be indicative of EJ concerns. The analysis is conducted at the county level and compares the demographic profile of the affected counties to that of the state where they are located. Over 43 million people, across more than 300 counties and 29 states, would be affected by changes resulting from the regulatory options. Of the 29 states affected, the majority of states (24) have affected counties that are poorer than the state average, 23 have affected counties that have a higher proportion of minority population, and 21 have affected counties that are both poorer and have a higher proportion of minority population. Details of this analysis are included in the docket for this proposed rule (DCN SE07640).

Table 14-3: Socio-economic Characteristics of Affected Counties, Compared to State Average

Number of Affected Counties	Total Affected Population (millions)	Number of Affected States	Number of States where Affected Counties…		
			are Poorer	have a Higher Proportion of Minority Population	are Poorer and have a Higher Proportion of Minority Population
			… than the State Average		
303	43.92	29	24	23	21

Source: U.S. EPA analysis, 2019

Table 14-4 summarizes the estimated tribal area population and population subgroups indicative of EJ concerns that are potentially exposed to trihalomethanes in drinking water as a result of steam electric power plant discharges. The analysis is conducted at the tribal area level and compares the demographic profile of the affected tribal areas to that of the state where they are located. Based on the population affected by stream electric plant discharges, an average of 40 percent of tribal area population is expected to be affected by the regulatory options (see Table 14-4).

Affected tribal areas consistently have a higher minority population than the state average; half of the tribal areas have minority population percentages greater than 90 percent. Nearly all of the affected tribal areas have a higher low-income population than the state average. The Otoe-Missouria Oklahoma Tribal Statistical Area (OTSA) has a *lower* low-income population percentage (12.6 percent) compared to the state average (16.5 percent). This difference, however, is not significant enough to influence the demographic index for the Otoe-Missouria OTSA. Therefore, all affected tribal areas have higher demographic indices compared to the state average.

Table 14-4: Socio-economic Characteristics of Affected Tribal Areas, Compared to State Average

Affected Tribal Areas	States	Population			Percent Minority		Percent Below Poverty Level		Demographic Index	
		Affected Population[a]	Total Population of Tribal Area	Affected Tribal Area Population Percentage	Tribal Area	State	Tribal Area	State	Tribal Area	State
Crow Creek Reservation	SD	1,357	2,190	62.0%	92.8%	17.1%	38.4%	13.9%	65.6%	15.5%
Fort Berthold Reservation	ND	5,846	7,435	79.0%	74.8%	13.6%	22.5%	11.0%	48.6%	12.3%
Lake Traverse Reservation	ND; SD	230	11,269	2.0%	47.2%	15.5%	21.3%	12.6%	34.2%	14.0%
Lower Brule Reservation	SD	2,116[b]	1,531	80.0%[c]	94.3%	17.1%	43.4%	13.9%	68.8%	15.5%
Navajo Nation	AZ; NM; UT	1,198	174,692	0.7%	98.2%	41.1%	41.4%	16.1%	69.8%	28.6%
Otoe-Missouria OTSA	OK	250	921	27.1%	51.0%	33.1%	12.6%	16.5%	31.8%	24.8%
Pine Ridge Reservation	NE; SD	8[b]	19,698	0.0%[d]	90.0%	18.9%	50.8%	12.6%	70.4%	15.7%
Rosebud Indian Reservation	SD	9[b]	11,324	0.1%	91.8%	17.1%	49.6%	13.9%	70.7%	15.5%
Standing Rock Reservation	ND; SD	6,839	8,612	79.4%	78.9%	15.5%	42.2%	12.6%	60.5%	14.0%
Yankton Reservation	SD	1,064	6,700	15.9%	50.3%	17.1%	27.6%	13.9%	39.0%	15.5%

a. Affected population is defined as the population served as reported in the EPA SDWIS database for PWS affected by steam electric power plant discharges associated with each tribal area.

b. PWS ID 84690026 serves several reservations and counties. Therefore, SDWIS reported population served was equally distributed over the three reservations served: Lower Brule Reservation, Pine Ridge Reservation, and Rosebud Indian Reservation.

c. PWS ID 84690441 serves the Lower Brule Reservation and surrounding South Dakota counties. As a result, the SDWIS reported population served exceeds the Census reported total population of the reservation. The affected percentage of tribal area was adjusted to 80 percent to reflect that the majority of the reservation is likely served by the affected PWS.

d. Value less than 0.1% but greater than 0.0%.

Source: U.S. EPA analysis, 2019

14.2.2 Socio-economic Characteristics of Populations Impacted by Changes in Exposure to Pollutants via Fish Ingestion Pathway

The EPA quantified the human health effects resulting from the small estimated changes in exposure to pollutants in fish tissue in individuals who consume fish caught in reaches immediately receiving or downstream from steam electric power plant discharges. The analysis relied on CBG-level data to estimate the number and characteristics of individuals exposed to steam electric pollutants through the consumption of self-caught fish, and race and ethnicity-specific data to estimate exposure.

This section presents results for the two types of anglers analyzed: recreational anglers and subsistence fishers. *Chapter 5* provides more details on the approach used to identify the affected population, estimate exposure, quantify health effects, and monetize benefits.

The EPA limited its analysis of the distribution of health effects and potential benefits to two pollutants (lead and mercury) since the regulatory options did not generate any changes in arsenic-related health effects. Further, for recreational anglers, the EPA focused on health effects in infants and children.

Table 14-5 summarizes the estimated number of individuals exposed to steam electric pollutants through consumption of self-caught fish in the general population and in population subgroups that may be indicative of EJ concerns. The population values included in Table 14-5 are based on the population potentially exposed to lead, which is larger than the population potentially exposed to mercury. As shown in the table, of the approximately 1.5 million people potentially exposed to steam electric pollutants through fish tissue consumption, 13.9 percent live below the poverty level, 63.5 percent are minority, and 11.5 percent both live below the poverty level and are minority. Overall, 68.5 percent of potentially exposed individuals are categorized in at least one or more EJ subgroup based on their poverty level or race/ethnicity, while 31.5 percent are neither minority nor live below the poverty level.

Table 14-5: Characteristics of Population Potentially Exposed to Lead from Steam Electric Power Plants via Consumption of Self-caught Fish

Subgroup	Minority		Non-Minority		Total	
Below Poverty Level	175,198	11.5%	77,077	5.1%	252,275	13.9%
Above Poverty Level	790,136	51.9%	478,694	31.5%	1,268,829	86.1%
Total	965,334	63.5%	555,770	36.5%	1,521,104	100.0%

Source: U.S. EPA Analysis, 2019

The distribution of adverse health effects is a function of the characteristics of the affected population (Table 14-5), including age and sex,[80] ethnicity-specific exposure factors,[81] and reach water quality. Table 14-6 shows the distribution of selected adverse health effects in the baseline. Table 14-7 shows the distribution of changes in adverse health effects under each of the four regulatory options. Note that monetary values follow the same distribution as changes in adverse health effects since each case is valued equally, irrespective of the socio-economic subgroup.

The two tables show results for three selected subgroups:

- Below the poverty level and minority (PAM) (11.5 percent of the exposed population),
- Below the poverty level or minority (POM) (*i.e.*, but not both; 57.0 percent of the exposed population), and
- All others (*i.e.*, above the poverty level and white; 31.5 percent of the exposed population).

The first two subgroups are the primary interest of this analysis as potentially indicative of EJ concerns.

The distribution health effects under baseline and regulatory options can be compared to the relative share of the population exposed to steam electric pollutants (from Table 14-5) to assess the degree to which the regulatory options contribute to mitigating or increasing any EJ concerns that may be present in the baseline.

Table 14-6 and Table 14-7 both summarize the percent of estimated changes that are incurred by the specific population subgroups (in the table body) and contrast this distribution to the share of the affected population represented by each subgroup (in the column headings).

Table 14-6: Estimated Distribution of Baseline IQ Point Decrements by Pollutant (2021 to 2047)

Pollutant	Below the poverty level and Minority (PAM) (11.5% of Population)		Below the poverty level or Minority (POM) (57.0% of Population)		All Others (31.5% of Population)		Total	
Lead	2,791,727	11.6%	13,784,647	57.1%	7,567,405	31.3%	24,143,779	100%
Mercury	88,042	12.7%	442,798	63.8%	162,782	23.5%	693,622	100%

Source: U.S. EPA Analysis, 2019

80 Some adverse health effects are analyzed only for individuals in certain age groups. For example, IQ point decrements from exposure to lead are calculated for children 0 to 7 years old and the baseline exposure therefore depends on the number of children within this age group in the affected population in each socio-economic subgroup. IQ point decrements from exposure to mercury are calculated for infants born within the analysis period and baseline exposure depends on the number of women of childbearing age (and fertility rates) in the affected population.

81 Ethnicity-specific factors that determine exposure to pollutants in fish tissue include the assumed fish consumption rates and average fertility rate. For example, Asian/Pacific Islander anglers have daily consumption rates that are 1.4 times and 1.9 times those of While (non-Hispanic) anglers for recreational and subsistence fishing modes, respectively.

Table 14-7: Distribution of Changes in IQ Point Relative to the Baseline, by Pollutant (2021 to 2047)

Pollutant and Population	Regulatory Option	Below the poverty level and Minority (PAM) (11.5% of Population)				Below the poverty level or Minority (POM) (57.0% of Population)				All Others (31.5% of Population)				Total			
		Positive IQ Change (percent of exposed population)		Negative IQ Change (percent of exposed population)		Positive IQ Change (percent of exposed population)		Negative IQ Change (percent of exposed population)		Positive IQ Change (percent of exposed population)		Negative IQ Change (percent of exposed population)		Positive IQ Change (percent of exposed population)		Negative IQ Change (percent of exposed population)	
Children Exposed to Lead[a]	Option 1	0.06	0.03%	-0.38	4.87%	0.24	0.10%	-1.87	29.9%	--	--	-1.63	31.3%	0.30	0.13%	-3.89	66.1%
	Option 2	0.33	0.04%	-0.44	4.86%	1.50	0.20%	-3.16	29.8%	--	--	-9.30	31.3%	1.83	0.25%	-12.90	66.0%
	Option 3	0.52	0.04%	-0.37	4.86%	2.41	0.20%	-1.66	29.8%	--	--	-0.54	31.3%	2.92	0.25%	-2.57	66.0%
	Option 4	0.54	0.04%	-0.33	4.86%	2.54	0.20%	-1.43	29.8%	--	--	-0.42	31.3%	3.08	0.25%	-2.18	66.0%
Infants Exposed to Mercury[a]	Option 1	--	--	-54	12.7%	--	--	-264	63.8%	--	--	-93	23.5%	--	--	-411	100%
	Option 2	--	--	-497	12.7%	--	--	-2,489	63.8%	--	--	-799	23.5%	--	--	-3,785	100%
	Option 3	--	--	-503	12.7%	--	--	-2,483	63.8%	--	--	-791	23.5%	--	--	-3,777	100%
	Option 4	--	--	-274	12.7%	--	--	-1,320	63.8%	--	--	-427	23.5%	--	--	-2,021	100%

a. Negative values represent forgone benefits and positive values represent realized benefits.

Source: U.S. EPA Analysis, 2019

As shown in Table 14-6, the PAM subgroup represents 11.5 percent of the potentially affected population, but accounts for 11.6 percent and 12.7 percent of the baseline estimated IQ point changes from lead and mercury exposure, respectively, in the exposed population. As shown in Table 14-8, a smaller percentage of children (4.9 percent of the exposed population) in the PAM subgroup experiences forgone benefits from an increase in exposure to lead than its share in the affected population (11.5 percent), while an even smaller percentage of children (less than 0.1 percent) experience realized benefits. However, a larger share of children (12.7 percent) in this subgroup experience forgone benefits from an increase in mercury exposure.

The POM group represents 57.0 percent of the potentially affected population, but accounts for 57.1 percent and 63.8 percent of the baseline estimated IQ point decrements from lead and mercury exposure, respectively, in the exposed population. Similar to the PAM subgroup, the POM subgroup experiences a smaller share of children lead exposure forgone benefits (29.8-29.9 percent, depending on the option) than its population but a larger share of mercury exposure forgone benefits (63.8 percent).

In the analysis of health benefits for the fish ingestion pathway (see *Chapter 5*), the EPA assumed that 5 percent of the exposed population are subsistence fishers, and that the remaining 95 percent are recreational anglers. This is based on the assumed 95th percentile fish consumption rate for subsistence fishers. Subsistence fishers consume more self-caught fish than recreational anglers and can therefore be expected to experience higher health risks associated with steam electric pollutants in fish tissue.

The results of the human health analysis suggest that subsistence fishers may be disproportionally exposed to pollutants in steam electric power plant discharges via fish consumption and may disproportionally incur adverse health effects from this exposure. As shown in Table 14-8, subsistence fishers incur 7 percent to 17 percent of the baseline IQ decrements, even though they represent only 5 percent of the overall population. As shown in ***Error! Reference source not found.***, 6 percent to 17 percent of the total exposed population are subsistence fishers who experience health changes and forgone benefits of the regulatory options.

Table 14-8: Estimated Distribution of Baseline IQ Point Decrements by Pollutant and Fishing Mode (2021 to 2047)

Pollutant and Exposed Population	Subsistence Fishers (5 percent of population)		Recreational Fishers (95 percent of population)		Total	
Children Exposed to Lead	1,605,246	6.6%	22,538,533	93.4%	24,143,779	100%
Infants Exposed to Mercury	119,747	17.3%	573,875	82.7%	693,622	100%

Source: U.S. EPA Analysis, 2019

Table 14-9: Estimated Distribution of Changes in IQ Point Decrements Relative to the Baseline by Fishing Mode, and Pollutant (2021 to 2047)

Pollutant and Exposed Population	Regulatory Option	Subsistence Fishers (5 percent of population)				Recreational Fishers (95 percent of population)				Total			
		Positive IQ Change (percent of exposed population)		Negative IQ Change (percent of exposed population)		Positive IQ Change (percent of exposed population)		Negative IQ Change (percent of exposed population)		Positive IQ Change (percent of exposed population)		Negative IQ Change (percent of exposed population)	
Children Exposed to Lead[a]	Option 1	0.30	0.13%	-2.68	6.52%	--	--	-1.21	59.6%	0.30	0.13%	-3.89	66.1%
	Option 2	1.83	0.25%	-11.7	6.40%	--	--	-1.21	59.6%	1.83	0.25%	-12.9	66.0%
	Option 3	2.92	0.25%	-1.36	6.40%	--	--	-1.21	59.6%	2.92	0.25%	-2.57	66.0%
	Option 4	3.08	0.25%	-0.97	6.40%	--	--	-1.21	59.6%	3.08	0.25%	-2.18	66.0%
Infants Exposed to Mercury[a]	Option 1	--	--	-71	17.3%	--	--	-340	82.7%	--	--	-411	100%
	Option 2	--	--	-652	17.3%	--	--	-3,134	82.7%	--	--	-3,785	100%
	Option 3	--	--	-650	17.3%	--	--	-3,127	82.7%	--	--	-3,777	100%
	Option 4	--	--	-347	17.3%	--	--	-1,673	82.7%	--	--	-2,021	100%

a. Negative values represent forgone benefits and positive values represent realized benefits.

Source: U.S. EPA Analysis, 2019

14.3 EJ Analysis Findings

Based on the EJ analyses discussed above, the EPA determined that the regulatory options would not exclude communities from the benefits of environmental improvements expected to result from the 2015 rule requirements, but the regulatory options may disproportionally affect communities in cases where the small changes in water quality increase pollutant exposure compared to the baseline.

Communities in close proximity to a steam electric power plant (between one and fifteen miles) tend to be less poor (*i.e.*, fewer people living below the poverty level) and minority than the national average. However, when compared to *state* averages, as shown in Table 14-2, a greater share of affected communities are poorer and/or are more minority than the state average. The communities in close proximity to steam electric power plants may be more likely to be affected by changes in pollutant discharges from these plants.

The majority of county populations potentially exposed to TTHM in drinking water as a result of steam electric power plant discharges are poorer and more minority than the state average. In addition, all affected tribal areas have lower demographic indices compared to the state average. Options 2, 3 and 4 would benefit the EJ communities served by affected PWS by reducing exposure to TTHM via drinking water. Conversely, an increase in exposure to TTHM has the potential to harm the same communities of concern under Option 1.

Recreational anglers and members of their household, including children, are estimated to experience small forgone benefits from an increase in pollutant concentrations in fish tissue compared to baseline. A large portion of forgone benefits to children (IQ decrements) from increased mercury exposure are estimated to occur within the PAM group and POM group. Increased lead exposure, however, is estimated to impact a smaller proportion of the PAM and POM. Close to 50 percent of greater IQ decrements are expected to occur within the non-minority, above the poverty level population.

Because communities at the census block, county, and tribal area levels are poorer and more minority than state averages, the regulatory options could benefit or harm populations with EJ concerns depending on the direction of changes in pollutant loadings for the regulatory options and the resulting change in potential exposure.

14.4 Limitations and Uncertainties

This EJ analysis inherits the limitations and uncertainties of the human health effects analysis (see *Chapter 4*, *Chapter 5*, and *Chapter 8*) regarding pollutant exposure, incidence of adverse health outcomes, and valuation. In addition, the EJ analysis embeds uncertainty derived from the application of uniform assumptions across the estimated population exposed to pollutant discharges when factors may instead vary across socioeconomic characteristics (see Table 14-10 for detail). In summary, use of average values across the entire population of the United States (or within a state or SDWIS-identified population served) instead of assumptions that reflect specific socioeconomic factors may over- or understate inequities present in the baseline and the differential impacts or benefits to populations living below the poverty level or minority populations from changes due to the regulatory options.

Table 14-10: Limitations and Uncertainties in EJ Analysis

Uncertainty/Assumption	Effect on EJ Analysis	Notes
The EPA does not have data to delineate airsheds affected by changes in air quality resulting from IPM-projected changes in emissions from EGUs, limiting EPA's ability to analyze the distribution of forgone benefits from increased air emissions.	Underestimate	Some population subgroups may be more susceptible to changes in air quality. While EPA estimated changes in the amount of air pollutants emitted by EGUs, EPA did not model the associated changes in the distribution of air pollutant levels to which populations may be exposed. The EJ analysis therefore does not account for EJ concerns that may arise from this exposure pathway.
The EPA assumed that all fishers travel up to 50 miles	Uncertain	Some anglers stay closer to home and certain EJ or sensitive subpopulations may tend to stay closer to home (*e.g.*, people living below the poverty level and subsistence fishers). To the extent that these people fish predominantly from waters receiving discharges from steam electric power plants, they may be exposed to relatively higher concentrations of pollutants. Conversely, people who live farther from steam electric power plants may predominantly fish from waters not affected by pollutants in steam electric power plant discharges and be exposed to relatively lower concentrations of pollutants.
The EPA assumed that subsistence fishers are 5 percent of all anglers, with this assumption applied uniformly across all socioeconomic groups.	Underestimate	A relatively higher share of EJ groups may be subsistence fishers. This would tend to increase the inequities already in the baseline and affect the extent to which the regulatory options may address or further these inequities.
The EPA applied uniform fishing participation rates, FCAs, and catch and release practices across the entire population.	Uncertain	Differences in behavior across socioeconomic groups may result in different distribution of baseline and regulatory option impacts.
The EPA assumed that the counties served by PWS, as reported in the SDWIS database, are representative of the population affected by changes in TTHM levels due to steam electric power plant discharges.	Uncertain	Counties and tribal areas can be served by multiple PWS and some PWS serve people across multiple counties, such that the affected population may have different socioeconomic characteristics.
The EPA used the SDWIS database to identify counties served by affected PWS. For any PWS IDs without any associated county information, the EPA used the PWS Name and the PWS latitude and longitude to identify associated tribal areas.	Uncertain	There may be some PWSs that serve counties and tribal areas. However, if only the county was listed in SDWIS, the EJ analysis does not account for the associated tribal area.

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Appendix A Changes to Benefits Methodology since 2015 Rule Analysis

The table below summarizes the principal methodological changes the EPA made to analyses of the benefits of the regulatory options, as compared to the analyses of the 2015 rule. The benefits analysis methodology for the 2015 rule is detailed in the BCA document (U.S. EPA, 2015a).

Table A-1: Changes to Benefits Analysis Since 2015 Final Rule

Benefits Category	Analysis Component [2015 rule analysis value]	Changes to Analysis for regulatory options [2019 rule analysis value]
General assumptions	Dollar year [all costs expressed in 2013 dollars].	Updated dollar year [2018].
	Promulgation year [all costs and revenue streams discounted back to 2015].	Updated promulgation year [2020].
	Period of analysis [2019-2042].	Updated period of analysis [2021-2047].
	Technology implementation years [2019-2023]. Technology implementation years constant across the options for a given plant.	Updated technology implementation years [2021-2028]. Technology implementation years vary between options and plants.
	Baseline is current conditions.	Baseline is 2015 ELG.
General pollutant loadings and concentrations	Affected reaches based on immediate receiving reaches and flow paths in medium-resolution NHD v1.	Updated immediate receiving reaches for selected plants. Affected reaches based on updated receiving reaches and flow paths in medium-resolution NHD v2.
	Risk-Screening Environmental Indicators (RSEI) modeling of toxics concentrations in immediate and downstream reaches, including [2012] TRI non-steam electric power plant releases.	Transport and dilution calculations for immediate and downstream reaches, including [2016] TRI non-steam electric power plant releases.
	Pollutant concentrations based on mean annual flows in NHDPlus v1.	Pollutant concentrations based on mean annual flows in NHDPlus v2.
	SPARROW modeling of nutrient and sediment concentrations in receiving and downstream reaches.	No change.
	Assumes loading changes occur at mid-point of technology implementation period [2021].	Uses the annual average loadings for analysis period [2021-2047], assuming that pre-implementation loads are equal to current loads.
Human health benefits from changes in exposure to trihalomethanes in drinking water		
Public water systems affected by bromide discharges	Qualitative discussion.	See *Section 3.3* for approach to modeling changes in trihalomethane concentrations in drinking water.
Lifetime changes in incidence of bladder cancer	Not addressed.	Lifetime risk model (See *Section 4.3.3* for approach to modeling changes in bladder cancer incidence).
Monetization of changes in incidence of bladder cancer	Not addressed	Mortality valued using VSL (U.S. EPA, 2010a). Morbidity valued based on COI (Greco et al, 2018).

Table A-1: Changes to Benefits Analysis Since 2015 Final Rule

Benefits Category	Analysis Component [2015 rule analysis value]	Changes to Analysis for regulatory options [2019 rule analysis value]
Human health benefits from changes in pollutant exposure in recreationally- and subsistence-caught fish		
Exposed populations	Population based on 2010 Census Data Population for future years is based on Woods & Poole (2012) forecasts for each year from 2000 through 2040.	Population based on the 2016 American Community Survey (U.S. Census Bureau, 2016) Population for future years is based on U.S. Census population projections for the United States: 2017 - 2060.
	Census block-focused analysis with [50 miles] travel distance.	No change
IQ losses in children from lead exposure	Blood lead level – IEUBK.	No change
	IQ losses - linking blood lead level to IQ based on Lanphear et al. (2005).	Linking blood lead level to IQ based on Crump et al. (2013)
	Monetization (value of an IQ point) is based on Salkever (1995) and Schwartz (1994).	Used a modified Salkever (1995) IQ point value (based on more recent data from the 1997 National Longitudinal Survey of Youth) (U.S. EPA, 2019e); removed Schwartz (1994) estimate; added sensitivity analysis using Lin et al. (2018) value.
Cardiovascular disease (CVD) in adults from lead exposure	Blood lead level – Legget model.	EPA did not quantify and monetize this benefit category given the small changes in exposure.
	Linking blood lead level to CVD mortality (Menke et al., 2006).	
	CVD quantification framework – lifetime table approach.	
	Monetization – VSL.	
IQ losses in infants from mercury exposure	IQ losses - linking maternal mercury hair content and subsequent childhood IQ loss from Axelrad et al. (2007).	No change.
	Monetization (value of an IQ point) is based on Salkever (1995) and Schwartz (1994).	Used a modified Salkever (1995) IQ point value (based on more recent data from the 1997 National Longitudinal Survey of Youth) (U.S. EPA, 2019e); removed Schwartz (1994) estimate; added sensitivity analysis using Lin et al. (2018) value.
Avoided cancer cases from arsenic exposure	Main analysis - cancer slope factor (CSF) based on incidences of skin cancer; monetization – cost of illness (COI).	Main analysis: No change to the approach.
	Sensitivity analysis – CSF for lung and bladder cancer; monetization - VSL.	Sensitivity analysis: Did not perform since the estimated change in pollutant load is small and the estimated change in cancer cases is essentially zero.
Non-market benefits from water quality improvements		
Willingness-to-pay for water quality improvements	8-parameter water quality index toxics subindex (arsenic, chromium, lead, manganese, mercury, nickel, selenium, and zinc.	9-parameter water quality index toxics subindex (arsenic, chromium, copper, lead, manganese, mercury, nickel, selenium, and zinc).
	Length weighted average ΔWQI for reaches within [100 miles] of census blocks.	No change.

Table A-1: Changes to Benefits Analysis Since 2015 Final Rule

Benefits Category	Analysis Component [2015 rule analysis value]	Changes to Analysis for regulatory options [2019 rule analysis value]
	Affected population consists of all households in a given Census Block Group (CBG). Households value all water quality changes in a 100-mile radius.	No change to the approach. Updated: • Population - 2016 American Community Survey (U.S. Census Bureau, 2016) • Population growth - U.S. Census population projections for the United States: 2017 – 2060 • Universe of the CBGs included in the analysis to reflect changes in the universe of affected reaches and changes in CBGs delineation between 2010 and 2016.
	Meta-regression model includes spatial characteristics of the affected water resources: size of the market, waterbody characteristics (length and flow), availability of substitute sites, land use type in the abutting counties.	Variables characterizing the availability of substitute site, size of the market, and land-use were revised based on changes in the universe of receiving reaches and CBGs included in the analysis.
Effects on endangered and threatened (T&E) species	Categorical analysis based on habitat overlap/proximity.	No change based on updated review of habitat overlap.
	Monetization based on meta-analysis of willingness-to-pay to protect T&E species (Richardson and Loomis 2009).	Qualitative discussion based on magnitude of impacts.
Effects on groundwater quality	Discussed qualitatively.	Not included in the analysis due to promulgation of the CCR rule.
	Air-related effects	
Emissions changes	Emissions from changes in electricity generation profile from 2015 IPM runs.	Emissions from changes in electricity generation profile from 2018 IPM runs. Transportation- and energy use-associated emissions were updated to reflect new technology basis for the options. Updates were made to reflect new universe of facilities and technology impacts.
Monetization	National average benefit-per-ton estimates for SO_2 and NO_X from Fann and Fulcher (2012), single estimate.	Qualitative discussion.
	Global social cost of carbon (SCC) value from Interagency Working Group on Social Cost of Carbon (IWGSCC 2013 a,b; 2015).	Domestic social cost of carbon (SC-CO_2) value (see *Appendix I*).
	Economic productivity	
Impoundment releases	Reduced risk of impoundment releases due to changes in the use of impoundment.	Not included in the analysis due to promulgation of the CCR rule.
	Avoided cost of clean-up, natural resource damages and transaction costs.	

Table A-1: Changes to Benefits Analysis Since 2015 Final Rule

Benefits Category	Analysis Component [2015 rule analysis value]	Changes to Analysis for regulatory options [2019 rule analysis value]
Changes in dredging costs	Use SPARROW for estimating sediment deposition.	No Change.
	Navigational dredging locations from USACE database (2013).	
	Reservoir locations from E2RF1 network (SPARROW).	
	Cost of dredging based on USACE data (2013).	
Beneficial use of ash	Reduced disposal costs and avoided life-cycle impacts from displaced virgin material.	Qualitative discussion due to *de minimis* changes in marketable ash tonnage.
Changes in groundwater withdrawals	Increased availability of groundwater resources.	No change (beyond updates to changes in withdrawals).
	Avoided cost of drinking water purchase.	
Tourism, commercial fisheries, property values, surface water withdrawals.	Qualitative discussion.	No change.

Appendix B WQI Calculation and Regional Subindices

B.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 option. Some parameter levels are field measurements while others are modeled values.

The second step involves transforming the parameter measurements into subindex values that express water quality conditions on a common scale of 0 to 100. The 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, the 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 the 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 Level III ecoregion (U.S. EPA, 2009a) using pre-compliance (before the implementation of the 2015 rule) TSS, TN, and TP concentrations calculated in SPARROW at the E2RF1 reach level.[82,83,84] For each of the 85 Level III ecoregions intersected by the E2RF1 reach network, the EPA derived the transformation curves by assigning a score of 100 to the 25th percentile of the reach-level TSS concentrations in the ecoregion (*i.e.*, using the 25th 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, the 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. To develop this subindex curve, the 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, the EPA's toxics subindex considers the number of parameters with exceedances of the relevant water quality criterion. With regards to frequency, the 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

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82 The SPARROW model was developed by the USGS for the regional interpretation of water-quality monitoring data. The model relates in-stream water-quality measurements to spatially referenced characteristics of watersheds, including contaminant sources and factors influencing terrestrial and aquatic transport. SPARROW empirically estimates the origin and fate of contaminants in river networks and quantifies uncertainties in model predictions. More information on SPARROW can be found at http://water.usgs.gov/nawqa/sparrow/FAQs/faq.html#1

83 The EPA's E2RF1 is a digital stream networks used in SPARROW models. This dataset extends over the continental United States and includes approximately 62,000 stream reaches.

84 Following the approach the EPA used for the analysis of the Construction and Development Effluent Guidelines and Standards (40 CFR Part 450) final rule in 2009 (74 FR 62995), the selected data exclude outlier TSS concentrations, defined as values that exceed the 95th percentile based on the universe of all E2RF1 reaches modeled in SPARROW (U.S. EPA, 2009a). In the Construction and Development ELG analysis, the USGS and the EPA had determined that these outlier values corresponded to headwater reaches and were an artifact of the model rather than expected concentrations.

the time (assumed to be 100 percent of the time). The 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 B-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 B-2 presents the subindex values for toxics. The equation parameters for each of the 85 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 subbindex score.

Table B-1: Freshwater Water Quality Subindices

Parameter	Concentrations	Concentration Unit	Subindex
Dissolved Oxygen (DO)			
DO saturation ≤100%			
DO	$DO \le 3.3$	mg/L	10
DO	$3.3 < DO < 10.5$	mg/L	$-80.29+31.88 \times DO-1.401 \times DO^2$
DO	$DO \ge 10.5$	mg/L	100
100% < DO saturation ≤ 275%			
DO	NA	mg/L	$100 \times \exp((DOsat - 100) \times -1.197 \times 10^{-2})$
275% < DO saturation			
DO	NA	mg/L	10
Fecal Coliform (FC)			
FC	$FC > 1{,}600$	cfu/100 mL	10
FC	$50 < FC \le 1{,}600$	cfu/100 mL	$98 \times \exp((FC - 50) \times -9.9178 \times 10^{-4})$
FC	$FC \le 50$	cfu/100 mL	98
Total Nitrogen (TN)[a]			
TN	$TN > TN_{10}$	mg/L	10
TN	$TN_{100} < TN \le TN_{10}$	mg/L	a × exp(TN×b); where a and b are ecoregion-specific values
TN	$TN \le TN_{100}$	mg/L	100
Total Phosphorus (TP)[b]			
TP	$TP > TP_{10}$	mg/L	10
TP	$TP_{100} < TP \le TP_{10}$	mg/L	a × exp(TP×b); where a and b are ecoregion-specific values
TP	$TP \le TP_{100}$	mg/L	100
Total Suspended Solids (TSS)[c]			
TSS	$TSS > TSS_{10}$	mg/L	10
TSS	$TSS_{100} < TSS \le TSS_{10}$	mg/L	a × exp(TSS×b); where a and b are ecoregion-specific values
TSS	$TSS \le TSS_{100}$	mg/L	100

Table B-1: Freshwater Water Quality Subindices

Parameter	Concentrations	Concentration Unit	Subindex
Biochemical Oxygen Demand, 5-day (BOD)			
BOD	BOD > 8	mg/L	10
BOD	BOD ≤ 8	mg/L	100 × exp(BOD × -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 TSS 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 using methodology in Cude (2001).

Table B-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. The 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 ($1/7^{th}$ 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 B-1 presents the EPA's calculation of the overall WQI score.

Equation B-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)

B.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 B-3 for TSS, Table B-4 for TN, and Table B-5 for TP.

Table B-3: TSS Subindex Curve Parameters, by Ecoregion

ID	Ecoregion Name	a	b	TSS_{100}	TSS_{10}
10.1.2	Columbia Plateau	126.56	-0.0038	63	668
10.1.3	Northern Basin and Range	112.42	-0.0007	160	3,457
10.1.4	Wyoming Basin	123.36	-0.0010	220	2,513
10.1.5	Central Basin and Range	121.22	-0.0018	109	1,386
10.1.6	Colorado Plateaus	144.44	-0.0010	363	2,670
10.1.7	Arizona/New Mexico Plateau	126.76	-0.0004	668	6,349
10.1.8	Snake River Plain	146.39	-0.0027	142	994
10.2.1	Mojave Basin and Range	119.34	-0.0015	121	1,653
10.2.2	Sonoran Desert	112.39	-0.0002	567	12,097
10.2.4	Chihuahuan Desert	214.39	-0.0005	1,419	6,130
11.1.1	California Coastal Sage, Chaparral, and Oak Woodlands	127.97	-0.0012	205	2,124
11.1.2	Central California Valley	171.86	-0.0044	122	646
11.1.3	Southern and Baja California Pine-Oak Mountains	115.12	-0.0007	197	3,491
12.1.1	Madrean Archipelago	261.35	-0.0005	2,053	6,527
13.1.1	Arizona/New Mexico Mountains	120.98	-0.0004	477	6,233
15.4.1	Southern Florida Coastal Plain	116.95	-0.0405	4	61
5.2.1	Northern Lakes and Forests	157.76	-0.0233	20	118
5.2.2	Northern Minnesota Wetlands	154.99	-0.0186	24	147
5.3.1	Northern Appalachian and Atlantic Maritime Highlands	174.99	-0.0261	21	110
5.3.3	North Central Appalachians	245.15	-0.0176	51	182
6.2.10	Middle Rockies	144.64	-0.0038	98	703
6.2.11	Klamath Mountains	238.90	-0.0068	129	467
6.2.12	Sierra Nevada	185.36	-0.0116	53	252
6.2.13	Wasatch and Uinta Mountains	124.28	-0.0014	160	1,800
6.2.14	Southern Rockies	153.42	-0.0031	140	881
6.2.15	Idaho Batholith	184.23	-0.0142	43	205
6.2.3	Columbia Mountains/Northern Rockies	180.70	-0.0168	35	172
6.2.4	Canadian Rockies	396.62	-0.0308	45	119
6.2.5	North Cascades	240.95	-0.0193	46	165
6.2.7	Cascades	192.94	-0.0181	36	164

Table B-3: TSS Subindex Curve Parameters, by Ecoregion

ID	Ecoregion Name	a	b	TSS_{100}	TSS_{10}
6.2.8	Eastern Cascades Slopes and Foothills	178.82	-0.0145	40	199
6.2.9	Blue Mountains	148.35	-0.0037	107	729
7.1.7	Strait of Georgia/Puget Lowland	181.06	-0.0224	27	129
7.1.8	Coast Range	174.78	-0.0114	49	251
7.1.9	Willamette Valley	210.30	-0.0114	65	267
8.1.1	Eastern Great Lakes and Hudson Lowlands	144.62	-0.0104	36	257
8.1.10	Erie Drift Plain	133.08	-0.0037	78	700
8.1.2	Lake Erie Lowland	112.79	-0.0049	25	494
8.1.3	Northern Appalachian Plateau and Uplands	322.68	-0.0113	103	307
8.1.4	North Central Hardwood Forests	148.68	-0.0108	37	250
8.1.5	Driftless Area	117.97	-0.0012	141	2,057
8.1.6	S. Michigan/N. Indiana Drift Plains	191.44	-0.0143	46	206
8.1.7	Northeastern Coastal Zone	158.48	-0.0164	28	168
8.1.8	Maine/New Brunswick Plains and Hills	156.02	-0.0250	18	110
8.2.1	Southeastern Wisconsin Till Plains	121.34	-0.0042	46	594
8.2.2	Huron/Erie Lake Plains	145.17	-0.0058	65	461
8.2.3	Central Corn Belt Plains	187.95	-0.0033	191	889
8.2.4	Eastern Corn Belt Plains	235.18	-0.0030	282	1,053
8.3.1	Northern Piedmont	175.82	-0.0042	135	683
8.3.2	Interior River Valleys and Hills	149.68	-0.0013	303	2,081
8.3.3	Interior Plateau	220.47	-0.0037	217	836
8.3.4	Piedmont	224.11	-0.0048	169	648
8.3.5	Southeastern Plains	205.30	-0.0085	85	356
8.3.6	Mississippi Valley Loess Plains	492.49	-0.0048	333	812
8.3.7	South Central Plains	184.36	-0.0045	136	648
8.3.8	East Central Texas Plains	162.32	-0.0013	362	2,144
8.4.1	Ridge and Valley	186.83	-0.0063	99	465
8.4.2	Central Appalachians	166.76	-0.0062	82	454
8.4.3	Western Allegheny Plateau	183.67	-0.0032	190	910
8.4.4	Blue Ridge	216.16	-0.0087	89	353
8.4.5	Ozark Highlands	175.16	-0.0018	317	1,591
8.4.6	Boston Mountains	329.77	-0.0062	193	564
8.4.7	Arkansas Valley	283.25	-0.0040	261	836
8.4.8	Ouachita Mountains	212.77	-0.0048	157	637
8.4.9	Southwestern Appalachians	207.09	-0.0071	103	427
8.5.1	Middle Atlantic Coastal Plain	182.17	-0.0178	34	163
8.5.2	Mississippi Alluvial Plain	131.35	-0.0029	93	888
8.5.3	Southern Coastal Plain	138.62	-0.0144	23	183
8.5.4	Atlantic Coastal Pine Barrens	283.76	-0.0463	23	72
9.2.1	Aspen Parkland/Northern Glaciated Plains	136.43	-0.0005	640	5,226
9.2.2	Lake Manitoba and Lake Agassiz Plain	174.13	-0.0042	131	680
9.2.3	Western Corn Belt Plains	135.01	-0.0009	347	2,892
9.2.4	Central Irregular Plains	201.19	-0.0010	673	3,002
9.3.1	Northwestern Glaciated Plains	133.98	-0.0006	483	4,325
9.3.3	Northwestern Great Plains	130.60	-0.0004	636	6,424
9.3.4	Nebraska Sand Hills	289.85	-0.0066	162	510

Table B-3: TSS Subindex Curve Parameters, by Ecoregion

ID	Ecoregion Name	a	b	TSS_{100}	TSS_{10}
9.4.1	High Plains	125.61	-0.0005	507	5,061
9.4.2	Central Great Plains	156.84	-0.0005	925	5,505
9.4.3	Southwestern Tablelands	137.77	-0.0003	1,280	8,743
9.4.4	Flint Hills	270.93	-0.0009	1,084	3,666
9.4.5	Cross Timbers	134.97	-0.0006	523	4,337
9.4.6	Edwards Plateau	173.77	-0.0010	544	2,855
9.4.7	Texas Blackland Prairies	134.23	-0.0005	624	5,194
9.5.1	Western Gulf Coastal Plain	124.47	-0.0025	88	1,009
9.6.1	Southern Texas Plains/Interior Plains and Hills with Xerophytic Shrub and Oak Forest	166.67	-0.0003	1,602	9,378

Table B-4: TN Subindex Curve Parameters, by Ecoregion

ID	Ecoregion Name	a	b	TN_{100}	TN_{10}
10.1.2	Columbia Plateau	116.58	-0.663	0.23	3.70
10.1.3	Northern Basin and Range	126.97	-0.626	0.38	4.06
10.1.4	Wyoming Basin	124.89	-0.445	0.50	5.67
10.1.5	Central Basin and Range	116.66	-0.335	0.46	7.33
10.1.6	Colorado Plateaus	146.41	-0.588	0.65	4.56
10.1.7	Arizona/New Mexico Plateau	116.33	-0.286	0.53	8.58
10.1.8	Snake River Plain	129.93	-0.594	0.44	4.32
10.2.1	Mojave Basin and Range	136.69	-0.593	0.53	4.41
10.2.2	Sonoran Desert	117.99	-0.495	0.33	4.99
10.2.4	Chihuahuan Desert	104.20	-0.450	0.09	5.21
11.1.1	California Coastal Sage, Chaparral, and Oak Woodlands	123.22	-0.889	0.23	2.82
11.1.2	Central California Valley	126.07	-0.548	0.42	4.62
11.1.3	Southern and Baja California Pine-Oak Mountains	122.76	-0.564	0.36	4.45
12.1.1	Madrean Archipelago	130.61	-0.325	0.82	7.91
13.1.1	Arizona/New Mexico Mountains	141.64	-0.541	0.64	4.90
15.4.1	Southern Florida Coastal Plain	1000000	-29.36	0.33	0.39
5.2.1	Northern Lakes and Forests	141.98	-0.985	0.36	2.69
5.2.2	Northern Minnesota Wetlands	142.55	-0.781	0.45	3.40
5.3.1	Northern Appalachian and Atlantic Maritime Highlands	142.60	-0.854	0.42	3.11
5.3.3	North Central Appalachians	180.92	-0.897	0.66	3.23
6.2.10	Middle Rockies	136.51	-0.991	0.31	2.64
6.2.11	Klamath Mountains	140.34	-1.805	0.19	1.46
6.2.12	Sierra Nevada	143.02	-1.424	0.25	1.87
6.2.13	Wasatch and Uinta Mountains	129.75	-0.452	0.58	5.67
6.2.14	Southern Rockies	131.07	-0.660	0.41	3.90
6.2.15	Idaho Batholith	149.42	-1.775	0.23	1.52
6.2.3	Columbia Mountains/Northern Rockies	136.14	-1.599	0.19	1.63
6.2.4	Canadian Rockies	151.95	-2.098	0.20	1.30
6.2.5	North Cascades	155.86	-1.231	0.36	2.23
6.2.7	Cascades	143.07	-1.473	0.24	1.81
6.2.8	Eastern Cascades Slopes and Foothills	123.99	-1.070	0.20	2.35
6.2.9	Blue Mountains	125.19	-0.786	0.29	3.22

Table B-4: TN Subindex Curve Parameters, by Ecoregion

ID	Ecoregion Name	a	b	TN_{100}	TN_{10}
7.1.7	Strait of Georgia/Puget Lowland	121.09	-0.723	0.26	3.45
7.1.8	Coast Range	136.15	-1.021	0.30	2.56
7.1.9	Willamette Valley	135.01	-0.809	0.37	3.22
8.1.1	Eastern Great Lakes and Hudson Lowlands	158.18	-0.563	0.81	4.90
8.1.2	Lake Erie Lowland	156.27	-0.380	1.18	7.23
8.1.3	Northern Appalachian Plateau and Uplands	431.78	-0.435	3.36	8.66
8.1.4	North Central Hardwood Forests	163.4	-0.599	0.82	4.66
8.1.5	Driftless Area	126.18	-0.272	0.85	9.32
8.1.6	S. Michigan/N. Indiana Drift Plains	130.25	-0.149	1.78	17.23
8.1.7	Northeastern Coastal Zone	125.75	-0.159	1.44	15.92
8.1.8	Maine/New Brunswick Plains and Hills	139.55	-0.553	0.60	4.77
8.1.10	Erie Drift Plain	148.99	-1.256	0.32	2.15
8.2.1	Southeastern Wisconsin Till Plains	134.85	-0.160	1.87	16.26
8.2.2	Huron/Erie Lake Plains	119.06	-0.091	1.91	27.22
8.2.3	Central Corn Belt Plains	135.57	-0.087	3.50	29.96
8.2.4	Eastern Corn Belt Plains	149.12	-0.122	3.28	22.15
8.3.1	Northern Piedmont	146.34	-0.314	1.21	8.55
8.3.2	Interior River Valleys and Hills	120.48	-0.131	1.43	19.00
8.3.3	Interior Plateau	146.39	-0.446	0.85	6.02
8.3.4	Piedmont	148.67	-0.637	0.62	4.24
8.3.5	Southeastern Plains	138.73	-0.727	0.45	3.62
8.3.6	Mississippi Valley Loess Plains	123.15	-0.379	0.55	6.62
8.3.7	South Central Plains	149.84	-0.706	0.57	3.83
8.3.8	East Central Texas Plains	136	-0.344	0.89	7.59
8.4.1	Ridge and Valley	158.11	-0.659	0.70	4.19
8.4.2	Central Appalachians	161.22	-0.907	0.53	3.07
8.4.3	Western Allegheny Plateau	125.25	-0.440	0.51	5.74
8.4.4	Blue Ridge	158.16	-0.777	0.59	3.55
8.4.5	Ozark Highlands	145.69	-0.513	0.73	5.22
8.4.6	Boston Mountains	168.59	-1.108	0.47	2.55
8.4.7	Arkansas Valley	135.4	-0.470	0.64	5.54
8.4.8	Ouachita Mountains	162.34	-0.942	0.51	2.96
8.4.9	Southwestern Appalachians	143.42	-0.645	0.56	4.13
8.5.1	Middle Atlantic Coastal Plain	123.43	-0.444	0.47	5.66
8.5.2	Mississippi Alluvial Plain	119.57	-0.310	0.58	8.00
8.5.3	Southern Coastal Plain	118.73	-0.701	0.24	3.53
8.5.4	Atlantic Coastal Pine Barrens	110.04	-0.482	0.20	4.98
9.2.1	Aspen Parkland/Northern Glaciated Plains	141.62	-0.086	4.06	30.82
9.2.2	Lake Manitoba and Lake Agassiz Plain	119.49	-0.082	2.18	30.25
9.2.3	Western Corn Belt Plains	129.28	-0.074	3.48	34.59
9.2.4	Central Irregular Plains	142.81	-0.184	1.93	14.45
9.3.1	Northwestern Glaciated Plains	120.91	-0.386	0.49	6.46
9.3.3	Northwestern Great Plains	125.65	-0.404	0.56	6.26
9.3.4	Nebraska Sand Hills	113.81	-0.324	0.40	7.51
9.4.1	High Plains	121.41	-0.161	1.21	15.51
9.4.2	Central Great Plains	129.36	-0.178	1.44	14.38

Table B-4: TN Subindex Curve Parameters, by Ecoregion

ID	Ecoregion Name	a	b	TN_{100}	TN_{10}
9.4.3	Southwestern Tablelands	136.03	-0.413	0.74	6.32
9.4.4	Flint Hills	142.74	-0.343	1.04	7.75
9.4.5	Cross Timbers	130.87	-0.278	0.97	9.25
9.4.6	Edwards Plateau	141.98	-0.588	0.60	4.51
9.4.7	Texas Blackland Prairies	133.84	-0.243	1.20	10.68
9.5.1	Western Gulf Coastal Plain	106.22	-0.301	0.20	7.85
9.6.1	Southern Texas Plains/Interior Plains and Hills with Xerophytic Shrub and Oak Forest	102.35	-0.374	0.06	6.22

Table B-5: TP Subindex Curve Parameters, by Ecoregion

ID	Ecoregion Name	a	b	TP_{100}	TP_{10}
10.1.2	Columbia Plateau	126.6	-3.83	0.06	0.66
10.1.3	Northern Basin and Range	147.4	-2.21	0.18	1.22
10.1.4	Wyoming Basin	165.9	-2.78	0.18	1.01
10.1.5	Central Basin and Range	143.8	-1.57	0.23	1.70
10.1.6	Colorado Plateaus	167.2	-2.54	0.20	1.11
10.1.7	Arizona/New Mexico Plateau	123.7	-0.78	0.27	3.21
10.1.8	Snake River Plain	168.7	-3.39	0.15	0.83
10.2.1	Mojave Basin and Range	140.8	-1.11	0.31	2.39
10.2.2	Sonoran Desert	139.9	-0.98	0.34	2.70
10.2.4	Chihuahuan Desert	122.9	-1.58	0.13	1.59
11.1.1	California Coastal Sage, Chaparral, and Oak Woodlands	132.9	-3.74	0.08	0.69
11.1.2	Central California Valley	125.1	-1.92	0.12	1.32
11.1.3	Southern and Baja California Pine-Oak Mountains	126.3	-2.14	0.11	1.19
12.1.1	Madrean Archipelago	212.0	-0.94	0.80	3.25
13.1.1	Arizona/New Mexico Mountains	140.6	-1.33	0.26	1.99
15.4.1	Southern Florida Coastal Plain	555.9	-306.0	0.01	0.01
5.2.1	Northern Lakes and Forests	157.9	-26.64	0.02	0.10
5.2.2	Northern Minnesota Wetlands	152.8	-16.37	0.03	0.17
5.3.1	Northern Appalachian and Atlantic Maritime Highlands	171.4	-21.87	0.02	0.13
5.3.3	North Central Appalachians	260.9	-21.53	0.04	0.15
6.2.10	Middle Rockies	157.8	-6.44	0.07	0.43
6.2.11	Klamath Mountains	189.0	-15.04	0.04	0.20
6.2.12	Sierra Nevada	205.2	-19.13	0.04	0.16
6.2.13	Wasatch and Uinta Mountains	142.6	-2.75	0.13	0.97
6.2.14	Southern Rockies	141.7	-5.46	0.06	0.49
6.2.15	Idaho Batholith	185.9	-21.89	0.03	0.13
6.2.3	Columbia Mountains/Northern Rockies	168.9	-17.88	0.03	0.16
6.2.4	Canadian Rockies	197.1	-27.87	0.02	0.11
6.2.5	North Cascades	289.6	-47.06	0.02	0.07
6.2.7	Cascades	227.9	-26.77	0.03	0.12
6.2.8	Eastern Cascades Slopes and Foothills	154.7	-10.55	0.04	0.26
6.2.9	Blue Mountains	141.6	-3.31	0.11	0.80
7.1.7	Strait of Georgia/Puget Lowland	165.3	-13.83	0.04	0.20
7.1.8	Coast Range	185.3	-14.77	0.04	0.20

Table B-5: TP Subindex Curve Parameters, by Ecoregion

ID	Ecoregion Name	a	b	TP_{100}	TP_{10}
7.1.9	Willamette Valley	159.5	-9.05	0.05	0.31
8.1.1	Eastern Great Lakes and Hudson Lowlands	148.0	-7.95	0.05	0.34
8.1.10	Erie Drift Plain	230.1	-9.61	0.09	0.33
8.1.2	Lake Erie Lowland	3,440.2	-8.89	0.40	0.66
8.1.3	Northern Appalachian Plateau and Uplands	317.2	-13.87	0.08	0.25
8.1.4	North Central Hardwood Forests	132.7	-4.91	0.06	0.53
8.1.5	Driftless Area	141.5	-2.26	0.15	1.17
8.1.6	S. Michigan/N. Indiana Drift Plains	184.3	-5.59	0.11	0.52
8.1.7	Northeastern Coastal Zone	174.0	-9.94	0.06	0.29
8.1.8	Maine/New Brunswick Plains and Hills	174.7	-28.94	0.02	0.10
8.2.1	Southeastern Wisconsin Till Plains	151.8	-3.59	0.12	0.76
8.2.2	Huron/Erie Lake Plains	141.2	-1.58	0.22	1.68
8.2.3	Central Corn Belt Plains	247.2	-2.67	0.34	1.20
8.2.4	Eastern Corn Belt Plains	223.4	-3.56	0.23	0.87
8.3.1	Northern Piedmont	196.0	-3.73	0.18	0.80
8.3.2	Interior River Valleys and Hills	161.0	-2.57	0.19	1.08
8.3.3	Interior Plateau	156.7	-3.62	0.12	0.76
8.3.4	Piedmont	197.7	-5.62	0.12	0.53
8.3.5	Southeastern Plains	223.4	-9.27	0.09	0.34
8.3.6	Mississippi Valley Loess Plains	177.2	-5.69	0.10	0.51
8.3.7	South Central Plains	168.0	-4.66	0.11	0.61
8.3.8	East Central Texas Plains	166.4	-1.68	0.30	1.68
8.4.1	Ridge and Valley	178.1	-6.41	0.09	0.45
8.4.2	Central Appalachians	225.7	-16.59	0.05	0.19
8.4.3	Western Allegheny Plateau	187.7	-8.37	0.08	0.35
8.4.4	Blue Ridge	174.1	-10.50	0.05	0.27
8.4.5	Ozark Highlands	152.7	-2.89	0.15	0.94
8.4.6	Boston Mountains	204.9	-7.36	0.10	0.41
8.4.7	Arkansas Valley	287.2	-5.79	0.18	0.58
8.4.8	Ouachita Mountains	158.5	-6.82	0.07	0.41
8.4.9	Southwestern Appalachians	169.7	-7.30	0.07	0.39
8.5.1	Middle Atlantic Coastal Plain	154.0	-6.82	0.06	0.40
8.5.2	Mississippi Alluvial Plain	141.3	-3.81	0.09	0.70
8.5.3	Southern Coastal Plain	144.7	-7.68	0.05	0.35
8.5.4	Atlantic Coastal Pine Barrens	126.8	-8.39	0.03	0.30
9.2.1	Aspen Parkland/Northern Glaciated Plains	156.1	-0.69	0.65	3.98
9.2.2	Lake Manitoba and Lake Agassiz Plain	132.2	-1.09	0.26	2.38
9.2.3	Western Corn Belt Plains	197.2	-1.68	0.40	1.77
9.2.4	Central Irregular Plains	201.0	-1.99	0.35	1.50
9.3.1	Northwestern Glaciated Plains	134.1	-1.65	0.18	1.58
9.3.3	Northwestern Great Plains	143.3	-1.27	0.28	2.10
9.3.4	Nebraska Sand Hills	185.0	-3.79	0.16	0.77
9.4.1	High Plains	153.1	-0.95	0.45	2.88
9.4.2	Central Great Plains	188.6	-1.18	0.54	2.49
9.4.3	Southwestern Tablelands	139.6	-0.97	0.34	2.71
9.4.4	Flint Hills	218.9	-2.35	0.33	1.31

Table B-5: TP Subindex Curve Parameters, by Ecoregion

ID	Ecoregion Name	a	b	TP_{100}	TP_{10}
9.4.5	Cross Timbers	131.7	-0.78	0.35	3.31
9.4.6	Edwards Plateau	160.0	-1.38	0.34	2.00
9.4.7	Texas Blackland Prairies	149.6	-1.06	0.38	2.54
9.5.1	Western Gulf Coastal Plain	127.2	-1.86	0.13	1.36
9.6.1	Southern Texas Plains/Interior Plains and Hills with Xerophytic Shrub and Oak Forest	104.2	-0.51	0.08	4.57

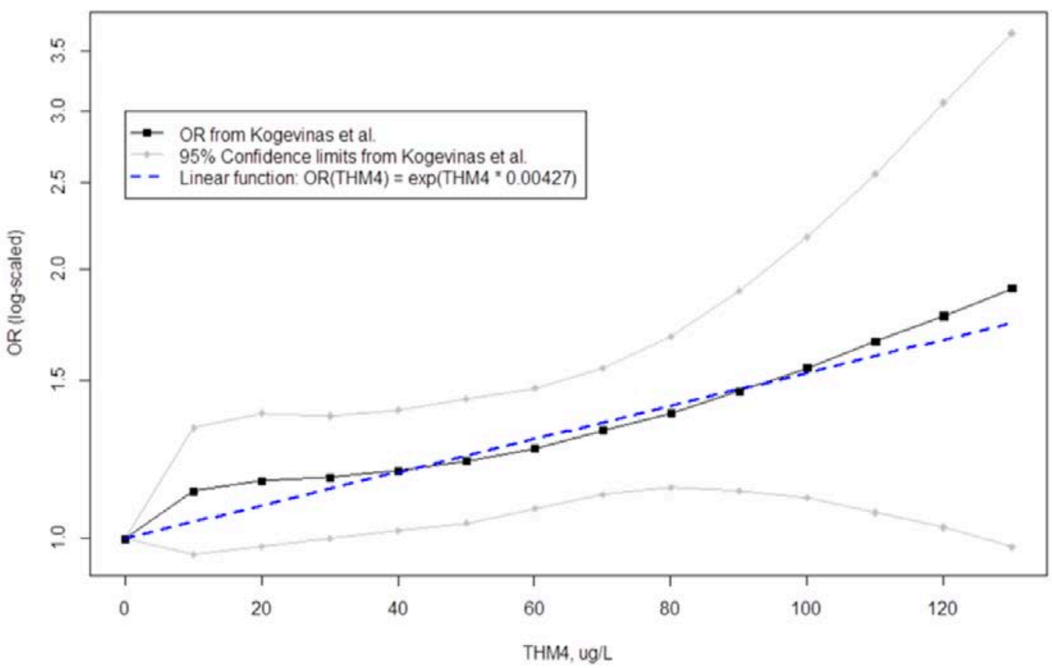
Appendix C Additional Details on Modeling Change in Bladder Cancer Incidence from Change in TTHM Exposure

C.1 Details on Life Table Approach

C.1.1 Health Impact Function

Figure C-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 C-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.[85]

Figure C-1: Estimated Relationships between Lifetime Bladder Cancer Risk and TTHM Concentrations in Drinking Water.



Source: Regli et al., 2015

The 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:

85 Regli et al (2015) addressed some of the limitations noted in the Hrudey et al. (2015) 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.

Equation C-1. $x_a = \frac{1}{a}\sum_{i=0}^{a-1} \text{TTHM}_i \,, x_0 = 0.$

See Table C-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 C-2. $RR(x_a, z_a) = \left(\frac{O(x_a)}{O(z_a)}\right)^{-1} \cdot \left(LR_a \cdot \frac{O(x_a)}{O(z_a)} - LR_a + 1\right)$

where LR_a is the lifetime risk of bladder cancer within age interval $[0, a]$ (Fay et al. 2003) under baseline conditions.

Combining Equation C-1 and Equation C-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 C-3.

$$RR_{\text{Regli et al.}}(x_a, z_a) = \left(\frac{O(0)\cdot e^{0.00427\cdot x_a}}{O(0)\cdot e^{0.00427\cdot z_a}}\right)^{-1} \cdot \left(LR_a \cdot \frac{O(0)\cdot e^{0.00427\cdot x_a}}{O(0)\cdot e^{0.00427\cdot z_a}} - LR_a + 1\right)$$
$$= e^{-0.00427\cdot(x_a - z_a)} \cdot \left(LR_a \cdot e^{0.00427\cdot(x_a - z_a)} - LR_a + 1\right)$$
$$= e^{-0.00427\cdot\Delta x_a} \cdot \left(LR_a \cdot e^{0.00427\cdot\Delta x_a} - LR_a + 1\right).$$

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 the EPA modeled,[86] the relationship based on Villanueva et al. (2004) requires detailed information on the baseline TTHM exposure for the population of interest which is not available.

C.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

[86] If the piece-wise linear relationship based on Villanueva et al. (2004) 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 et al. (2015) linear approximation.

implementation year (in this case 2021) and to alternative TTHM levels that reflect the impact of technology implementation under each regulatory option starting in 2021.

To capture these effects while being consistent with the remainder of the cost-benefit framework, the EPA modeled changes in health outcomes resulting from changes in exposure between 2021 and 2047. For these exposures, the EPA modeled effects out to 2121 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 2047.[87]

The EPA tracks mortality and bladder cancer experience for a set of model populations defined by sex, location, and age attained by 2021, which is denoted by $A = 0,1,2,3, \ldots 100$. Each model population is followed from birth (corresponding to calendar year $2021 - A$) 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 ($A = 0,1,2,3, \ldots 100$).

Evolution of Model Population A under Baseline TTHM Exposure

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, the 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 deaths that occur with probability[88] $q_{C=0,a}$ 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, the EPA assumes that the new cancer diagnoses occur after general population deaths and uses the following recurrent equations for ages $a > 0$:[89]

87 This approach is equivalent to assuming that TTHM levels revert back to baseline conditions at the end of the regulatory option costing period.

88 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.

89 The 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

Equation C-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 C-5. $$d_{C=0,a,y}(z_{a,y}) = q_{C=0,a} \cdot l_{C=0,a,y}(z_{a,y})$$

Equation C-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, the 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 2021, denoted by P. To this end, Equation C-4, Equation C-5, and Equation C-6 are solved to find $l_{C=0,0,y-A}(z_{0,y-A})$ such that $l_{C=0,A,2021}(z_{A,2021}) = P$.

Consistent with available bladder cancer survival statistics, the 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 $\delta_{S=s,a}$, the EPA calculates the number of new stage s cancers occurring at age a in year y:

Equation C-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 2021 and cancer stage s, the EPA separately tracks $100 - A + 1$ new stage-specific bladder cancer populations from age-at-onset a to age 100.[90] Next, a set of cancer duration k-dependent annual death probabilities is derived for each population from available data on relative survival rates[91] $r_{S=s,a,k}$ and general population annual death probabilities $q_{C=0,a+k}$ as follows:

Equation C-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 $k = 0$), the 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 C-9. $$\tilde{d}_{S=s,a,y,0}(z_{a,y}) = \left(\tilde{q}_{S=s,a,0} - q_{C=0,a}\right) \cdot \tilde{l}_{S=s,a,y,0}(z_{a,y}),$$

diagnoses occur before general population deaths. In a limited sensitivity analysis, the EPA found that estimates generated using this alternative assumption were approximately 5 percent larger than the estimates reported here.

90 In total, there are $4 \cdot (100 - A + 1)$ new cancer populations being tracked for each model population.

91 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.

In years that follow the initial diagnosis year (*i.e.*, $k > 0$), the 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 C-10. $$\tilde{l}_{S=s,a,y,k}(z_{a,y-k}) = \tilde{l}_{S=s,a,y,k-1}(z_{a,y-k}) - \tilde{d}_{S=s,a,y,k-1}(z_{a,y-k}),$$

Equation C-11. $$\tilde{d}_{S=s,a,y,k}(z_{a,y-k}) = \tilde{q}_{S=s,a,k} \cdot \tilde{l}_{S=s,a,y,k}(z_{a,y-k}).$$

Because the EPA is interested in bladder cancer-related deaths rather than all deaths in the bladder cancer population, the 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 C-12. $$\tilde{e}_{S=s,a,y,k}(z_{a,y-k}) = \tilde{q}_{S=s,a,k} \cdot \tilde{l}_{S=s,a,y,k}(z_{a,y-k}) - q_{C=0,a+k} \cdot \tilde{l}_{S=s,a,y,k}(z_{a,y-k})$$

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 2021), the 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 4.3.3*, current empirical evidence links TTHM exposure to the lifetime bladder cancer risk, rather than annual bladder cancer probability. The EPA computes the TTHM-dependent annual new bladder cancer cases under the regulatory option conditions, $l_{C=1,a,y}(x_{a,y})$, in three steps. First, the EPA recursively estimates $LR_{a,y}(z_{a,y})$, the lifetime risk of bladder cancer within age interval $[0, a]$ under the baseline conditions:

Equation C-13. $$LR_{a,y}(z_{a,y}) = \frac{1}{l_{C=0,0,y-A}(z_{0,y-A})} \cdot \sum_{j=0}^{a-1} l_{C=1,j}(z_{j,y-A+j}),\ a > 0 \text{ and } LR_{0,y-A}(z_{0,y-A}) = 0$$

Second, the result of Equation C-13 is combined with the relative risk estimate $RR(x_{a,y}, z_{a,y})$, based on Regli et al. (2015):

Equation C-14. $$LR_{a,y}(x_{a,y}) = RR(x_{a,y}, z_{a,y}) LR_{a,y}(z_{a,y})$$

This results in a series of lifetime bladder cancer risk estimates under the option conditions. Third, the EPA computes a series of new annual bladder cancer case estimates under the option conditions as follows:

Equation C-15. $$l_{C=1,a,y}(x_{a,y}) = \left(LR_{a+1,y+1}(x_{a+1,y+1}) - LR_{a,y}(x_{a,y})\right) \cdot l_{C=0,0,y-A}(z_{0,y-A})$$

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 2021, sex, and location, the 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 C- 16.

$$NC_{A,y,s} = [0 \leq y - 2021 + A \leq 100] \cdot \left(\tilde{l}_{S=s,y-2021+A,y,0}\left(z_{y-2021+A,y}\right) - \tilde{l}_{S=s,y-2021+A,0}\left(x_{y-2021+A,y}\right)\right)$$

Equation C- 17.

$$LC_{A,y,s} = \sum_{k=1}^{100} [0 \leq y - 2021 + A + k \leq 100] \cdot \left(\tilde{l}_{S=s,y-2021+A-k,y,k}\left(z_{y-2021+A-k,y-k}\right) - \tilde{l}_{S=s,y-2021+A-k,y,k}\left(x_{y-2021+A-k,y-k}\right)\right)$$

Equation C- 18.

$$ED_{A,y} = \sum_{k=0}^{100} [0 \leq y - 2021 + A + k \leq 100] \sum_{s \in S} \left(\tilde{e}_{S=s,y-2021+A-k,y,k}\left(z_{y-2021+A-k,y-k}\right) - \tilde{e}_{S=s,y-2021+A-k,y,k}\left(x_{y-2021+A-k,y-k}\right)\right)$$

These calculations are carried out to 2121, when those aged 0 years in 2021 attain the age of 100.

Table C-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
A	Age in 2021 (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
$d_{C=0,a,y}\left(z_{a,y}\right)$	The baseline number of deaths among bladder cancer-free individuals at age a given that this age occurs in year y
$l_{C=1,a,y}\left(z_{a,y}\right)$	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
$\tilde{l}_{S=s,a,y,0}\left(z_{a,y}\right)$	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

Table C-1: Health Risk Model Variable Definitions

Variable	Definition
$\tilde{q}_{S=s,a,k}$	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 2021.
$LC_{A,y,s}$	The incremental number of individuals living with stage s bladder cancer in year y for the model population aged A in 2021.
$ED_{A,y}$	The incremental number of excess in stage s bladder cancer population in year y for the model population aged A in 2021.

C.1.3 Detailed Input Data

As noted in *Section 4.3.3*, the EPA relied on the federal government data sources including EPA SDWIS, ACS 2017 (U.S. Census Bureau, 2018), 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 4-6 in *Section 4.3.3* summarizes the sex- and age group-specific share of general population mortality rates and bladder cancer incidence. Table C-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 C-2: Summary of Sex- and Age-specific Bladder Cancer Stage Distribution and Relative Survival Rates

Sex	Age	Stage	Stage-specific proportion of bladder cancers*	Relative 0th year survival rate*	Relative 1st year survival rate*	Relative 2nd year survival rate*	Relative 3rd year survival rate*	Relative 4th year survival rate*	Relative 5th year survival rate*
Male	0s	Localized	0.6667	1	0.9493	0.9199	0.8892	0.8823	0.8472
Male	0s	Regional	0.1424	1	0.8513	0.5967	0.5086	0.486	0.4459
Male	0s	Distant	0.1333	1	0.4269	0.2237	0.1679	0.1475	0.1475
Male	0s	Unstaged	0.0576	1	0.9662	0.8989	0.8989	0.8989	0.8989
Male	10s	Localized	0.6667	1	0.9493	0.9199	0.8892	0.8823	0.8472
Male	10s	Regional	0.1424	1	0.8513	0.5967	0.5086	0.486	0.4459
Male	10s	Distant	0.1333	1	0.4269	0.2237	0.1679	0.1475	0.1475
Male	10s	Unstaged	0.0576	1	0.9662	0.8989	0.8989	0.8989	0.8989
Male	20s	Localized	0.6667	1	0.9493	0.9199	0.8892	0.8823	0.8472
Male	20s	Regional	0.1424	1	0.8513	0.5967	0.5086	0.486	0.4459
Male	20s	Distant	0.1333	1	0.4269	0.2237	0.1679	0.1475	0.1475
Male	20s	Unstaged	0.0576	1	0.9662	0.8989	0.8989	0.8989	0.8989
Male	30s	Localized	0.6667	1	0.9493	0.9199	0.8892	0.8823	0.8472
Male	30s	Regional	0.1424	1	0.8513	0.5967	0.5086	0.486	0.4459
Male	30s	Distant	0.1333	1	0.4269	0.2237	0.1679	0.1475	0.1475
Male	30s	Unstaged	0.0576	1	0.9662	0.8989	0.8989	0.8989	0.8989
Male	40s	Localized	0.6745	1	0.9524	0.9173	0.8851	0.8692	0.8424
Male	40s	Regional	0.1581	1	0.8206	0.5944	0.4971	0.4599	0.4307
Male	40s	Distant	0.1161	1	0.4122	0.1944	0.134	0.1051	0.099
Male	40s	Unstaged	0.0513	1	0.909	0.8305	0.825	0.825	0.8194
Male	50s	Localized	0.6865	1	0.9471	0.899	0.8656	0.839	0.8141
Male	50s	Regional	0.1706	1	0.7793	0.5657	0.4738	0.426	0.4042
Male	50s	Distant	0.0997	1	0.3648	0.1599	0.0988	0.0688	0.0611
Male	50s	Unstaged	0.0432	1	0.8565	0.791	0.7595	0.7571	0.7338
Male	60s	Localized	0.7095	1	0.9347	0.8766	0.8369	0.8066	0.7798
Male	60s	Regional	0.1587	1	0.7563	0.5401	0.4609	0.4171	0.3864
Male	60s	Distant	0.0905	1	0.3318	0.1531	0.0924	0.0642	0.0587
Male	60s	Unstaged	0.0414	1	0.8309	0.7793	0.7358	0.7186	0.6887
Male	70s	Localized	0.7339	1	0.8885	0.8157	0.7647	0.7272	0.7011
Male	70s	Regional	0.1361	1	0.6912	0.4992	0.4245	0.3824	0.3484
Male	70s	Distant	0.0772	1	0.2845	0.1293	0.0778	0.0461	0.0412
Male	70s	Unstaged	0.0528	1	0.7137	0.6387	0.5944	0.5432	0.5097

Table C-2: Summary of Sex- and Age-specific Bladder Cancer Stage Distribution and Relative Survival Rates

Sex	Age	Stage	Stage-specific proportion of bladder cancers*	Relative 0th year survival rate*	Relative 1st year survival rate*	Relative 2nd year survival rate*	Relative 3rd year survival rate*	Relative 4th year survival rate*	Relative 5th year survival rate*
Male	80s	Localized	0.7364	1	0.8254	0.7344	0.6783	0.633	0.6002
Male	80s	Regional	0.1202	1	0.6105	0.4347	0.369	0.3279	0.3007
Male	80s	Distant	0.0736	1	0.211	0.0919	0.0605	0.0326	0.0326
Male	80s	Unstaged	0.0698	1	0.5827	0.4887	0.4265	0.347	0.2969
Male	90s	Localized	0.7364	1	0.8254	0.7344	0.6783	0.633	0.6002
Male	90s	Regional	0.1202	1	0.6105	0.4347	0.369	0.3279	0.3007
Male	90s	Distant	0.0736	1	0.211	0.0919	0.0605	0.0326	0.0326
Male	90s	Unstaged	0.0698	1	0.5827	0.4887	0.4265	0.347	0.2969
Female	0s	Localized	0.5651	1	0.9159	0.849	0.832	0.8119	0.793
Female	0s	Regional	0.1818	1	0.7186	0.5379	0.4703	0.4362	0.4132
Female	0s	Distant	0.1572	1	0.3893	0.1676	0.1177	0.0295	0.0295
Female	0s	Unstaged	0.0958	1	0.866	0.8376	0.7778	0.7778	0.7778
Female	10s	Localized	0.5651	1	0.9159	0.849	0.832	0.8119	0.793
Female	10s	Regional	0.1818	1	0.7186	0.5379	0.4703	0.4362	0.4132
Female	10s	Distant	0.1572	1	0.3893	0.1676	0.1177	0.0295	0.0295
Female	10s	Unstaged	0.0958	1	0.866	0.8376	0.7778	0.7778	0.7778
Female	20s	Localized	0.5651	1	0.9159	0.849	0.832	0.8119	0.793
Female	20s	Regional	0.1818	1	0.7186	0.5379	0.4703	0.4362	0.4132
Female	20s	Distant	0.1572	1	0.3893	0.1676	0.1177	0.0295	0.0295
Female	20s	Unstaged	0.0958	1	0.866	0.8376	0.7778	0.7778	0.7778
Female	30s	Localized	0.5651	1	0.9159	0.849	0.832	0.8119	0.793
Female	30s	Regional	0.1818	1	0.7186	0.5379	0.4703	0.4362	0.4132
Female	30s	Distant	0.1572	1	0.3893	0.1676	0.1177	0.0295	0.0295
Female	30s	Unstaged	0.0958	1	0.866	0.8376	0.7778	0.7778	0.7778
Female	40s	Localized	0.5616	1	0.9197	0.8583	0.8387	0.8245	0.813
Female	40s	Regional	0.2096	1	0.7083	0.538	0.4485	0.4013	0.3835
Female	40s	Distant	0.1626	1	0.3715	0.1553	0.1064	0.0466	0.0401
Female	40s	Unstaged	0.0663	1	0.8791	0.8457	0.7731	0.7731	0.7427
Female	50s	Localized	0.588	1	0.9266	0.8667	0.8381	0.8184	0.8038
Female	50s	Regional	0.2248	1	0.7015	0.5234	0.4238	0.3682	0.352
Female	50s	Distant	0.1449	1	0.344	0.1406	0.091	0.0648	0.0587

Table C-2: Summary of Sex- and Age-specific Bladder Cancer Stage Distribution and Relative Survival Rates

Sex	Age	Stage	Stage-specific proportion of bladder cancers*	Relative 0th year survival rate*	Relative 1st year survival rate*	Relative 2nd year survival rate*	Relative 3rd year survival rate*	Relative 4th year survival rate*	Relative 5th year survival rate*
Female	50s	Unstaged	0.0423	1	0.8572	0.8013	0.7539	0.7445	0.7036
Female	60s	Localized	0.638	1	0.902	0.8341	0.7981	0.7668	0.7424
Female	60s	Regional	0.1978	1	0.6912	0.499	0.41	0.3651	0.3417
Female	60s	Distant	0.1188	1	0.2937	0.117	0.0751	0.0509	0.0509
Female	60s	Unstaged	0.0453	1	0.7756	0.7048	0.6922	0.6669	0.6335
Female	70s	Localized	0.6745	1	0.809	0.7259	0.6782	0.6457	0.6188
Female	70s	Regional	0.157	1	0.5905	0.4232	0.3551	0.3215	0.3029
Female	70s	Distant	0.1072	1	0.2133	0.085	0.0615	0.0365	0.031
Female	70s	Unstaged	0.0613	1	0.5692	0.493	0.4627	0.4308	0.3993
Female	80s	Localized	0.6897	1	0.7242	0.6268	0.5644	0.5318	0.502
Female	80s	Regional	0.1276	1	0.4691	0.3327	0.2929	0.2632	0.2588
Female	80s	Distant	0.0983	1	0.1665	0.0739	0.0611	0.0438	0.0304
Female	80s	Unstaged	0.0845	1	0.3592	0.2713	0.2168	0.1873	0.1748
Female	90s	Localized	0.6897	1	0.7242	0.6268	0.5644	0.5318	0.502
Female	90s	Regional	0.1276	1	0.4691	0.3327	0.2929	0.2632	0.2588
Female	90s	Distant	0.0983	1	0.1665	0.0739	0.0611	0.0438	0.0304
Female	90s	Unstaged	0.0845	1	0.3592	0.2713	0.2168	0.1873	0.1748

Notes: * Single age-specific proportions and rates were aggregated up to the age groups reported in the table using the individual age-specific number of affected persons as weights.

C.2 Detailed Results from Analysis

The health impact model assumes that the proposed regulatory changes begin in 2021 and end by 2047 and thus TTHM changes are in effect during this period. After 2047, 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 2047 were included in the final calculations for each option. Table C-3 summarizes the health impact and valuation results in millions of 2018 dollars for each proposed regulatory option, as shown graphically and discussed in *Section 4.4*.

Table C-3: Number of Adverse Health Effects Avoided Over Time Starting from 2021

Option	Evaluation decade										Total[c]
	2021-2030	2031-2040	2041-2050	2051-2060	2061-2070	2071-2080	2081-2090	2091-2100	2101-2110	2111-2121	
Cancer morbidity cases avoided[a]											
Option 1	0	-1	-1	0	0	0	0	0	0	0	-3
Option 2	42	63	72	42	42	38	29	16	2	-2	343
Option 3	48	71	81	47	47	43	33	17	2	-2	387
Option 4	94	140	161	94	93	86	65	34	5	-4	769
Excess cancer deaths avoided[b]											
Option 2	0	0	0	0	0	0	0	0	0	0	-1
Option 2	13	24	29	17	17	16	13	8	2	0	139
Option 3	15	27	33	19	19	18	15	9	2	0	157
Option 4	30	53	65	39	38	36	29	18	4	-1	311
Annual value of morbidity avoided (million dollars)											
Option 1	-$0.01	-$0.01	-$0.02	-$0.01	-$0.01	-$0.01	-$0.01	-$0.01	$0.00	$0.00	-$0.09
Option 2	$0.83	$1.38	$1.72	$1.20	$1.18	$1.11	$0.88	$0.52	$0.14	-$0.02	$8.95
Option 3	$0.95	$1.57	$1.95	$1.35	$1.33	$1.24	$0.99	$0.59	$0.16	-$0.02	$10.10
Option 4	$1.87	$3.09	$3.88	$2.70	$2.65	$2.47	$1.96	$1.16	$0.31	-$0.04	$20.05
Annual value of mortality avoided (million dollars)											
Option 1	-$1.42	-$2.69	-$3.55	-$2.27	-$2.32	-$2.23	-$1.85	-$1.19	-$0.27	$0.06	-$17.75
Option 2	$152.78	$285.10	$361.88	$222.39	$232.55	$229.39	$192.14	$124.14	$28.21	-$5.81	$1,822.77
Option 3	$174.12	$324.01	$410.02	$250.50	$260.61	$257.16	$215.79	$139.07	$31.45	-$6.50	$2,056.22
Option 4	$342.88	$637.67	$813.85	$501.80	$520.59	$511.90	$428.15	$274.55	$61.79	-$12.83	$4,080.34

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.

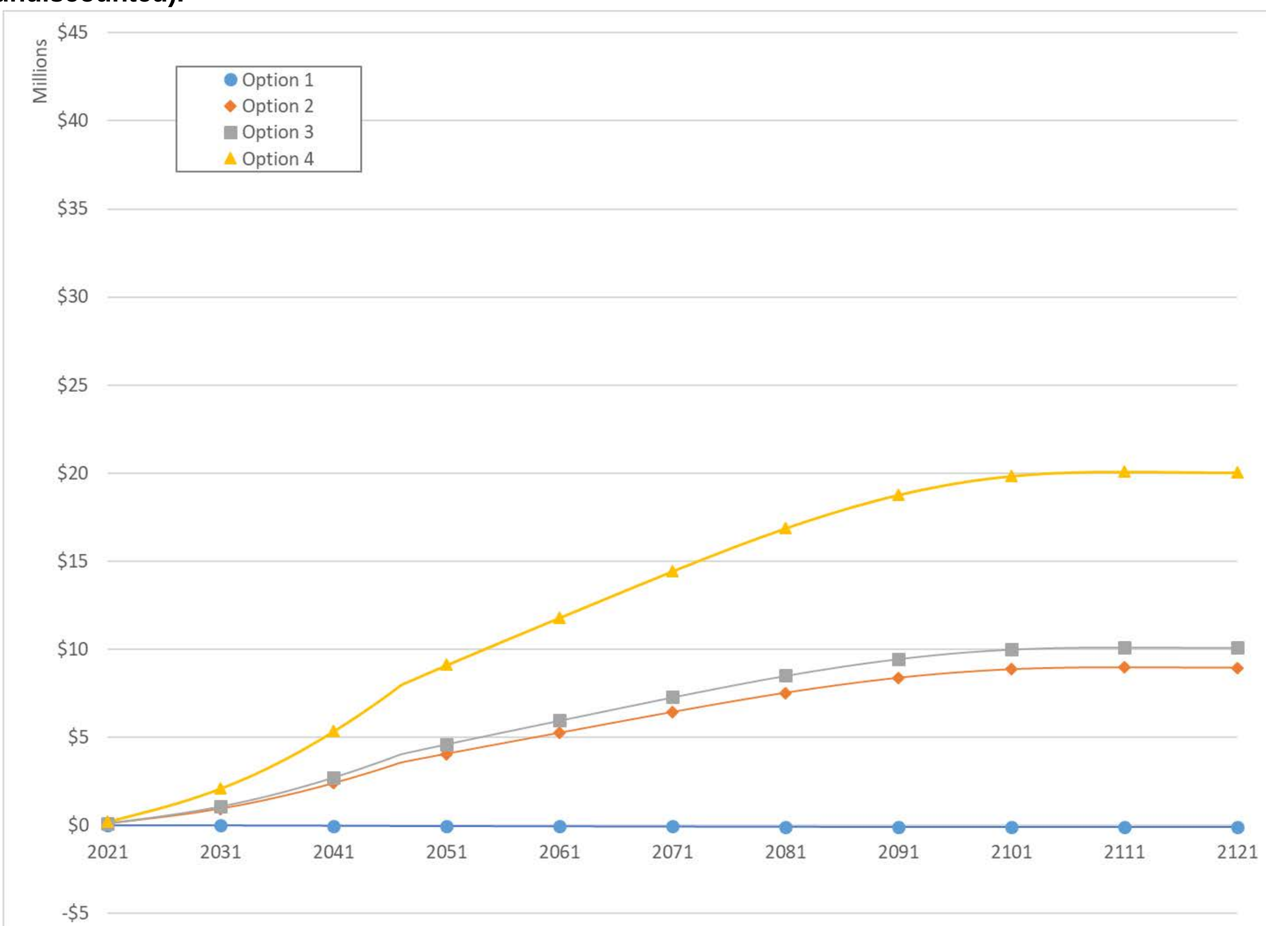
[c] Total TTHM-attributable adverse health effects that are expected to be avoided between 2021 and 2121 as a result of the regulatory option changes in 2021-2047.

Source: U.S. EPA Analysis, 2019

C.3 Temporal Distribution of Benefits

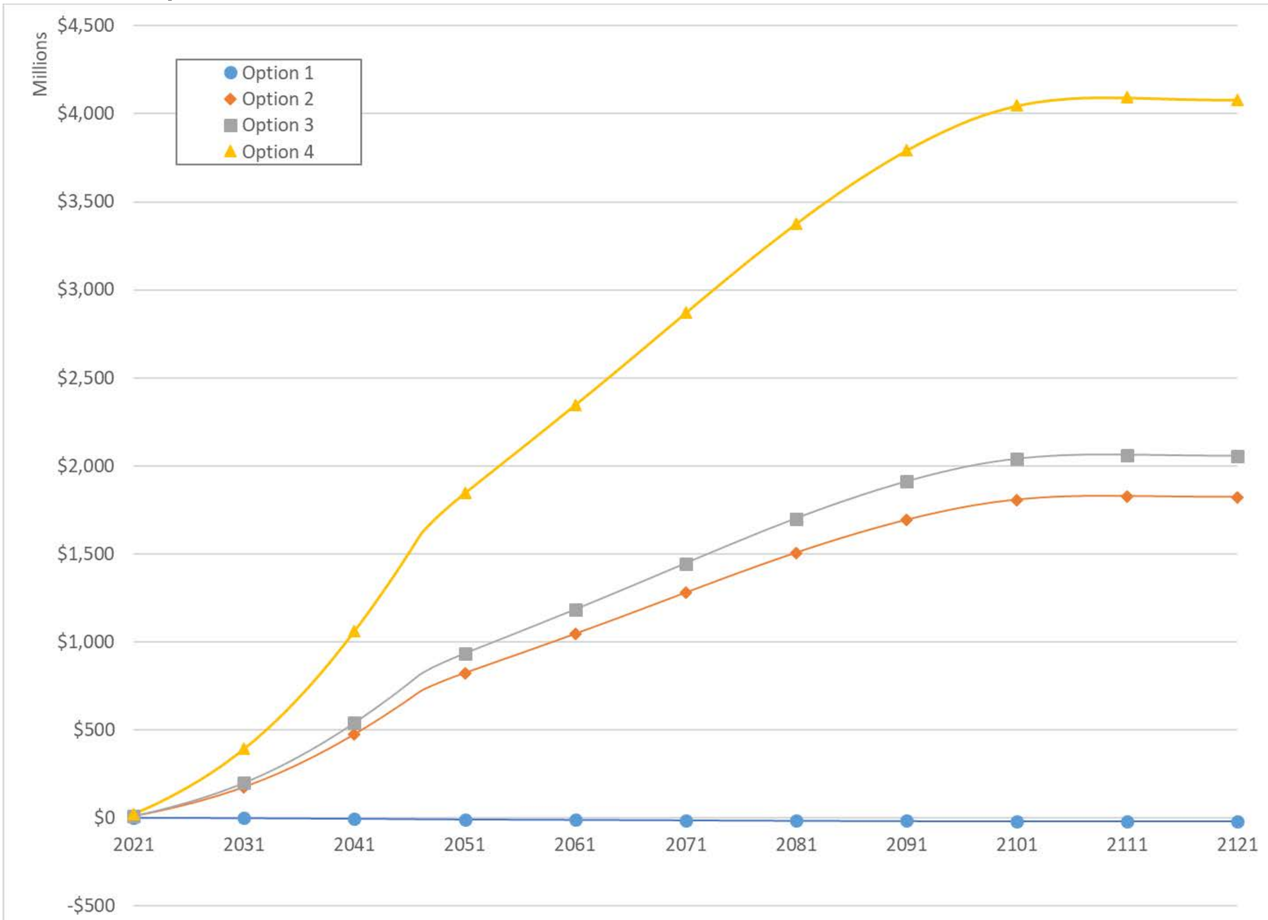
Figure C-2 and Figure C-3 illustrate patterns of changes in benefits for the four regulatory options for the 100-year simulation period of 2021 through 2121 based on the estimated cumulative annual value of morbidity avoided and the estimated cumulative annual value of mortality, respectively (values are undiscounted). These figures show the gradual increase in benefits for Options 2, 3, and 4 between 2021 and 2047, which continues but at a reduced rate after 2047 until levelling off around 2101. As discussed in *Section 4.4*, benefits decrease during the final decade for Options 2, 3, and 4. The magnitude of benefits associated with Option 1 are much smaller and generally follow the inverse pattern when compared to Options 2, 3, and 4, due to the option increasing bromide concentrations as compared to the baseline.

Figure C-2: Estimated Cumulative Annual Value of Cancer Morbidity Avoided, 2021-2121 (2018$ undiscounted).



Source: U.S. EPA Analysis, 2019.

Figure C-3. Estimated Cumulative Annual Value of Mortality Avoided, 2021-2121 (2018$ undiscounted).



Source: U.S. EPA Analysis, 2019.

C.4 Sensitivity Analysis Results

For FGD wastewater bromide loadings, the EPA developed three scenarios that reflect different assumptions regarding bromide content: 1) lower bound loadings based solely on native bromide content in coal at all plants, 2) upper bound loadings based on both native bromide content in coal and the use of bromide additives and brominated activated carbon at all plants, and 3) best estimate loadings based on the EPA's estimates of the native bromide content in coal and the most likely bromide usage for each plant (see *Supplemental TDD*). In total, the EPA considered nine different loadings scenarios: the EPA's best estimate loadings for the baseline, Option 1, Option 2, Option 3, and Option 4 (used in the analysis presented in *Chapter 4*); lower bound loadings for baseline and Option 4; and upper bound loadings for baseline and Option 4. The next section presents the results of scenarios based on the lower and upper bound loadings.

Section C.4.2 presents the results of scenarios based on alternative relationships between bromide concentrations and TTHM concentrations changes.

C.4.1 Sensitivity to bromide loads

The EPA analyzed the sensitivity of the benefits to estimated bromide loadings from steam electric power plants under lower bound and upper bound scenarios for regulatory Option 4. As detailed in the *Supplemental*

TDD, the lower bound scenario derives bromide loadings based solely on bromide levels occurring naturally in coal whereas the upper bound scenario derives loadings based on both natural bromide content in coal and bromide product additions for control of mercury emissions at all facilities (U.S. EPA, 2019b).

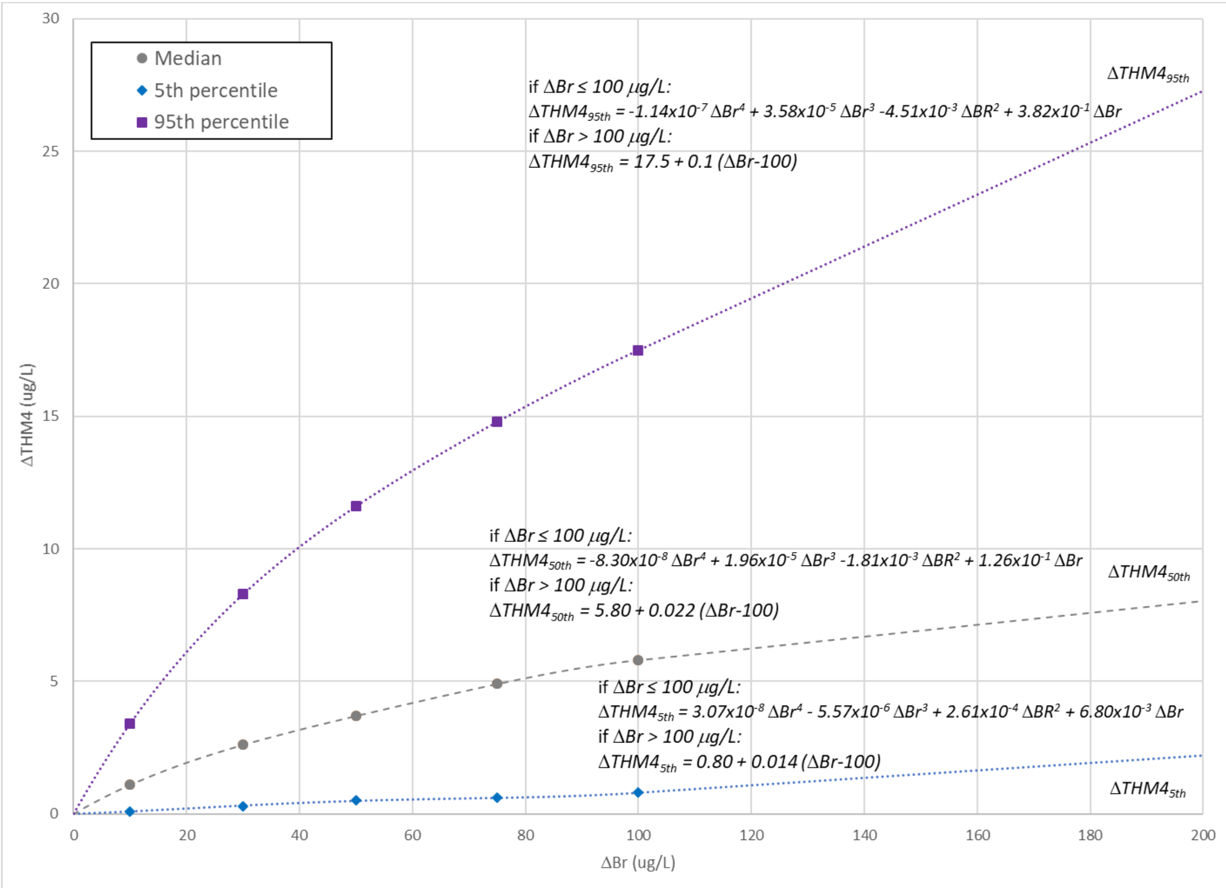
Results of this assessment yielded estimated annualized benefits over 27 years ranging from $25 million to $215 million (3 percent discount rate) and from $16 million to $139 million (7 percent discount rate) for the lower bound and upper bound scenarios, respectively.

C.4.2 Sensitivity to relationship between bromide and TTHM changes

As described in *Section 4.3.2.3*, the EPA used the relationship shown in Figure 4-2 to estimate the changes in TTHM concentrations resulting from changes in bromide concentrations in source water as a result of the regulatory options in comparison to the baseline. The median conversion factor used to develop the best-fit curve reflects operating conditions for a diverse set of water treatment plants with varying treatment processes and source water quality. The median conversion factor developed by Regli et al. (2015) was based on monthly bromide-TTHM relationships and is used in this analysis to represent year-round conditions at PWS potentially affected by steam electric power plant discharges. Long-term conditions are most relevant to analyzing the relationship between TTHM and bladder cancer incidence.

To evaluate the sensitivity of the analysis to variability in the relationship between source water bromide level changes and changes in treated water TTHM levels (such as those due to variability in PWS treatment processes), the EPA also analyzed benefits using the 5^{th} and 95^{th} percentile estimates from Regli et al. (2015) (Figure C-4). EPA determined that the TTHM values derived from the 5^{th} and 95^{th} percentile estimates are useful for a sensitivity analysis, but notes that the conditions they reflect may be episodic and therefore less likely to reflect long-term TTHM exposure and the resulting changes in bladder cancer incidence.

Figure C-4: Modeled Sensitivity Analysis Relationship between Changes in Bromide Concentration and Changes in TTHM Concentrations based on Regli et al. (2015).



Source: U.S. EPA Analysis, 2019. Based on data in Regli et al. (2015).

Table C-4 summarizes the changes in bromide concentrations and associated changes in TTHM concentrations, number of PWS, and populations affected for the 5th and 95th percentile sensitivity analyses under Option 4.

Table C-4: Distribution of Estimated Changes in TTHM Concentration, Number of PWS and Populations.

ΔBr range (µg/L)	ΔTTHM range (µg/L)[a]	Number of PWS[b]	Total population served (million people)[c]
Option 4 – 5th Percentile			
>0 to 10	6.16E-06 to 0.0879	626	24.6
10 to 30	0.0902 to 0.313	280	5.1
30 to 50	0.315 to 0.478	24	0.2
50 to 75	0.5 to 0.575	10	0.6
>75	0.606 to 3.8	29	0.9
Option 4 – 95th Percentile			
>0 to 10	0.000347 to 3.38	626	24.6
10 to 30	3.45 to 8.28	280	5.1
30 to 50	8.31 to 11.4	24	0.2
50 to 75	11.8 to 13.9	10	0.6

Table C-4: Distribution of Estimated Changes in TTHM Concentration, Number of PWS and Populations.

∆Br range (µg/L)	∆TTHM range (µg/L)[a]	Number of PWS[b]	Total population served (million people)[c]
>75	14.9 to 37.5	29	0.9

[a] Nonzero changes in concentrations estimated under EPA's best estimate scenario using the 5th and 95th percentile relationships between changes in bromide and changes in TTHM.

[b] Includes systems that are directly and indirectly affected by steam electric power plant discharges.

[c] Approximately 0.3 percent of the population served by PWS affected by bromide discharges from steam electric power plants saw no change in bromide concentration under Option 4.

Source: U.S. EPA analysis, 2019.

Table C-5 summarizes results for the Br-TTHM relationship sensitivity scenarios. Total bladder cancer cases avoided under Option 4 range from 97 to 2,417 and total cancer deaths avoided range from 39 to 978 for the 5th and 95th percentile estimates, respectively. Estimated annualized benefits associated with avoided cancer cases and deaths range from \$11 million to \$265 million. These two bounds illustrate the range in benefits associated with potential variability in TTHM formation.

Table C-5: Sensitivity of Estimated Bromide-related Benefits of Regulatory Option 4.

Option	Br-TTHM Relationship	Changes in health outcomes from TTHM exposure 2021-2047		Benefits (million 2018\$, discounted to 2020 at 3% and 7%)					
		Total bladder cancer cases avoided	Total cancer deaths avoided	Total PV of avoided mortality		Total PV of avoided morbidity avoided		Annualized benefits over 27 years	
				3% Discount Rate	7% Discount Rate	3% Discount Rate	7% Discount Rate	3% Discount Rate	7% Discount Rate
4	5th Percentile	97	39	\$198.9	\$86.7	\$1.0	\$0.4	\$10.6	\$6.8
4	95th Percentile	2,417	978	\$4,977.9	\$2,178.2	\$24.9	\$11.2	\$265.0	\$170.7

Source: U.S. EPA Analysis, 2019

Appendix D Derivation of Ambient Water and Fish Tissue Concentrations in Receiving and Downstream Reaches

This appendix describes the methodology the EPA used to estimate in-stream and fish tissue concentrations under the baseline and each of the four regulatory options. The concentrations are used as inputs to estimate the water quality changes and human health benefits of the regulatory options. Specifically, the EPA used in-stream 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 sediment 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 *Supplemental EA* and *Supplemental TDD* for the regulatory options (U.S. EPA, 2019a; 2019b). The following sections discuss calculations of the toxics concentrations in streams and fish tissue and nutrient and sediment concentrations in streams.

D.1 Toxics

D.1.1 Estimating Water Concentrations in each Reach

The EPA first estimated the baseline and post-compliance 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.[92] The hydrography network represented in the D-FATE model consists of 10,315 reaches within 300 km of a steam electric power plant, 10,284 of which are determined to be potentially fishable.[93]

The analysis involved the following key steps for the baseline and each of the four regulatory options:

- **Summing plant-level loadings to the receiving reach**. The EPA summed the estimated plant-level annual average loads (see *TDD*) for each unique reach receiving plant discharges from steam electric power plants in the baseline and four regulatory options. For a description of the approach EPA used to identify the receiving waterbodies, see U.S. EPA (2019a).

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92 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 a number of 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.

93 Reaches represented in the D-FATE model are those determined 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. Additionally, some types of reaches are excluded from the set of fishable reaches, such as those designated as having Strahler Stream Order 1 in the NHDPlus, because they do not have the flow rates and species diversity to support trophic level 3 and 4 species."

- **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 release its annual load at a constant rate throughout the year. Each source-pollutant release is tracked throughout the NHD reach network until the release has traveled 300 km (186 miles) downstream.

- **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 2016. The EPA added background concentrations where available to concentration estimates from steam electric power plant dischargers.

The EPA used the approach above to estimate annual average concentrations of ten toxics: arsenic, cadmium, chromium VI, copper, lead, mercury, nickel, selenium, thallium, and zinc.

D.1.2 Estimating Fish Tissue Concentrations in each Reach

To support analysis of the human health benefits associated with water quality improvements (see *Chapter 4*), the 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 *Supplemental EA* for estimating fish tissue concentrations for receiving reaches (U.S. EPA, 2019a), 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 four regulatory options:

- **Obtaining the relationship between water concentrations and fish tissue concentrations**. The EPA used the results of the Immediate Receiving Water (IRW) model (see *Supplemental EA*, U.S. EPA 2019a) 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.

- **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), the EPA used the relationship obtained in Step 1 to calculate a preliminary fish tissue concentration for each pollutant.

- **Imputing the fish tissue concentrations for all other modeled reaches**. For reaches for which the D-FATE model calculates water concentrations, the EPA added background fish tissue concentrations based on the 10th percentile of the distribution of reported concentrations in fish tissue samples in the National Listing Fish Advisory (NLFA) data[94] (see Table D-1). The EPA found that the distribution

[94] See https://fishadvisoryonline.epa.gov/general.aspx.

of these samples was consistent with values reported in Wathen et al (2015) and used the 10th percentile as representative of background, "clean" reaches not affected by point source discharges.

- **Validating and adjusting the fish tissue concentrations based on empirical data, if needed**. The EPA then applied the same method used to validate and adjust estimated fish tissue data in the IRW model to ensure that the fish tissue concentrations calculated based on the D-FATE model outputs are reasonable when compared to measured data. The approach involves applying order-of-magnitude adjustments in cases where the preliminary concentrations are greater than empirical measurements for a given reach or geographic area by an order of magnitude or more. The *Supplemental EA* describes the methodology in greater detail.

The analysis provides background toxics-specific composite fish fillet concentrations for each reach modeled in the D-FATE model. Total fish tissue concentrations (D-FATE modeled concentrations plus background concentrations) are summarized in Table D-2.

Table D-1: Assumed 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, 2019

Table D-2: Imputed and Validated Fish Tissue Concentrations by Regulatory Option

Regulatory Option	Fish fillet concentration (mg/kg)								
	Arsenic			Lead			Mercury		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Baseline	0.0390	0.0742	0.0390	0.0390	0.4919	0.0393	0.0580	4.2878	0.0628
Option 1	0.0390	0.0955	0.0390	0.0390	0.7650	0.0395	0.0580	5.5269	0.0657
Option 2	0.0390	0.0955	0.0390	0.0390	0.7650	0.0395	0.0580	54.694	0.0769
Option 3	0.0390	0.0955	0.0390	0.0390	0.7650	0.0395	0.0580	6.5401	0.0679
Option 4	0.0390	0.0955	0.0390	0.0390	0.7650	0.0395	0.0580	5.5269	0.0665

Source: U.S. EPA Analysis, 2019.

D.2 Nutrients and Suspended Sediment

The EPA used the USGS's SPARROW model to estimate nutrient and sediment concentrations in receiving and downstream reaches. The calibrated, national models used for this analysis are the same as those used to estimate in-stream concentrations of TN, TP and TSS in the Construction and Development (C&D) Industry Category ELGs (see U.S. EPA, 2009a). The approach involved the following steps:

- **Referencing the receiving reaches to E2RF1 reaches**. The EPA overlaid the medium resolution NHD and E2RF1 features in GIS to develop the crosswalk between the two hydrologic networks.

- **Summing the loads for each E2RF1**. The EPA summed the plant-level loadings over each E2RF1 in the baseline and under each of the four regulatory options.

- **Calculating the change in loading for each E2RF1**. The EPA calculated the difference between the baseline and post-compliance loadings under each of the four regulatory options.

- **Specifying the change in loading in SPARROW**. The national SPARROW models for nutrients do not have an explicit explanatory variable for point source loadings in mass units. In the TN and TP SPARROW models, point sources (*e.g.*, wastewater treatment plants) are represented by a population variable. The national calibrated models show contributions of 2.2514 kg TN/capita and 0.2319 kg TP/capita for point sources. The EPA used these calibrated loading factors to express the load reductions obtained under each of the regulatory options into population-equivalent in SPARROW. This population-equivalent loading was subtracted from the baseline population value for each reach when running the SPARROW model. For the suspended sediment model, the EPA used the same approach as used for the C&D ELG analysis, which involved adjusting the mass flux attributed to the urban land explanatory variable in the model to subtract the change in loading achieved under each option, under the assumption that steam electric power plant loadings are implicitly accounted for in the urban land component of the model (see U.S. EPA, 2009a).

The model provides estimated annual average post-compliance concentrations in each E2RF1, which the EPA compared with baseline conditions obtained directly from the national, calibrated model.

Appendix E Georeferencing Surface Water Intakes to the Medium-resolution Stream Network

The 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 closest (simple cartesian distance) medium-resolution NHD feature (including Flowline, Area, and Waterbody) to each PWS intake.

2. If the closest feature to a given intake was an NHD Flowline, reference the intake to this flowline.

3. If the closest feature to a given intake was an NHD Area or Waterbody, consider the Flowlines contained within or intersected by the Area/Waterbody.

    a. If any of the Flowlines associated with the Area/Waterbody were on the flowpath downstream from a steam electric power plant, select the Flowline within this set and closest to the intake.

    b. If none of the Flowlines were on the flowpath downstream from a steam electric power plant, select the Flowline closest to the intake.

    c. If there were no Flowlines associated with the Area/Waterbody, select the closest Flowline.

The EPA then compared the set of Flowline COMIDs identified in steps 2 and 3 to NHD COMIDs in the downstream flowpath of steam electric power plant discharges. COMIDs that georeferenced directly to the downstream flowpath received a "Category 1" designation. Intakes that were georeferenced to COMIDs within 10 km of the downstream flowpath received a "Category 2" designation. The EPA included all intakes within 10 km of the discharge flow path to account for cases where georeferencing did not select the correct COMID based on uncertainty in the flow direction or stream network connectivity. For example, if a PWS intake was located on a wide reach like the Mississippi River, the above methods may assign that intake to a tributary COMID.

As discussed in *Chapter 3*, the EPA did not model complex waterbodies (*e.g.*, Great Lakes) explicitly. Therefore, the Agency reviewed all intakes within 50 miles of the plants discharging to the Great Lakes or other non-modeled waterbodies to classify intakes that withdraw directly from the non-modeled waterbodies as "Category 3". These intakes are excluded from the subsequent analysis.

Table E-1 summarizes the intake categorization following the above steps.

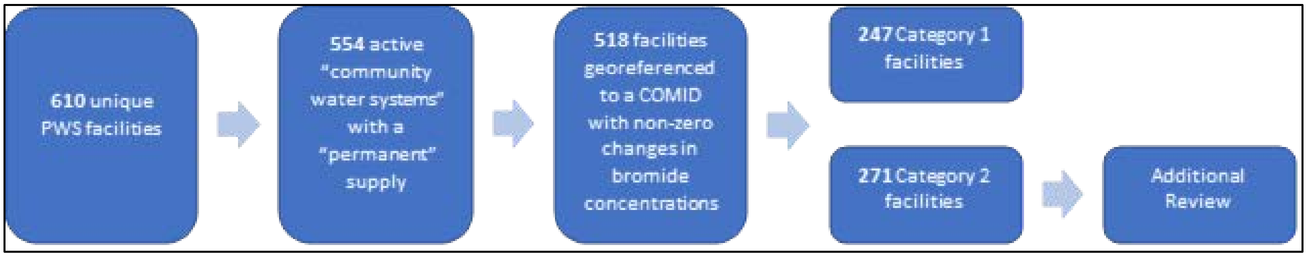
Table E-1: Summary of Intakes Potentially Affected by Steam Electric Power Plant Discharges

Categorization	Number of Intakes
Category 1 (on flow path)	297
Category 2 (within 10 km of flow path) but not Category 1	313
Category 3 (on Great Lakes or other non-modeled waterbodies)	67
Total all categories	677

Source: U.S. EPA Analysis, 2019.

Figure E-1 summarizes how the EPA subset Category 1 and 2 PWS intakes for a more targeted categorization review.

Figure E-1: PWS Intakes Review Subset



Source: U.S. EPA Analysis, 2019.

The EPA evaluated the "Category 2" PWS intakes further using spatial reference to any steam electric downstream flow paths and SDWIS facility information, namely facility name.

The EPA excluded intakes from the benefits analysis if they were:

- on an upstream or visually unconnected body of water from the steam electric downstream flow path,
- did not sit on a visible body of water when looking at the topographical maps and/or orthophotos,
- had a PWS facility name indicating that it was not a surface water intake (*i.e.*, included the word "well").[95]

The EPA recategorized intakes as Category 1 if they were:

- on the same NHD waterbody as the steam electric downstream flow path (prominent examples include intakes on Lake Norman, Upper or Lower Potomac River, and Missouri River) or
- the PWS facility name in SDWIS corresponded with the named reach of the steam electric downstream flow path.

Of the 271 Category 2 facilities that the EPA reviewed, 102 facilities were recategorized into Category 1. Therefore, the EPA included a total number of 349 PWS intakes[96] in the human health benefits analysis.

95 This criterion resulted in the omission of only one facility in Tennessee.

96 Only intakes with facility types categorized by SDWIS as "Intake" or "Reservoir" were retained in the human health benefits analysis. One of the 349 PWS intakes (PWS ID IA9778045) was categorized as "Infiltration Gallery" and was thus not included, bringing the total number of PWS intakes included in the analysis to 348 (see Table 4-1).

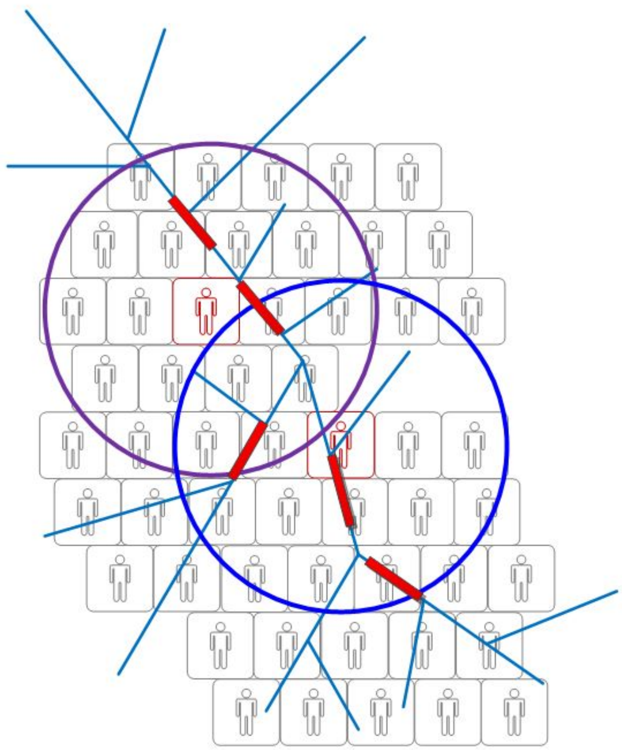
Appendix F Estimation of Exposed Population for Fish Ingestion Pathway

The assessment uses the Census Block Group as the geographic unit of analysis, assigning a radial distance (*e.g.*, 50 miles) from the Census Block Group centroid. The EPA assumes that all modeled reaches within this range are viable fishing sites, with all unaffected reaches viable substitutes for affected reaches within the area around the Census Block Group.

By focusing on distance from the Census Block Group, rather than distances from affected reaches, each household is only included in the assessment once, eliminating the potential for double-counting of households that are near multiple affected waterbodies.

Figure F-1 presents a hypothetical example focusing on two Census Block Groups (square at the center of each circular area), each near five waterbodies with water quality changes under the regulatory options (thick red lines).

Figure F-1. Illustration of Intersection of Census Block Groups and COMIDs.



Source: U.S. EPA (2015a).

Note that a similar approach is used to identify populations for the analysis of non-market benefits in *Chapter 6*. In that case, the circles represent the outer edge of the 100-mile buffer around each block group. Highlighted in red are the affected NHD reaches under regulatory options for which baseline WQI and ΔWQI would be estimated

Appendix G Sensitivity Analysis for IQ Point-based Human Health Effects

The EPA monetized the value of an IQ point based on the methodology from Salkever (1995). As a sensitivity analysis of the benefits of lead and mercury exposure, the EPA used alternative, more conservative estimates provided in Lin et al. (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, 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 et al (2018), using 3 percent and 7 percent discount rates.

Table G-1: Value of an IQ Point (2018$) based on Expected Reductions in Lifetime Earnings

Discount Rate	Value of an IQ Point[a] (2018$)
	Value of an IQ point Discounted to Age 3
3 percent	$11,279
7 percent	$2,371
	Value of an IQ point Discounted to Birth
3 percent	$10,322
7 percent	$1,936

a. Values are adjusted for the cost of education.

Source: U.S. EPA (2019e,2019h) analysis of data from Lin et al. (2018)

G.1 Health Effects in Children from Changes in Lead Exposure

Table G-2 shows the social welfare effects associated with changes in IQ losses from lead exposure via fish consumption. The EPA estimated that all regulatory options lead to slight increases in lead exposure and, as a result, forgone benefits. The total net change in IQ points over the entire population of children with changes in lead exposure ranges from -11.07 points to 0.90 points. Annualized monetary values of changes in IQ losses from differences in lead exposure, based on the Lin et al. (2018) IQ point value, range from -$4,950 to $400 (3 percent discount rate) and from -$1,080 to $90 (7 percent discount rate).

Table G-2: Estimated Monetary Value of Changes in IQ Losses for Children Exposed to Lead

Regulatory Option	Average Annual Number of Affected Children 0 to 7[c]	Total Change in IQ Points, 2021 to 2047 in All Affected Children 0 to 7	Annualized Value of Changes in IQ Point Losses[a,b] (Thousands 2018$)	
			3 Percent Discount Rate	7 Percent Discount Rate
Option 1	1,521,036	-3.58	-$1.6	-$0.35
Option 2	1,521,036	-11.07	-$4.95	-$1.08
Option 3	1,521,036	0.35	$0.16	$0.03
Option 4	1,521,036	0.90	$0.40	$0.09

a. Assumes that the loss of one IQ point results in the loss of 1.39 percent of lifetime earnings (following Lin et al., 2018 values from U.S. EPA (2019e)).

b. Negative values represent forgone benefits.

c. The number of affected children is based on reaches analyzed across the four options. Some of the children included in this count see no changes in exposure under some options.

Source: U.S. EPA Analysis, 2019

G.2 Heath Effects in Children from Changes in Mercury Exposure

Table G-3 shows the estimated changes in IQ point losses for infants exposed to mercury in-utero and the corresponding monetary values, using a 3 percent and 7 percent discount rates. All regulatory options result in a net increase in IQ losses and, as a result, in forgone benefits to society. Annualized monetary values of increased IQ losses from changes in mercury exposure, based on the Lin et al. (2018) IQ point value, range from -$0.17 million (Option 1) to -$1.54 million (Options 2 and 3) using a 3 percent discount rate.

Table G-3: Estimated Monetary Values from Changes in IQ Losses for Infants from Mercury Exposure

Regulatory Option	Number of Affected Infants per Year[c]	Total Changes in IQ Losses, 2021 to 2047 in All Affected Infants	Annualized Value of Changes in IQ Point Losses[a,b] (Millions 2018$)	
			3 Percent Discount Rate	7 Percent Discount Rate
Option 1	225,272	-411	-$0.17	-$0.03
Option 2	225,272	-3,785	-$1.54	-$0.30
Option 3	225,272	-3,777	-$1.54	-$0.30
Option 4	225,272	-2,021	-$0.81	-$0.16

a. Assumes that the loss of one IQ point results in the loss of 1.39 percent of lifetime earnings (following Lin et al., 2018 values from U.S. EPA (2019e and 2019h)).

b. Negative values represent forgone benefits.

c. The number of affected children is based on reaches analyzed across the four options. Some of the children included in this count see no changes in exposure under some options.

Source: U.S. EPA Analysis, 2019

Appendix H Methodology for Estimating WTP for Water Quality Changes

To estimate the nonmarket benefits of the water quality changes resulting from the regulatory options, the EPA used results from a meta-analysis of stated preference studies briefly summarized below and described in greater detail in Appendix H in the 2015 BCA document (U.S. EPA, 2015a). The meta-model satisfies the adding-up condition, a theoretically desirable property. [97] This condition ensures that if the model were used to estimate WTP for the cumulative water quality change resulting from a number of Clean Water Act (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.

The meta-analysis is based on a meta-dataset of 51 stated preference studies, published between 1985 and 2011. Each of these studies used a stated preference approach to elicit survey respondents' willingness to pay for water quality changes. The variables in meta-data fall into four general categories:

1. *Study methodology and year variables* characterize such features as the year in which a study was conducted, payment vehicle and elicitation formats, WTP estimation method, 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.

2. *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.

3. *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.

4. *Water quality (baseline and change) variables* characterize baseline conditions and the extent of the water quality change. To standardize the results across these studies, the 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.

Using this meta-dataset, the EPA developed a meta-regression model that predicts how marginal WTP for water quality improvements depends on a variety of methodological, population, resource, and water quality change characteristics. The estimated meta-regression model (MRM) predicts the marginal 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 where not possible. As noted in the 2015 BCA report (U.S. EPA 2015a), the EPA developed two versions of the meta-regression model. Model 1 is used to provide EPA's central estimate of non-market benefits and Model 2 is used to develop a range of estimates to account for uncertainty in the resulting 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:

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[97] 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).

- Model 1 assumes that individuals' marginal WTP depends on the level of water quality, but not on the magnitude of the water quality change specified in the survey. This restriction means that, the meta-model satisfies the adding-up condition, a theoretically desirable property.

- Model 2 allows marginal WTP to depend not only on the level of water quality but also on the magnitude of the water quality change specified in the survey. The model allows for the possibility that marginal WTP for improving from 49 to 50 on the water quality index depends on whether respondents were asked to value a total water quality change of 10, 20, or 50 points on a WQI scale. This model provides a better statistical fit to the meta-data, but it satisfies the adding-up conditions 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, the 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. When the water quality change is fixed at the mean of the meta-data, the predicted WTP is very close to the central estimate from Model 1.

The EPA used the two meta-regression models in a benefit transfer approach that follows standard methods described by Johnston et al. (2005), Shrestha et al. (2007), and Rosenberger and Phipps (2007). In particular, literature on benefit transfer recommends selecting values for methodological variables included in the regression equation with the goal of providing conservative WTP estimates, subject to consistency with methodological guidance in the literature. 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.[98] The transfer approach involved projecting benefits in each CBG and year, based on the following general benefit function:

Equation H-1.

$$\ln\left(MWTP_{Y,B}\right) = Intercept + \sum (coefficient_i) \times (independent\ variable\ value_i)$$

Where

$ln(MWTP_{Y,B})$	=	The predicted natural log of marginal 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.

98 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 217,740 block groups in the 2010 Census. See http://www.census.gov/geo/maps-data/data/tallies/tractblock.html .

Here, $ln(MWTP_{Y,B})$ is the dependent variable in the meta-analysis—the log of approximated marginal WTP per household, in a given CBG *B* for water quality in a given year *Y*.[99] 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 at waterbodies within a 100-mile buffer of the centroid of each CBG. A buffer of 100 miles is consistent with Viscusi et al. (2008) and with the assumption that the majority of recreational trips would occur within a 2-hour drive from home. Because marginal 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 ($WQI\text{-}PC_{Y,B}$), the EPA estimated the marginal 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, the EPA estimated WTP for the households in each CBG for waters within a 100-mile radius of that CBG's centroid. The 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.[100] Total national WTP is calculated as the sum of estimated CBG-level WTP across all block groups that have at least one affected waterbody within 100 miles. Using this approach, the EPA is unable to analyze the WTP for CBGs with no affected waters within 100 miles. *Appendix F* 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, the EPA assumed that household income (an independent variable) changes over time, resulting in household WTP values that vary by year.

Table H-1 provides details on how the EPA used the meta-analysis to predict household WTP for each CBG and year. The table presents the estimated regression equation intercept, variable coefficients ($coefficient_i$) for the two models, and the corresponding independent variable names and assigned values. The meta-regression 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. The EPA assigned a value to each model variable corresponding with theory, characteristics of the water resources, and sites potentially affected by the regulatory options. This follows general guidance from Bergstrom and Taylor (2006) that meta-analysis benefit transfer should incorporate theoretical expectations and structures, at least in a weak form.

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99 To satisfy the adding-up condition, as noted above, the EPA normalized WTP values reported in the studies included in the meta-data so that the dependent variable is MWTP per WQI point. This 'average' marginal WTP value is an approximation of the MWTP value elicited in each survey scenario.

100 Population double-counting issues can arise when using "distance to waterbody" to assess simultaneous improvements to many waterbodies.

In this instance, the EPA assigned six study and methodology variables, (*thesis, volunt, nonparam, non_reviewed, lump_sum, and WTP_median*) a value of zero. One methodological variable, *outliers_trim*, was included with an assigned value of 1. Because the interpretation of the study year variable *(Lnyear)* is uncertain, the EPA gave the variable a value of 3.0796, which is the 75th percentile of the year values in the meta-data. This value assignment reflects an equal probability that the variable represents a real time trend (in which case its value should be set to the most recent year of the analysis) and spurious effects (in which case its values should be set to the mean value from the meta-data). The choice experiment variable *(ce)* was set to 1 to reflect recent trends in the use of choice experiments within the environmental valuation literature. Model 2 includes an additional variable, water quality change (*ln_quality_ch*), which as discussed above allows the function to reflect differences in marginal WTP based on differences in the magnitude of changes presented to survey respondents when eliciting values. To ensure that the benefit transfer function satisfies the adding-up condition, this 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 values of WTP for water quality changes resulting from the regulatory options, the EPA estimated marginal WTP using two alternative settings of the *ln_quality* variable: ΔWQI = 5 units and ΔWQI = 50 units, which represent the low and high end of the range of values observed in the meta-data.

All but one of the region and surveyed population variables vary based on the characteristics of each CBG. For median household income, the EPA used CBG-level median household income data from the 2016 American Community Survey (5-year data) and used a stepwise autoregressive forecasting method to estimate future annual state level median household income. The EPA set the variable *nonusers_only* to zero 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). The EPA set the variable r*iver* to 1 and *mult_type* to 0 because the analysis focuses only on rivers and streams. Other waterbody types (*e.g.*, lakes and estuaries) are excluded from the analysis.

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 10,315 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 10,315 reaches that fall 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 CBGs included in the analysis of benefits from water quality changes resulting from the regulatory options, 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, boat_use*) are set to zero, which corresponds to "unspecified" or "all" recreational uses in the meta-data.[101] 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 at affected resources within the 100-mile buffer of each CBG.

[101] If a particular recreational use was not specified in the survey instrument, EPA assumed that survey respondents were thinking of all relevant uses.

Table H-1: Independent Variable Assignments for Surface Water Quality Meta-Analysis

Variable Type	Variable	Coefficient Model 1	Coefficient Model 2	Assigned Value	Explanation
Study Methodology and Year	intercept	-1.040	-6.14		
	Ce	0.377	0.423	1	Binary variable indicating that the study is a choice experiment. Set to one to reflect that choice experiments represent current state-of-art methods in stated preference literature.
	thesis	0.866	0.774	0	Binary variable indicating that the study is a thesis or dissertation. Set to zero because studies published in peer-reviewed journals are preferred.
	lnyear	-0.412	-0.5	3.0796	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 75th percentile of the year index value for studies in the metadata (21.7) to reflect uncertainty in the variable interpretation. If the variable represents a real time trend, the appropriate value should reflect the most recent year of the analysis. If it represents spurious effects, the values should reflect the mid-point from meta-data. Both interpretations are equally probable.
	volunt	-1.390	-1.184	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 (Mitchell and Carson 1989).
	outliers_trim	-0.367	-0.291	1	Binary variable indicating that outlier bids were excluded when estimating WTP. Set to one because WTP estimates that exclude outlier bids are preferable.
	nonparam	-0.408	-0.39	0	Binary variable indicating that regression analysis was not used to model WTP. Set to zero because use of the regression analysis to estimate WTP values is preferred.
	non_reviewed	-0.709	-0.871	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.
	lump_sum	0.843	0.773	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.

Table H-1: Independent Variable Assignments for Surface Water Quality Meta-Analysis

Variable Type	Variable	Coefficient		Assigned Value	Explanation
		Model 1	Model 2		
	wtp_median	-0.161	-0.151	0	Binary variable indicating that the WTP measure from the study is the median. Set to zero because only average or mean WTP values in combination with the number of affected households would mathematically yield total benefits if the distribution of WTP is not perfectly symmetrical.
Region and Surveyed Population	northeast	1.180	0.593	Varies	Binary variable indicating that the affected population is located in a Northeast U.S. state, defined as ME, NH, VT, MA, RI, CT, and NY. Set based on the state in which the CBG is located.
	central	0.561	0.726	Varies	Binary variable indicating that the affected population is located in a Central U.S. state, defined as OH, MI, IN, IL, WI, MN, IA, MO, ND, SD, NE, KS, MT, WY, UT, and CO. Set based on the state in which the CBG is located.
	south	1.400	1.563	Varies	Binary variable indicating that the affected population is located in a Southern U.S. state, defined as NC, SC, GA, FL, KY, TN, MS, AL, AR, LA, OK, TX, and NM. Set based on the state in which the CBG is located.
	nonusers_only	-0.586	-0.54	0	Dummy variable indicating that the sampled population included nonusers only; the alternative case includes all households. Set to zero to estimate the total value for aquatic habitat changes for all households, including users and nonusers.
	lnincome	0.333	0.96	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	mult_type[a]	-0.827	-0.63	0	Binary variable indicating that multiple waterbody types are affected (*e.g.*, river and lakes). Set to zero because calculations are based exclusively on rivers.
	River	-0.079	-0.174	1	Binary variable indicating that rivers are affected. Set to one because calculations are based exclusively on stream miles. The EPA did not estimate water quality changes for other waterbody types (*e.g.*, lakes and estuaries).
	swim_use	-0.234	-0.27	0	Binary variables that identify studies in which swimming, gamefish, and boating uses are specifically identified. Since data on specific recreational uses of the reaches affected by steam electric power plant discharges are not available, set to zero, which corresponds to all recreational uses.
	Gamefish	0.233	-0.01	0	
	boat_use	-0.725	-0.32	0	

Table H-1: Independent Variable Assignments for Surface Water Quality Meta-Analysis

Variable Type	Variable	Coefficient Model 1	Coefficient Model 2	Assigned Value	Explanation
	ln_ar_agr	-0.271	-0.413	Varies	Natural log of the proportion of the affected resource area which is agricultural based on 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 (NLCD). The *ln_ar_agr* variable was coded in the metadata to reflect the area surrounding the affected resources.
	ln_ar_ratio	-0.034	-0.057	1.238	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*). Set to the mean value from the CBG's with 100-mile buffers containing waters affected by the regulatory options.
	sub_proportion	1.100	0.607	Varies	The size of the affected resources 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 order(s) as the affected reaches within the buffer. Its value can range from 0 to 1.
Water Quality	Q	-0.015	-0.004	Varies	Because marginal WTP is assumed to depend on both baseline water quality and expected water quality under the regulatory option, this variable is set to 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 COMIDs within the 100-mile buffer of each CBG.
	lnquality_ch	NA	-0.746	ln(5) or ln(50)	*Ln_quality_ch* was set to the natural log of ΔWQI=5 or ΔWQI=50 for high and low estimates of the marginal WTP, respectively.

a. The meta-data includes six waterbody categories (1) river and stream, (2) lake, (3) all freshwater, (4) estuary, (5) river and lake, (6) salt pond/marshes, Variable *multi-type* takes on a value of 1 if the study focused on waterbody categories (3) and (6). The EPA notes that the overall effect of this variable should be considered in conjunction with the regional dummies (*e.g.*, a study of the Lake Okeechobee basin in Florida) and that only eight percent of all observations in the meta-data fall in the multiple waterbody categories.

The central estimates for total WTP results shown in Table 6-2 are closer to the low estimates than the high estimates for each regulatory option. The EPA tested several different functional forms for Model 2 and found that the model has the highest explanatory power (R-squared) when water quality change is included in logged form. This implies that water quality change has a nonlinear effect on marginal WTP (MWTP). In particular, small initial increases in the scale of the water quality change scenario have a larger effect on

MWTP than subsequent increases. Therefore, the central estimate of MWTP (based on a water quality change scenario of approximately 20 units) is closer to the low MWTP estimate (based on a water quality change scenario of 50) than to the high MWTP estimate (based on a water quality change scenario of 5). In addition, when Model 2 is used in a benefits transfer application with a water quality change of +20, the mean of the meta-data, the results are very close to the results of Model 1. The EPA presents the results as a range because a water quality change of +5 is closer to the size of water quality changes projected to result from the regulatory options than the +20 analog to the central estimate, while the +50 represents the upper end of water quality changes in existing surveys (and the lower end of the sensitivity benefits range).

Appendix I Uncertainty Associated with Estimating the Social Cost of Carbon

The methodology used to develop interim domestic SC-CO_2 estimates and uncertainty associated with the interim SC-CO_2 values are the same as described in the RIA for the Affordable Clean Energy (ACE) final rule (see U.S. EPA, 2019f). This appendix applies the methodology to the analysis of the climate benefits of changes in CO_2 emissions under the steam electric ELG regulatory options.

I.1 Overview of Methodology Used to Develop Interim Domestic SC-CO_2 Estimates

The domestic SC-CO_2 estimates rely on the same ensemble of three integrated assessment models (IAMs) that were used to develop the global SC-CO_2 estimates (DICE 2010, FUND 3.8, and PAGE 2009)[102] used in the benefits analysis of the 2015 ELG (see U.S. EPA, 2015a). The three IAMs translate emissions into changes in atmospheric greenhouse concentrations, atmospheric concentrations into changes in temperature, and changes in temperature into economic damages. The emissions projections used in the models are based on specified socio-economic (GDP and population) pathways. These emissions are translated into atmospheric concentrations, and concentrations are translated into warming based on each model's simplified representation of the climate and a key parameter, equilibrium climate sensitivity. The effect of the changes is estimated in terms of consumption-equivalent economic damages. As in the estimation of SC-CO_2 estimates used in the 2015 benefits analysis (U.S. EPA, 2015a), three key inputs were harmonized across the three models: a probability distribution for equilibrium climate sensitivity; five scenarios for economic, population, and emissions growth; and discount rates.[103] All other model features were left unchanged. Future damages are discounted using constant discount rates of both 3 and 7 percent, as recommended by OMB Circular A-4. The domestic share of the global SC-CO_2 – *i.e.*, an approximation of the climate change impacts that occur within U.S. borders – are calculated directly in both FUND and PAGE. However, DICE 2010 generates only global SC-CO_2 estimates. Therefore, EPA approximated U.S. damages as 10 percent of the global values from the DICE model runs, based on the results from a regionalized version of the model (RICE 2010) reported in Table 2 of Nordhaus (2017).[104]

The steps involved in estimating the social cost of CO_2 are as follows. The three integrated assessment models (FUND, DICE, and PAGE) are run using the harmonized equilibrium climate sensitivity distribution, five socioeconomic and emissions scenarios, constant discount rates described above. Because the climate sensitivity parameter is modeled probabilistically, and because PAGE and FUND incorporate uncertainty in other model parameters, the final output from each model run is a distribution over the SC-CO_2 in year t based on a Monte Carlo simulation of 10,000 runs. For each of the IAMs, the basic computational steps for calculating the social cost estimate in a particular year t are:

[102] The full models names are as follows: Dynamic Integrated Climate and Economy (DICE); Climate Framework for Uncertainty, Negotiation, and Distribution (FUND); and Policy Analysis of the Greenhouse Gas Effect (PAGE).

[103] See the summary of the methodology in the 2015 Clean Power Plan docket, document ID number EPA-HQ-OAR-2013-0602-37033, "Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866, Interagency Working Group on Social Cost of Carbon (May 2013, Revised July 2015)". See also National Academies (2017) for a detailed discussion of each of these modeling assumptions.

[104] Nordhaus, William D. 2017. Revisiting the social cost of carbon. Proceedings of the National Academy of Sciences of the United States, 114(7): 1518-1523.

1.) calculate the temperature effects and (consumption-equivalent) damages in each year resulting from the baseline path of emissions;

2.) adjust the model to reflect an additional unit of emissions in year *t*;

3.) recalculate the temperature effects and damages expected in all years beyond *t* resulting from this adjusted path of emissions, as in step 1; and

4.) subtract the damages computed in step 1 from those in step 3 in each model period and discount the resulting path of marginal damages back to the year of emissions. In PAGE and FUND step 4 focuses on the damages attributed to the US region in the models. As noted above, DICE does not explicitly include a separate US region in the model and therefore, EPA approximates U.S. damages in step 4 as 10 percent of the global values based on the results of Nordhaus (2017).

This exercise produces 30 separate distributions of the SC-CO_2 for a given year, the product of 3 models, 2 discount rates, and 5 socioeconomic scenarios. Following the approach used by the IWG, the estimates are equally weighted across models and socioeconomic scenarios in order to reduce the dimensionality of the results down to two separate distributions, one for each discount rate.

I.2 Treatment of Uncertainty in Interim Domestic SC-CO_2 Estimates

There are various sources of uncertainty in the SC-CO_2 estimates used in this BCA. Some uncertainties pertain to aspects of the natural world, such as quantifying the physical effects of greenhouse gas emissions on Earth systems. Other sources of uncertainty are associated with current and future human behavior and well-being, such as population and economic growth, GHG emissions, the translation of Earth system changes to economic damages, and the role of adaptation. It is important to note that even in the presence of uncertainty, scientific and economic analysis can provide valuable information to the public and decision makers, though the uncertainty should be acknowledged and when possible taken into account in the analysis (Institute of Medicine, 2013). OMB Circular A-4 also requires a thorough discussion of key sources of uncertainty in the calculation of benefits and costs, including more rigorous quantitative approaches for higher consequence rules. This section summarizes the sources of uncertainty considered in a quantitative manner in the domestic SC-CO_2 estimates.

The domestic SC-CO_2 estimates consider various sources of uncertainty through a combination of a multi-model ensemble, probabilistic analysis, and scenario analysis. We provide a summary of this analysis here; more detailed discussion of each model and the harmonized input assumptions can be found in the 2017 National Academies report. For example, the three IAMs used collectively span a wide range of Earth system and economic outcomes to help reflect the uncertainty in the literature and in the underlying dynamics being modeled. The use of an ensemble of three different models at least partially addresses the fact that no single model includes all of the quantified economic damages. It also helps to reflect structural uncertainty across the models, which is uncertainty in the underlying relationships between GHG emissions, Earth systems, and economic damages that are included in the models. Bearing in mind the different limitations of each model and lacking an objective basis upon which to differentially weight the models, the three integrated assessment models are given equal weight in the analysis.

Monte Carlo techniques were used to run the IAMs a large number of times. In each simulation the uncertain parameters are represented by random draws from their defined probability distributions. In all three models the equilibrium climate sensitivity is treated probabilistically based on the probability distribution from Roe and Baker (2007) calibrated to the IPCC AR4 consensus statement about this key parameter.[105] The equilibrium climate sensitivity is a key parameter in this analysis because it helps define the strength of the climate response to increasing GHG concentrations in the atmosphere. In addition, the FUND and PAGE models define many of their parameters with probability distributions instead of point estimates. For these two models, the model developers' default probability distributions are maintained for all parameters other than those superseded by the harmonized inputs (*i.e.*, equilibrium climate sensitivity, socioeconomic and emissions scenarios, and discount rates). More information on the uncertain parameters in PAGE and FUND is available upon request.

For the socioeconomic and emissions scenarios, uncertainty is included in the analysis by considering a range of scenarios selected from the Stanford Energy Modeling Forum exercise, EMF-22. Given the dearth of information on the likelihood of a full range of future socioeconomic pathways at the time the original modeling was conducted, and without a basis for assigning differential weights to scenarios, the range of uncertainty was reflected by simply weighting each of the five scenarios equally for the consolidated estimates. To better understand how the results vary across scenarios, results of each model run are available in the docket for the ACE final rule (Docket ID EPA-HQ-OAR-2017-0355).

The outcome of accounting for various sources of uncertainty using the approaches described above is a frequency distribution of the SC-CO_2 estimates for emissions occurring in a given year for each discount rate. Unlike the approach taken for consolidating results across models and socioeconomic and emissions scenarios, the SC-CO_2 estimates are not pooled across different discount rates because the range of discount rates reflects both uncertainty and, at least in part, different policy or value judgements; uncertainty regarding this key assumption is discussed in more detail below. The frequency distributions reflect the uncertainty around the input parameters for which probability distributions were defined, as well as from the multi-model ensemble and socioeconomic and emissions scenarios where probabilities were implied by the equal weighting assumption. It is important to note that the set of SC-CO_2 estimates obtained from this analysis does not yield a probability distribution that fully characterizes uncertainty about the SC-CO_2 due to impact categories omitted from the models and sources of uncertainty that have not been fully characterized due to data limitations.

Figure I-1 presents the frequency distribution of the domestic SC-CO_2 estimates for emissions in 2030 for each discount rate. Each distribution represents 150,000 estimates based on 10,000 simulations for each combination of the three models and five socioeconomic and emissions scenarios. In general, the distributions are skewed to the right and have long right tails, which tend to be longer for lower discount rates. To highlight the difference between the impact of the discount rate on the SC-CO_2 and other quantified sources of uncertainty, the bars below the frequency distributions provide a symmetric representation of quantified variability in the SC-CO_2 estimates conditioned on each discount rate. The full set of SC-CO_2 results through 2050 is available in the docket for the ACE final rule (Docket ID EPA-HQ-OAR-2017-0355).

[105] Specifically, the Roe and Baker distribution for the climate sensitivity parameter was bounded between 0 and 10 with a median of 3 °C and a cumulative probability between 2 and 4.5 °C of two-thirds.

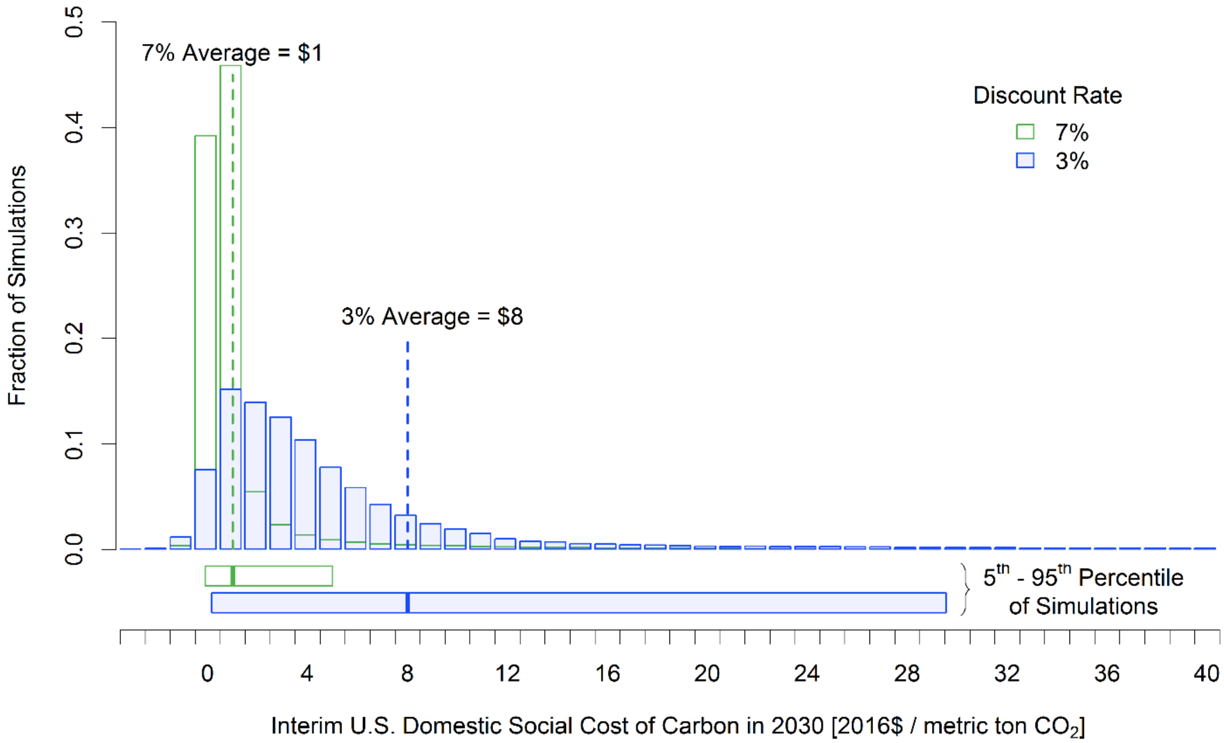

Figure I-1: Frequency Distribution of Interim Domestic SC-CO_2 Estimates for 2030 (in 2016$ per metric ton CO2)

As illustrated by the frequency distributions in Figure I-1, the assumed discount rate plays a critical role in the ultimate estimate of the social cost of carbon. This is because CO_2 emissions today continue to impact society far out into the future, so with a higher discount rate, costs that accrue to future generations are weighted less, resulting in a lower estimate. Circular A-4 recommends that costs and benefits be discounted using the rates of 3 percent and 7 percent to reflect the opportunity cost of consumption and capital, respectively. Circular A-4 also recommends quantitative sensitivity analysis of key assumptions[106], and offers guidance on what sensitivity analysis can be conducted in cases where a rule will have important intergenerational benefits or costs. To account for ethical considerations of future generations and potential uncertainty in the discount rate over long time horizons, Circular A-4 suggests "further sensitivity analysis using a lower but positive discount rate in addition to calculating net benefit using discount rates of 3 and 7 percent" (page 36) and notes that research from the 1990s suggests intergenerational rates "from 1 to 3 percent per annum" (OMB 2003). We consider the uncertainty in this key assumption by calculating the domestic SC-CO_2 based on a 2.5 percent discount rate, in addition to the 3 and 7 percent used in the main analysis. Using a 2.5 percent discount rate, the average domestic SC-CO_2 estimate across all the model runs for emissions occurring over 2020-2045 ranges from $10 to $14 per metric ton of CO_2 (in 2018 dollars). In this case the forgone domestic climate benefits in 2025 are $25 million and $4 million under Options 2and 4, respectively; by 2035, the

[106] "If benefit or cost estimates depend heavily on certain assumptions, you should make those assumptions explicit and carry out sensitivity analyses using plausible alternative assumptions." (OMB 2003, page 42).

estimated forgone benefits increase to $30 million and $14 million under Options 2 and 4, respectively; and by 2045, the estimated forgone benefits are $37 million and $20 million under Options 2 and 4, respectively.

In addition to the approach to accounting for the quantifiable uncertainty described above, the scientific and economics literature has further explored known sources of uncertainty related to estimates of the SC-CO_2. For example, researchers have published papers that explore the sensitivity of IAMs and the resulting SC-CO_2 estimates to different assumptions embedded in the models (see, *e.g.*, Hope (2013), Anthoff and Tol (2013), and Nordhaus (2014)). However, there remain additional sources of uncertainty that have not been fully characterized and explored due to remaining data limitations. Additional research is needed in order to expand the quantification of various sources of uncertainty in estimates of the SC-CO_2 (*e.g.*, developing explicit probability distributions for more inputs pertaining to climate impacts and their valuation). On the issue of intergenerational discounting, some experts have argued that a declining discount rate would be appropriate to analyze impacts that occur far into the future (Arrow et al., 2013). However, additional research and analysis is still needed to develop a methodology for implementing a declining discount rate and to understand the implications of applying these theoretical lessons in practice. The 2017 National Academies report also provides recommendations pertaining to discounting, emphasizing the need to more explicitly model the uncertainty surrounding discount rates over long time horizons, its connection to uncertainty in economic growth, and, in turn, to climate damages using a Ramsey-like formula (National Academies 2017). These and other research needs are discussed in detail in the 2017 National Academies' recommendations for a comprehensive update to the current methodology, including a more robust incorporation of uncertainty.

I.3 Forgone Global Climate Benefits

In addition to requiring reporting of impacts at a domestic level, OMB Circular A-4 states that when an agency "evaluate[s] a regulation that is likely to have effects beyond the borders of the United States, these effects should be reported separately" (OMB, 2003; page 15).[107] This guidance is relevant to the valuation of damages from CO_2 and other GHGs, given that GHGs contribute to damages around the world independent of the country in which they are emitted. Therefore, in this section we present the forgone global climate benefits in 2030 from this proposed rulemaking using the global SC-CO_2 estimates corresponding to the model runs that generated the domestic SC-CO_2 estimates used in the main analysis. The average global SC-CO_2 estimate across all the model runs for emissions occurring over 2025-2045 range from $6 to $13 per metric ton of CO_2 emissions (in 2018 dollars) using a 7 percent discount rate, and $55 to $76 per metric ton of CO_2 emissions (in 2018 dollars) using a 3 percent discount rate. The domestic SC-CO_2 estimates presented above are approximately 18 percent and 14 percent of these global SC-CO_2 estimates for the 7 percent and 3 percent discount rates, respectively.

Applying these estimates to the forgone CO_2 emission reductions results in estimated forgone global climate benefits in 2025 of $14.9 million and $2.3 million under Options 2 and 4, respectively, using a 7 percent

[107] While Circular A-4 does not elaborate on this guidance, the basic argument for adopting a domestic only perspective for the central benefit-cost analysis of domestic policies is based on the fact that the authority to regulate only extends to a nation's own residents who have consented to adhere to the same set of rules and values for collective decision-making, as well as the assumption that most domestic policies will have negligible effects on the welfare of other countries' residents (EPA 2010a; Kopp et al. 1997; Whittington et al. 1986). In the context of policies that are expected to result in substantial effects outside of U.S. borders, an active literature has emerged discussing how to appropriately treat these impacts for purposes of domestic policymaking (e.g., Gayer and Viscusi 2016, 2017; Anthoff and Tol, 2010; Fraas et al. 2016; Revesz et al. 2017). This discourse has been primarily focused on the regulation of GHGs, for which domestic policies may result in impacts outside of U.S. borders due to the global nature of the pollutants.

discount rate; the forgone benefits increase to $126.3 million and $19.3 million under options 2 and 4, respectively, using a 3 percent discount rate. By 2045, the estimated forgone global climate benefits are $34.8 million and $18.8 million, for options 2 and 4, respectively, using a 7 percent discount rate. Using a 3 percent discount rate, the estimated forgone benefits increase to $198.8 million and $107.2 million, for options 2 and 4, respectively.

Under the sensitivity analysis considered above using a 2.5 percent discount rate, the average global SC-CO_2 estimate across all the model runs for emissions occurring over 2025-2045 ranges from $80 to $105 per metric ton of CO_2 (2018 dollars); in this case the forgone global climate benefits in 2025 are $185.7 million and $28.4 million under options 2 and 4, respectively; by 2045, the forgone global benefits in this sensitivity case increase to $276.6 million and $149.1 million, for options 2 and 4, respectively.