

Cross-Sectoral Economic Impact Analysis of Climate Change in New York State

Appendix B: Detailed Methods

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New York State Energy Research
and Development Authority

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Cross-Sectoral Economic Impact Analysis of Climate Change in New York State

Appendix B: Detailed Methods

Final Report

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Notice

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Acronyms and Abbreviations

ΔT	change in temperature
~	approximately
<	less than
>	greater than
°F	degrees Fahrenheit
AADT	average annual daily traffic
AC	air conditioners
ACS	American Community Survey
AHRQ	Agency for Healthcare Research and Quality
ASHP	air source heat pump
ATUS	American Time Use Survey
BenMAP	Environmental Benefits Mapping and Analysis Program
BLS	U.S. Bureau of Labor Statistics
CDC	Centers for Disease Control and Prevention
CDD	cooling degree day
CDF	cumulative density function
CE	Community Edition
cells/ml	cells per milliliter
CES	Clean Energy Standard
CIL	Climate Impact Lab
CIRA	Climate Change Impacts and Risk Analysis
Climate Act	Climate Leadership and Community Protections Act
cm	centimeter
CMIP	Coupled Model Intercomparison Project
CO ₂	carbon dioxide
ConEd	Consolidated Edison, Inc.
CONUS	contiguous U.S.
COVID-19	coronavirus disease 2019
cyanoHABs	cyanobacterial harmful algal blooms
d	day
DO	dissolved oxygen
DOE	U.S. Department of Energy
DOH	New York State Department of Health
DOT	U.S. Department of Transportation
EAD	expected annual damage
ED	emergency department
EIA	U.S. Energy Information Administration

ELCC	effective load carrying capability
EPA	U.S. Environmental Protection Agency
EPIC	Environmental Policy Integrated Climate
PPA	Emissions Prediction and Policy Analysis
ER	electric resistance
ERSTs	electric retail service territories
ESRI	Environmental Systems Research Institute
EV	electric vehicle
FEMA	Federal Emergency Management Agency
FERC	Federal Energy Regulatory Commission
FRA	Federal Road Administration
g/d	grams per day
g/L	grams per liter
g/L	micrograms per liter
g/m ³	grams per cubic meter
g/m ³ /d	grams per cubic meter per day
GCM	global climate model
GDP	gross domestic product
GIS	Geographic Information System
GMSL	global mean sea level
GSHP	ground-source heat pump
GW	gigawatt
GWh	gigawatt-hour
HABs	harmful algal blooms
HCUP	Healthcare Cost and Utilization Project
HDD	heating degree day
HDV	heavy-duty vehicle
HIF	health impact function
HPMS	Highway Performance Monitoring System
TF	high-tide flooding
HUC	Hydrologic Unit Code
HVAC	heating, ventilation, and air conditioning
ICLUS	Integrated Climate and Land-Use Scenarios
IRI	International Roughness Index
ISC	short-circuit current
kg	kilogram
LDV	light-duty vehicles
LIDAR	light detection and ranging
LOCA	Localized Constructed Analogs

LOSS	milk production losses
M&I	municipal and industrial
m/m ³ /d	milligrams per cubic per day
mg/d	milligrams per day
mg/L	milligrams per liter
mg/m ³	milligrams per cubic meter
MHHW	mean high or higher water
MSA	Metropolitan Statistical Area
NASS	National Agricultural Statistics Service
NCA	National Climate Assessment
NCHRP	National Cooperative Highway Research Program
NCPM	National Coastal Property Model
NETs	nonenergy technologies
NOAA	National Oceanographic and Atmospheric Administration
NRCS	Natural Resources Conservation Service
NSAA	National Ski Areas Association
NYC	New York City
NYISO	New York Independent System Operator
NYS	New York State
NYSCIA	New York State Climate Impacts Assessment
NYSDOT	New York State Department of Transportation
O ₃	ozone
OEWS	Occupational Employment and Wage Estimates
OSW	offshore wind
PAD	Program on Applied Demographics
PJM	Pennsylvania-New Jersey-Maryland Interconnection
PM _{2.5}	particulate matter with diameter 2.5 micrometers or less
PRISM	Parameter-Elevation Regressions on Independent Slopes Model
PRM	planned resource margin
PSR	Present Serviceability Rating
PV	photovoltaic
RCP	Representative Concentration Pathway
RECAP	Renewable Energy Capacity Planning Model
RH	relative humidity
RNG	renewable natural gas
RR	relative risk
RTO	regional transmission organization
RUVD	Recreation Use Valuation Database
SCORP	Statewide Comprehensive Outdoor Recreation Plan

SLR	sea-level rise
SRES	Special Report on Emissions Scenarios
SSP	Shared Socioeconomic Pathway
Tdp	average monthly dew point temperature
THI	temperature–humidity index
Tmax	daily maximum temperature
Tmin	daily minimum temperature
TWh	terawatt-hour
UCAP	unforced capacity
UKESM	UK Earth System Model
USD	U.S. dollars
USDA	U.S. Department of Agriculture
USGS	U.S. Geological Survey
VOC	open circuit voltage
VSL	value of statistical life
WASH	water, sanitation, and health
WaSSI	Water Supply Stress Index
WHO	World Health Organization
WNV	West Nile virus
ONDER	Wide-Ranging ONline Data for Epidemiologic Research
WQI	water quality index
WTP	willingness to pay

B1 Overall Methods

The objective of the literature search was to identify and characterize research, studies, and other resources salient to the task of estimating the economic impacts of climate change to New York State (NYS). We created an Excel database to collect and organize these resources. Sources were identified through analyses of three previous impact assessment studies, consultation with experts and their networks, and a formal literature search. The project team applied simple filters to the search results to identify relevant studies, then further analyzed the results by conducting more complex searches and consulting with climate change impact experts on the project team, within NYSERDA, and among professional networks for the purpose of providing recommendations on practical and state-of-the-art methods to support New York State's climate change economic impact assessment. The following sections detail the three components of the literature review process and introduce the literature database.

B1.1 Review of Major Multisectoral Climate Impact Studies

Three previous multisectoral studies provided an initial set of sectoral impact studies that have been used in large-scale assessments and could potentially be relevant for the New York State Energy Research and Development Authority (NYSERDA):

- **NYSERDA 2011 ClimAID Report (NYSERDA 2011):** The ClimAID sectoral economic impact studies (see Annex III), including the research papers underlying the results, are included in the database. The 2024 NYS Climate Impacts Assessment was still under way at the time of this review, so those underlying research papers were not yet available to be included here.
- **U.S. Environmental Protection Agency (EPA) Climate Change Impacts and Risk Analysis (CIRA) 2.0 Technical Report (EPA 2017a):** The CIRA 2.0 (2017) report primarily presents damages by county, with the majority of results available at the state level and smaller spatial scales (i.e., where NYS-specific results could be extracted).¹ The CIRA models cover a large number of sectors and involve a wide variety of researchers in this field who could be called upon to support an NYS assessment. Industrial Economics, Inc., (IEc) continues to be directly involved in this effort with the EPA and, therefore, supplemented the CIRA 2.0 sector studies with recently completed and ongoing studies.

¹ Results at the NYS level and smaller spatial scales are available for 15 of the 20 CIRA 2.0 sectors relevant to NYSERDA: Air Quality, Extreme Temperature, Labor, Aeroallergens, Harmful Algal Blooms (HABs), West Nile Virus (WNV), Roads, Bridges, Rail, Urban Drainage, Coastal Properties, Agriculture, Winter Recreation, Freshwater Fish, and Wildfire.

- **Climate Impact Lab (CIL), various studies summarized in part in Hsiang et al. (2017):**
CIL estimates damages at the county level across numerous sectors. The CIL team of researchers continues to publish studies quantifying the economic impacts of climate change in the U.S. and beyond.

B1.2 Expert Network Contacts

The IEc team, which includes four experts with an array of sectoral specialties, has years of experience in the climate impacts and economic valuation field. Through this experience, we have developed an extensive network of collaborators and peers who provide expertise in numerous specialties within the field. Our four specialized experts reached out to their networks of researchers and practitioners with sector-specific knowledge to identify any studies that our formal literature search may have missed, including recent publications, ongoing developments, and studies with impacts beyond our search terms.

Table B-1 lists the experts from our network who were contacted for this review.

Table B-1. Expert Contacts and Affiliations

Contact	Sector Specialty	Organization
Jeffrey Dukes	Ecosystems	Purdue University
Michael Craig	Energy Systems	University of Michigan
Paul Chinowsky	Infrastructure	University of Colorado
Kim Knowlton	Public Health	Columbia University
Susan Anenberg	Public Health	George Washington University
John Balbus	Public Health	National Institute for Environmental Health Services
Kaz Ito	Public Health	New York City Department of Health
Sarah Johnson	Public Health	New York City Department of Health
Seema Nayak	Public Health	New York State Department of Health
Shao Lin	Public Health	University at Albany
Upmanu Lall	Water Resources	Columbia University
Len Wright	Water Resources	Eagle River Water and Sanitation District
Sarah Fletcher	Water Resources	Stanford University
Steve Chapra	Water Resources	Tufts University
Rich Vogel	Water Resources	Tufts University

Additionally, the primary IEc team for this effort contributed citations derived from our ongoing and previous work on numerous sectors in the CIRA effort. This expert consultation process resulted in an additional 55 citations for the database.

B1.3 Formal Literature Search

The IEc team conducted a formal literature search using Scopus and Google Scholar. To perform a systematic search, we created a set of keywords pertaining to different aspects of the search and constructed a series of queries based on these keywords. The keywords were informed by the findings of the initial major multisectoral studies review.

B1.3.1 Search Criteria

The search prioritized results from the last 10 years but did not explicitly limit results to a certain time period. For most queries, up to the first 50 results per search were added to the formal literature results database, with exceptions made to include up to the first 100 results where appropriate. Relevant studies included single-sector studies and those covering multiple sectors. The list of keywords fell into the following categories: “climate change” or related terms, cost/impact terms and modifiers, regions of interest, and sector or impact type.² Multiple query strings were created using one or more keywords from each keyword category as query components.

Table B-2 shows the general structure, query structure, and query components (i.e., the list of keyword categories and their associated keywords). Overall, a formal search was conducted for 250 unique query strings.

² Sector and impact types were informed by the initial review of ClimAID (NYSERDA 2011), CIRA (EPA 2017a), and CIL (Hsiang et al. 2017) reports and studies.

Table B-2. Summary of Scopus and Google Scholar Queries

Query Structure	
[Climate-related keyword(s)] and [Cost/impact term(s)] and [Cost/impact modifier(s)] and [Region(s) of interest] and [Sector/impact type(s)]	
Query Component	Keywords
Climate-related	Climate change, warming, climate, carbon emissions, emissions scenario
Cost/impact terms	Impacts, damages, losses, costs
Cost/impact modifiers	Economic, socioeconomic, welfare, adaptation
Regions of interest	U.S., Mid-Atlantic, Northeast, Tri-state Area, New York, New York State, Upstate New York, Catskills, New York Metropolitan Area, New York City, Buffalo, Albany, Syracuse
Sector/impact type	Agriculture: Agriculture, crop insurance, crop yield, dairy and livestock, field crops, perennial crops Ecosystem Services/Environment: Environment, ecosystem services Energy: Energy, electricity, energy infrastructure, energy of the built environment, energy supply and demand, energy transmission and distribution Infrastructure: Infrastructure, bridges, coastal flooding, coastal impacts, coastal properties, SLR, storm surge, communication, rail, highways, roads, transportation Human Health and Safety: Public health, health, aeroallergens, asthma, extreme temperature, heat stress, cyanobacteria, harmful algal blooms, mortality, vector-borne illness, West Nile Virus Society and Economy: Property crime, violent crime, freshwater fish, recreational fishing, shellfish, forestry, timber, wildfire, skiing, snowmobiling, winter recreation, labor, labor productivity Water Resources: Water resources; inland flooding; storm runoff; desalination; Water, Sanitation, and Health (WASH); water recycling; water supply; eutrophication; water quality; urban drainage

B1.3.2 Results Filtering

The formal literature search resulted in 326 unique citations, representing 153 unique publications.

Publication dates for search results ranged from 1997 to 2020.

We performed several layers of filters to identify the studies relevant for this work from the 326 initial search results.

During the first round of filtering, we excluded master's theses, honors theses, and citations that either did not appear to be relevant to the NYS context (e.g., coral reef impacts, Southwest dust health outcomes) or did not address climate impact assessment (e.g., studies on perceptions of climate change). Citations that appeared likely to be relevant but required additional examination were flagged but kept on the list and included in the second round of filtering. The first filtering round excluded 176 articles, resulting in 150 remaining articles.

For the second round of filtering, we used Google Scholar to gather additional information for all citations that initially lacked the information necessary for full evaluation, focusing particularly on abstracts. We used similar criteria to the first round to evaluate the remaining 150 citations in terms of the additional information. The second round of filtering excluded 53 articles, leading to a corpus of 97 studies. As in the first round, citations requiring additional examination were flagged; 31 of the 97 remaining sources fell in this category.

The third round of filtering focused on evaluating the flagged articles identified in the first two rounds of filtering. We examined abstracts more closely and referenced the full articles when necessary. We continued to evaluate the citations with our criteria from the first two rounds of coding and extended the evaluation criteria to consider the utility of the results and/or methods for the NYS assessment. Our assessment of the utility to New York State included the spatial scope of the analysis, the spatial and temporal scale of results, and whether economic impacts were presented and/or could be reasonably calculated.³ An additional 15 studies were excluded in round three, leaving 82 remaining articles. Finally, we compared the list of 82 citations from the formal literature search to the citation list compiled from the other two search methods (our review of major, multisectoral climate impact studies and results from our expert contacts). This exercise identified and removed 20 duplicate studies, leaving 62 unique citations.

The final studies were then categorized based on the type of information they provide to the assessment, as seen in Table B-3.

³ For instance, we kept studies that reported increased mortality due to climate change because increased mortality can be transformed into an economic assessment using the VSL. We excluded studies that reported only physical impacts that would be difficult to translate into an economic value, such as changes in temperature or precipitation.

Table B-3. Formal Literature Review Search Results by Citation Category

Citation Category	Description	Count
Impact projection	Climate impact study with projections to future climate scenarios	31
Impact model	Climate/weather impact study with no future climate projections	8
Qualitative source: Sectoral	Literature review or other qualitative discussion of impacts, either for a specific sector or generally	14
Qualitative source: General	Literature review or other qualitative discussion of impacts, either for a specific sector or generally	7
Supporting study: Impacts	Source that may be of use to a particular sectoral study, but does not itself provide a climate impact function	2
Total		62

B1.4 Database Design

The results of the literature search are stored in a literature review database. The database was built in Excel and may be shared upon request. The purpose of the database was to provide a clear format for organizing information about the reviewed articles and to facilitate assessment of studies and the creation of recommendations for NYSERDA.

The database has three main tabs that organize the findings of the literature search:

- **Citations:** Contains a full list of the articles we identified as relevant to NYSERDA's efforts through our three search methods (major study review, general search, or expert network).
- **Modeling Efforts:** Provides information on the major multisectoral modeling efforts that launched the search effort.
- **Sector Impacts:** Organizes relevant citations by sector and outlines key information about the underlying study, including climate models, emissions scenarios, and impacts assessed.

The citations in the Sector Impacts tab are the primary studies evaluated for the NYSERDA assessment, and include studies that forecast climate damage, those that define relationships between climate and outcomes using historical data, and major literature review efforts that provide insight to the general state of the science for the given sector. The tables in three tabs are linked using key identifiers.

The Citations tab stores information about the citations identified through our literature review. This information includes the citation itself, bibliographic data (e.g., the publication year), the type of publication (e.g., journal article, government report), and the citation category (e.g., impact

projection, impact model, qualitative source). This table also tracks where the citation originated from in this study—from the major modeling efforts, through expert review, or through the formal literature search. Each entry in the citations tab is a unique citation. Citations that support or underlie an impact model or climate impacts study are linked to one or more entries in the Sector Impacts tab.

Where each entry in the Citations tab is a unique citation, each entry in the Sector Impacts tab (Impact Sector entry) is a unique sectoral impact model or study. Each Impact Sector entry is associated with a single primary citation and may be associated with additional citations. For example, a sector appearing in ClimAID might cite the ClimAID report, the underlying research paper, and a third source for population projection in New York State. Conversely, a citation could be associated with multiple impact studies. Using the same example, the citations for the ClimAID report and the population projection source might be linked to multiple sectoral studies. Where a study was run with multiple sets of assumptions (e.g., two or more adaptation scenarios), we include just one Impact Sector entry and note the multiple scenarios in the notes.

The data elements reflected within the Sector Impacts table columns were developed in conjunction with NYSERDA with the aim of characterizing the scope of each Impact Sector entry and its potential applicability to a New York State climate assessment. Table B-4 summarizes the Sector Impact columns.

Table B-4. Data Fields in Sector Impacts

Sector Impacts Field	Description
Source type	Impact Projection, Impact Model, Qualitative Source
Modeling effort	CIRA2.0 (EPA 2017a), ClimAID (NYSERDA 2011), CIL (Hsiang et al. 2017)
Sector and impact category	Major classification of the sector (e.g., Agriculture, Public Health, Infrastructure)
Physical and economic impact variables	Outcome metrics from the study in terms of something physical (e.g., percent change in yields, labor hours lost, premature deaths, hospitalization rates) and economic (e.g., changes in income from reduced crop yield, changes in productivity, hospitalization costs)
Adaptation assumptions	Description of adaptation scenarios modeled if any
Damages and climate baselines	Range(s) of years that serve as the baseline for evaluating climate change impacts and damages
Climate models	List of climate projection models used in the study
Emissions scenarios	Climate trajectories simulated in the model (often in terms of RCPs or SRES)
Spatial scope and scale	Spatial scope (e.g., national, regional) and scale of results (e.g., county level)

Table B-4. (continued)

Sector Impacts Field	Description
Temporal scope	Temporal scope and resolution of results (e.g., through 2100, whether results are annual or for multiyear eras)
Socioeconomic trend inputs	Details, where provided, on assumed trends in nonclimatic factors that affect economic impacts, such as GDP and population growth
Approach taken	Identification of the model as process-based, economic, or mixed
Related notes and citations	Summary of the sector, typically adapted from the citation abstract to highlight factors relevant to the NYSERDA assessment

These fields in the Sector Impacts table (summarized in Table B-4) were developed to identify studies that meet specific criteria. For example, if NYSERDA chooses to project impacts out through 2100 in the upcoming assessment, we can filter the database to include only sector models that provide impact projections through the end of this century.⁴

B1.5 Summary of Impact Study Inventory

The database contains 292 citations as of the writing of this report. As described elsewhere in this appendix, these citations were identified through multiple literature review processes. Table B-5 summarizes the contributions of each of these processes to the citations in the database. The majority of citations in the database originated from the three main studies (CIRA, CIL, and ClimAID), which may be due to these citations having been entered in the database first. Duplicate citations identified from later search processes would not have been entered into the list.

Table B-5. Summary of Citations by Literature Review Process

Literature Review Process	Count
Main Studies: CIRA (EPA 2017a), CIL (Hsiang et al. 2017), ClimAID (NYSERDA 2011)	98
Formal Search	63
Experts	62
Other Studies	4
Post-Draft Report Research	65
Total	292

⁴ This is not to say that a sectoral impact study that only projects through 2050 in the existing publication could not be extended through the end of century for a new effort; there are nuances to the ability to adapt existing studies for specific frameworks that are discussed where applicable in the main text of this report.

Of the 292 citations, we evaluated 182 unique sectoral impact sources, 105 of which included economic outcomes. Although our search terms prioritized economic impact studies, we also included physical impact studies to the extent they could either be useful either future physical impact assessments or be coupled with a valuation technique to produce economic outcomes.

Table B-6 shows the sector impact studies categorized across six mega-sectors. Public health, a large societally important category of damage, has the most impact studies in the database. Infrastructure, which covers a wide range of assets and impact types has the second-most studies. The water resources category has the fewest studies (seven); however, water is a cross-cutting issue and plays a role in most other sectors (e.g., floods and irrigation in agriculture, freshwater fish habitat in ecosystem services).

Table B-6. Count of Impact Studies by Sector

Five additional studies were general references or climate stressor references, not tied to specific sectors. Additionally, at this stage of the project, the sector working titles did not match the final sector titles used in Climate Impact Assessment and the Economic Analysis. The initial infrastructure sector was affected by the final buildings and transportation sectors. Impacts on the final society and economy sector can be found in the initial public health (e.g., labor), ecosystem services, or infrastructure sectors.

Sector	All Impacts Count	Economic Impacts Count
Agriculture	18	14
Ecosystem Services	31	19
Energy	19	10
Infrastructure	42	28
Public Health	64	27
Water Resources	8	7
Total	182	105

Of the 105 sector impact studies with economic impacts, 62 provided results at the state or finer spatial scale, including 19 NYS-specific studies. The majority of studies estimated impacts through the end of the twenty-first century and most summarized results by era, although era definition varied by study.

B1.6 Socioeconomic Scenarios

Several types of socioeconomic data were used in some of the modeling.

B1.6.1 Population Dynamics

As noted in Chapter 1, Methodology, this study adopts county-level population forecasts from the EPA's Integrated Climate and Land-Use Study (ICLUS), ver. 2.0, model for population (EPA 2017b). However, projections from the County Projections Explorer from Cornell University's Program on Applied Demographics (Cornell PAD 2018a) were used for electricity demand modeling in the electricity supply and demand sector, consistent with prior work conducted for New York State's Integration Analysis to support the work of the Climate Action Council.

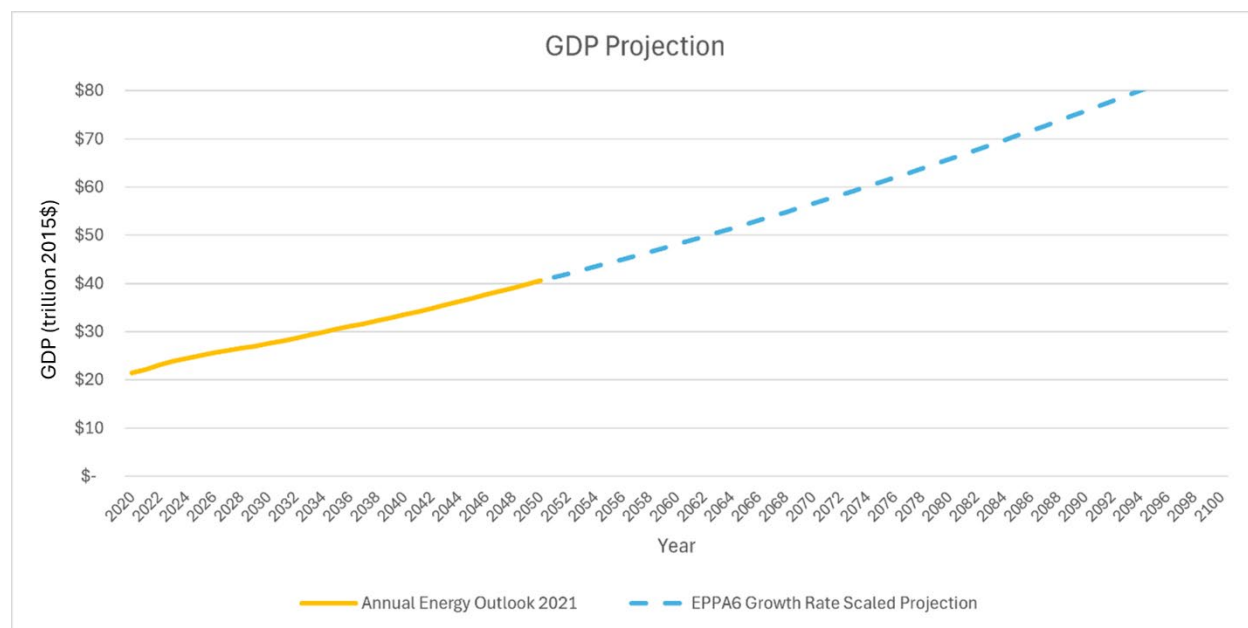
The Cornell PAD projections come from a cohort component model: For year N, $\text{PopN} = \text{PopN-1} + \text{Births} - \text{Deaths} + \text{In-Migration} - \text{Out-Migration}$ is calculated for each age group. The model starts with 2015 population data from Vintage 2017 Bridged-Race Postcensal Population Estimates. Age-specific birth and death rates are derived from the linked postcensal datasets. Age-specific rates of in-migration (currently unavailable) and out-migration are derived from the linked American Community Survey (ACS) datasets. For ages in the 15–34 range (a group with high mobility, for example, due to fluctuating student populations among other factors), these rates were replaced with cohort change rates calculated from the same postcensal population estimates linked above to arrive at more plausible results. For a more detailed description of the methods used to calculate these components, see the PAD methodology write-up (Cornell PAD 2018b).

B1.6.2 Gross Domestic Product Projections

The longer-term gross domestic product (GDP) projection used as the economic output projection basis for this study was developed by a team at the Massachusetts Institute of Technology, using the Emissions Prediction and Policy Analysis (EPPA), ver. 6 model (Chen et al. 2015). The EPPA projections are used as a relative scaler, beginning with the 2050 Annual Energy Outlook (USEIA 2017) GDP value as a starting point, and reflect a declining rate of growth between 2051 (when the growth rate is 1.75% per year), with a decline of 0.05% every five years, to 1.3% in 2100. Figure B-1 illustrates this projection of GDP growth.

Figure B-1. Projected Change in U.S. Gross Domestic Product

The GDP projection shown below uses results from the Annual Energy Outlook for years 2021 through 2050 (solid yellow), and a scaled projection using EPPA6 growth rates from 2051 through 2100 (dotted blue). See text for details.



The impacts of climate change on economic activity (e.g., losses to labor supply or increased capital expenditures for adaptation) are not accounted for in this projection. As such, the usage of this scenario in impact analyses may be overestimating GDP growth when considering the multisector damages. Additionally, the use of a single national-scale economic growth projection that omits region-specific socioeconomic changes may introduce inaccuracies on the regional level when national GDP is used as an indicator of regional economic activity.⁵

B1.6.3 Other Socioeconomic Data

Human health studies make use of additional data sources, such as baseline mortality rates and health incidence rates. This study uses projections of baseline mortality rates through 2060 that were developed for the EPA's Environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP-CE). These include details for age- and race-stratified baseline mortality rates, derived from published data from the Centers for Disease Control and Prevention (CDC Wonder n.d.). Baseline rates of

⁵ To our knowledge, no long-term GDP forecasts yet incorporate COVID-19 impacts. There is some reason to believe that long-term forecasts could be relatively unaffected, at least for future annual growth, once the coronavirus disease 2019 (COVID-19) is brought under control.

hospitalization and emergency department (ED) visits are derived using data from the Healthcare Cost and Utilization Project (HCUP). HCUP is a family of healthcare databases developed through a federal-state-industry partnership and sponsored by the Agency for Healthcare Research and Quality (AHRQ). Baseline incidence rates for some other acute or chronic morbidity categories are from study-specific estimates, documented in EPA (2022).

B1.7 Discounting in the Report

In general, the results in this report are presented as undiscounted. In particular, the economic impact results are summarized by era (e.g., near century, midcentury) and are all presented in undiscounted 2021 U.S. dollars (USD).

In some impact categories, however, a cost of capital is required to develop an annualized estimate, either to convert capital costs to annualized financial flows, or to estimate the response of agents acting to optimize an adaptation response (e.g., in the proactive adaptation scenarios) or the timing of an infrastructure deployment action. Those procedures are not discounting, but could more accurately be termed application of a cost of capital parameter. When applied, the cost of capital is stated in the sector-specific detailed methodology in this appendix; a standard NYSERDA-estimated rate for capitalization (3.6%) is used wherever possible.

B1.8 Key Uncertainties

The approach used in this study estimates climate change economic impacts in a deterministic framework and examines outcomes across multiple climate projections—combinations of Coupled Model Intercomparison Project ver. 6 (CMIP6) global climate models (GCMs) and Shared Socioeconomic Pathways (SSPs)—usually a total of 12 alternative futures (6 GCMs and 2 SSPs).

Attempting to propagate quantitative uncertainty estimates across analytic steps in this study would involve mixing estimates of variability (e.g., across GCMs) with estimates of statistical uncertainty (e.g., for sector impacts that rely on estimated exposure-response or stressor-response relationships) and could not be comprehensively applied across sectors. As a result, quantitative uncertainty analysis beyond characterizations of differences across climate scenarios is not attempted here.

As an alternative, Table B-7 provides a qualitative summary of aspects of uncertainty associated with data sources, modeling, and analytic choices made in the development of this study. Future work to address these uncertainties may further strengthen confidence in the estimates presented in this report.

Limitations specific to the overall framework (such as geographic and sectoral scope) are described in the next section of this chapter. Limitations of individual sectoral analyses are summarized in the respective sector chapters of this report and detailed more fully in the peer-reviewed literature underlying the sectoral analyses.

Table B-7. Summary of Estimated Influence of Key Sources of Uncertainty on Economic Impact Results

This table provides a summary of the known influence of key sources of uncertainty on the economic impact results in this study, including discussion of sources of uncertainty that derive from pre-processing steps that are not inherent to the economic impact analysis. For each identified source of uncertainty, the table provides comments on the relative importance of the likely influence of that source of uncertainty on the economic impact results.

Source of Uncertainty	Analytical Step	Influence of Uncertainty on Economic Impact Results
Greenhouse gas emissions associated with climate policy scenarios	Incorporated in the climate scenarios	Potentially large uncertainties: Identifying the greenhouse gas emissions reductions associated with emissions reduction policies is challenging and is not estimated in this report. The framework is not capable of estimating the impact of this uncertainty on economic impact results.
Climate sensitivity to changes in greenhouse gas emissions	Incorporated in the climate scenarios	Major impact on central estimates: Climate change scenarios are provided as an input to this work. Differences in climate outcomes that result from the climate sensitivity to changes in greenhouse gas emissions can have a large influence on economic impact results and these are characterized by the inclusion of six GCMs representing a range of future climate outcomes for NYS.
Use of six climate models and SLR trajectories to assess variability in climate outcomes	Climate hazard projections	Likely minor impact on central estimates; potentially major impact on variability: The six GCMs used in most of the underlying sector impacts literature were chosen based mostly on the variation in outcome across their results for the full NYS domain. These GCMs do not represent the full range of outcomes that could be considered for temperature and precipitation. Variability across GCMs at the local scale in particular for both temperature and precipitation can be substantial. For SLR scenarios, research has quantified broad uncertainty bands for both GMSL and location specific relative SLR could occur, as summarized in Kopp et al. (2016), and these uncertainties estimates are reflected in the SLR scenarios.

Table B-7. (continued)

Source of Uncertainty	Analytical Step	Influence of Uncertainty on Economic Impact Results
Socioeconomic and demographic change over time	Climate impact estimation	Unknown impact; limited ability to assess within the framework: This report estimates climate change impacts using a consistent default population and GDP forecast. The ability to fully evaluate uncertainty in impacts associated with socioeconomic inputs is limited for three reasons: 1. The underlying peer-reviewed impact studies may incompletely incorporate the effect of changes in population, GDP, demographic distribution, or other socioeconomic factors on impact estimates. 2. The underlying studies generally do not assess how socioeconomic factors affect adaptive capacity, which in turn can affect impact estimation. 3. Socioeconomic drivers may have important correlative dependency on climate scenarios because of the feedback of climate impacts, mitigation policy costs, and incidence on population and economic output, and its spatial distribution.
Structural uncertainty associated with specific impact sector modeling approaches	Climate impact estimation, not assessed	Unknown impact: In general, each analysis was developed using a single-impact model. These models are complex analytical tools, and choices regarding their structure and parameter values can influence the estimation of impacts. The use of additional models would help improve the understanding of potential impacts, but because so few impact models are currently available for use, the impact of adding new models is uncertain. The overall impact across sectors may be minor because: 1. The models applied represent the best available information. 2. Impacts chosen for quantification reflect the best researched and understood climate change impacts, often with multiple lines of evidence supporting the choice of a modeling approach. 3. Most of the models applied have been recently refined to reflect more recent data and improved understanding of impacts through peer review and other process-improvement methods.
Missing analysis of interactive or correlative effects	Climate impact estimation, not assessed	Likely underestimation of impacts; unknown magnitude: In general, the impact analyses were developed independently of one another and, as a result, the estimated impacts may omit important interactive or correlative effects. Cross-sectoral impacts, particularly in infrastructure sectors, have been shown to amplify effects.

Table B-7. (continued)

Source of Uncertainty	Analytical Step	Influence of Uncertainty on Economic Impact Results
Treatment of adaptation to climate impacts and consideration of adaptive capacity	Climate impact estimation, assessed in selected impact categories, but in a limited fashion	Likely overestimation of impact in sectors where adaptation is not assessed; potentially major: Populations will adapt to climate change in many ways, with some actions reducing impacts and others potentially exacerbating impacts. To the extent the underlying sectoral studies do not adequately address the potential for adaptation to cost-effectively mitigate climate vulnerabilities, estimates presented could overestimate impacts. Adaptation response can lead to orders of magnitude differences in impact estimation in some infrastructure sectors (e.g., HTF). For sectors where the impact of adaptation has not yet been assessed in the underlying sector study, impacts are not yet known to be as sensitive to cost-effective adaptation responses as an order of magnitude. The effectiveness of some adaptation measures can be limited because of varied technological feasibility, difficulties in changing human adaptive behavior, high upfront cost, or all three of these factors. See additional discussion of adaptation's influence on estimates in text below.
Impact of population migration that differs from the base case population projection	Climate impact estimation, not assessed	Impact direction unknown; potentially major: Recent demographic and migration trends reflect increasing urbanization in the U.S., and recent literature suggests that climate change impacts and vulnerabilities could be a driver of migration. For the Extreme Temperature Mortality analysis in particular, urban areas display a pronounced heat island effect, which is not incorporated in the framework. As a result, increased urbanization could lead to increased impacts – or migration away from climate hazards, such as extreme temperature and coastal flooding, could decrease impacts. These types of impacts will need to be assessed in the underlying demographic and sectoral impact literature before they can be reflected in impact estimates here or elsewhere.

B2 Agriculture

B2.1 Dairy Production

A cow's response to heat stress can be captured by the temperature–humidity index (THI), which is calculated based on maximum daily temperatures and relative humidity. Decreases in milk production occur as the THI exceeds an identified threshold, and thus, climate-driven milk production losses can be forecasted by calculating projected daily maximum THI. THI has been used in a number of studies in the U.S. and internationally to measure the effect of rising temperatures on milk production. The quantification of milk production loss follows methods outlined in Mauger et al. (2015), which estimates national milk production losses from Holstein dairy cows due to climate change.

Following Equation 1, daily maximum THI is calculated as a function of daily maximum temperature ($T_{\max}$) and relative humidity (RH). Daily relative humidity values are calculated following the August-Roche-Magnus approximation (Equation 2) and using daily maximum temperature $T_{\max}$ and average monthly dew point temperature (T_{dp}) in the baseline period.⁶

Equation 1. $THI = (1.8 T_{\max} + 32) - (0.55 - 0.55 * RH) (1.8 * T_{\max} - 26)$

Equation 2. $RH = 100 * [e^{(17.625 * T_{dp})/(243.04 + T_{dp})}] / [e^{(17.625 * T_{\max})/(243.04 + T_{\max})}]$

Milk production loss begins when the daily maximum THI exceeds an identified threshold as cows move beyond their ideal thermoneutral zone. Following Mauger et al. (2015), milk production losses are assumed to begin at a THI threshold of 70, and consider the proportion of hours throughout the day for which daily THI, calculated in Equation 1, is greater than 70. The climate projections generated for the New York State Climate Impacts Assessment (NYSCIA) provide daily minimum temperature ($T_{\min}$) and ($T_{\max}$); these are distributed across hours of the day using our triangular approximation of the logistic function for hourly temperature from St-Pierre, Cobanov, and Schnitkey (2003). In our work, we approximated the logistic curve as a triangle with the point being $THI_{\max}$. We assumed that since relative humidity was remaining constant throughout the day, this meant that $THI_{\max}$ would occur at $T_{\max}$.

⁶ Baseline dew point temperature values are used here because projected dew point temperatures are not available from the climate projections used in this study. Holding dew point temperature at baseline values while increasing air temperature may result in lower relative humidity values, and consequently somewhat lower impacts.

We also assumed that temperature was increasing linearly from $T_{\min}$ at 12 a.m. until 12 p.m., then decreasing linearly until reaching $T_{\min}$ again at 12 a.m. the next day. Then:

1. We solved for the difference between $T_{\max}$ and $T_{\min}$, then divided that by 24 hours to get hourly change in temperature (ΔT)
2. Using the $THI_{\text{threshold}}$ of 70 that Mauger et al. (2015) reports, we solved for the temperature at which a cow would reach a THI of 70 on a given day ($TEMP_{\text{threshold}}$).
3. We calculated the number of hours above the threshold temperature as $(T_{\max} - TEMP_{\text{threshold}})/(\Delta T)$
4. To calculate D , we assumed:
 - If $t_{\max} < \text{temp threshold}$, threshold hours = 0 then $D = 0$
 - If $t_{\min} > \text{temp threshold}$, threshold hours = 24 then $D = 1$
 - If $t_{\min} < \text{temp threshold} < t_{\max}$ then $0 < D < 1$ and we solved for D as (threshold hours/24)

The D term in Equation 3 below is calculated as the fraction of the day the THI maximum is above 70 ($0 \leq D \leq 1$), and milk production losses (LOSS) are modeled using the regression coefficient $\alpha = 0.0695$ following Mauger et al. (2015) and St-Pierre, Cobanov, and Schnitkey (2003), which is calibrated for Holstein cows. LOSS is calculated at a daily time step in kilograms per cow following Equation 3.

Equation 3. **LOSS = $\alpha (THI_{\max} - THI_{\text{threshold}})^2 \times D$**

This approach is used to calculate daily production losses per cow by county. Total losses are estimated by weighting per-cow results based on the number of dairy cows per county from 2017 to 2021, using data from New York Dairy Statistics (NYS Agriculture and Markets 2020). In the projected period the number of cows is assumed to remain constant in each county and across the State, primarily because projections for changes in dairy cow populations are not available. Forecasted losses are predicted using climate variables (e.g., daily maximum temperature and daily minimum temperatures) from six GCMs and compared to losses in a baseline period from 1981-2010. Daily losses are considered relative to a daily production of 30.11 kilograms per cow (kg/cow) in the absence of heat stress. To quantify economic impacts of milk production losses, a 2022 average wholesale whole milk price from a U.S. Department of Agriculture (USDA) source, which applies to the Northeast region of \$0.53 per kg of milk, is used—USDA wholesale prices are reported in USD per hundred weight, so a conversion of 50.8 kg/hundredweight milk is used. Reported losses, therefore, represent loss of revenue for the dairy industry.

Table B-8. Milk Production Loss Analysis Data Sources

Data	Description	Source
Number of cows	2017–2021, by county	NYS Agriculture and Markets, Division of Milk Control and Dairy Services (2020)
Daily milk production per cow	2017–2021, NYS	USDA NASS (2022).
Price of whole milk	Regional average wholesale price of Class 1 raw milk	USDA, Agricultural Marketing Service (2017)

Table B-9 provides additional county-level detail on the milk production loss results.

Table B-9. County-Level Annual Economic Impacts Associated with Milk Production Losses

Change from baseline. Economic impacts are calculated using the cost per kilogram of milk times milk production loss. Results are reported in millions of 2021 USD per year and averaged across GCMs. Values may not sum due to rounding.

County	Baseline	2030s		2050s		2080s	
		SP2-4.5	SSP5-8.5	SSP2-4.5	SSP5-8.5	SSP2-4.5	SSP5-8.5
Albany	\$0.08	\$0.12	\$0.14	\$0.23	\$0.37	\$0.35	\$0.96
Allegany	\$0.18	\$0.45	\$0.51	\$0.78	\$1.26	\$1.19	\$3.67
Bronx	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
Broome	\$0.18	\$0.38	\$0.43	\$0.65	\$1.02	\$0.97	\$2.76
Cattaraugus	\$0.38	\$0.81	\$0.92	\$1.63	\$2.57	\$2.42	\$7.16
Cayuga	\$2.91	\$4.00	\$4.56	\$7.53	\$11.53	\$10.93	\$28.23
Chautauqua	\$0.93	\$1.58	\$1.79	\$3.15	\$4.83	\$4.59	\$12.28
Chemung	\$0.11	\$0.19	\$0.21	\$0.29	\$0.45	\$0.44	\$1.17
Chenango	\$0.39	\$0.80	\$0.93	\$1.44	\$2.30	\$2.17	\$6.25
Clinton	\$0.67	\$1.20	\$1.42	\$2.28	\$3.71	\$3.48	\$9.79
Columbia	\$0.32	\$0.47	\$0.55	\$0.94	\$1.50	\$1.41	\$3.85
Cortland	\$0.40	\$0.79	\$0.91	\$1.47	\$2.34	\$2.21	\$6.34
Delaware	\$0.13	\$0.30	\$0.36	\$0.62	\$1.04	\$0.97	\$3.11
Dutchess	\$0.14	\$0.17	\$0.20	\$0.36	\$0.57	\$0.54	\$1.36
Erie	\$0.51	\$1.04	\$1.17	\$1.89	\$2.87	\$2.75	\$7.41
Essex	\$0.04	\$0.06	\$0.08	\$0.16	\$0.26	\$0.24	\$0.71
Franklin	\$0.35	\$0.67	\$0.82	\$1.50	\$2.52	\$2.32	\$7.02
Fulton	\$0.04	\$0.08	\$0.10	\$0.15	\$0.26	\$0.24	\$0.72
Genesee	\$1.60	\$2.85	\$3.17	\$4.99	\$7.49	\$7.22	\$18.68
Greene	\$0.01	\$0.02	\$0.02	\$0.04	\$0.06	\$0.06	\$0.18
Hamilton	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
Herkimer	\$0.20	\$0.48	\$0.58	\$1.02	\$1.72	\$1.60	\$5.02

Table B-9. (continued)

County	Baseline	2030s		2050s		2080s	
		SP2-4.5	SSP5-8.5	SSP2-4.5	SSP5-8.5	SSP2-4.5	SSP5-8.5
Jefferson	\$1.61	\$2.68	\$3.13	\$4.96	\$7.71	\$7.31	\$19.07
Kings	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
Lewis	\$0.77	\$1.61	\$1.93	\$3.12	\$5.08	\$4.73	\$13.82
Livingston	\$1.24	\$2.15	\$2.41	\$3.88	\$5.92	\$5.65	\$15.24
Madison	\$0.76	\$1.42	\$1.64	\$2.63	\$4.19	\$3.95	\$11.14
Monroe	\$0.13	\$0.20	\$0.22	\$0.35	\$0.52	\$0.50	\$1.26
Montgomery	\$0.52	\$0.91	\$1.06	\$1.79	\$2.87	\$2.71	\$7.52
Nassau	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
New York	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
Niagara	\$0.66	\$1.11	\$1.22	\$1.88	\$2.78	\$2.69	\$6.72
Oneida	\$0.62	\$1.14	\$1.32	\$2.25	\$3.61	\$3.40	\$9.57
Onondaga	\$1.65	\$2.24	\$2.56	\$4.26	\$6.54	\$6.20	\$16.16
Ontario	\$1.45	\$2.35	\$2.63	\$4.19	\$6.31	\$6.06	\$15.68
Orange	\$0.30	\$0.40	\$0.45	\$0.73	\$1.12	\$1.07	\$2.62
Orleans	\$0.24	\$0.36	\$0.40	\$0.63	\$0.93	\$0.90	\$2.24
Oswego	\$0.17	\$0.28	\$0.33	\$0.54	\$0.84	\$0.79	\$2.14
Otsego	\$0.25	\$0.48	\$0.56	\$0.99	\$1.63	\$1.53	\$4.51
Putnam	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
Queens	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
Rensselaer	\$0.16	\$0.27	\$0.31	\$0.51	\$0.83	\$0.78	\$2.18
Richmond	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
Rockland	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
St. Lawrence	\$1.61	\$2.55	\$3.02	\$5.11	\$8.05	\$7.59	\$20.53
Saratoga	\$0.39	\$0.68	\$0.79	\$1.24	\$1.98	\$1.87	\$5.20
Schenectady	\$0.01	\$0.02	\$0.03	\$0.04	\$0.07	\$0.07	\$0.18
Schoharie	\$0.15	\$0.29	\$0.34	\$0.60	\$0.99	\$0.93	\$2.75
Schuyler	\$0.40	\$0.70	\$0.79	\$1.10	\$1.69	\$1.63	\$4.33
Seneca	\$0.68	\$0.96	\$1.07	\$1.70	\$2.57	\$2.47	\$6.15
Steuben	\$0.83	\$1.65	\$1.88	\$2.70	\$4.26	\$4.07	\$11.61
Suffolk	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
Sullivan	\$0.05	\$0.07	\$0.08	\$0.16	\$0.26	\$0.25	\$0.70
Tioga	\$0.24	\$0.49	\$0.55	\$0.82	\$1.29	\$1.24	\$3.48
Tompkins	\$0.48	\$0.92	\$1.04	\$1.50	\$2.34	\$2.24	\$6.08
Ulster	\$0.02	\$0.03	\$0.03	\$0.06	\$0.10	\$0.09	\$0.25

Table B-9. (continued)

County	Baseline	2030s		2050s		2080s	
		SP2-4.5	SSP5-8.5	SSP2-4.5	SSP5-8.5	SSP2-4.5	SSP5-8.5
Warren	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
Washington	\$0.97	\$1.65	\$1.93	\$3.06	\$4.91	\$4.62	\$12.92
Wayne	\$0.58	\$0.86	\$0.97	\$1.56	\$2.35	\$2.25	\$5.69
Westchester	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01	<\$0.01
Wyoming	\$1.13	\$2.73	\$3.08	\$4.96	\$7.77	\$7.37	\$21.80
Yates	\$0.75	\$1.36	\$1.53	\$2.31	\$3.55	\$3.41	\$8.99
Statewide	\$28	\$49	\$56	\$91	\$142	\$134	\$367

B2.2 Crop Production

In this analysis, we focus on the impacts of climate change on six major field crops: corn, soybean, wheat, hay, potato, and barley. Field crops are a USDA category of agricultural production that includes annual plants grown on a large scale in cultivated fields—it is distinguished from perennial crops, including horticultural crops that can also be grown on a field scale, such as fruits, vegetables, tree nuts, nursery crops, and floricultural crops. We rely on Beach et al. (2015) to provide the relationship between climate and crop yields. Beach et al. use the Environmental Policy Integrated Climate (EPIC) biophysical crop model to generate changes in crop yield by U.S. agricultural region, due to precipitation, relative humidity, wind speed, and solar radiation, with varied impacts by regional climate, soil type, irrigation status, and carbon dioxide (CO₂) levels. The six modeled crops account for approximately \$37 million in annual production value but can provide broader insights into growing conditions.⁷ Effects on other regionally important crops, such as apples and wine grapes; on nondairy livestock and poultry; and on forest-based maple sugar and syrup are addressed qualitatively. Because Beach et al. project yields based on CMIP5 climate scenarios, instead of the CMIP6 scenarios used in this analysis, we derive a reduced-form relationship between projected yields and CMIP5 climate variables and then apply the derived functions to the CMIP6 scenarios.

⁷ Baseline production value is the average values, collected every 5 years, from 2007 to 2017 (USDA 2017).

B2.2.1 Deriving a Reduced-form Relationship to Project Crop Yields

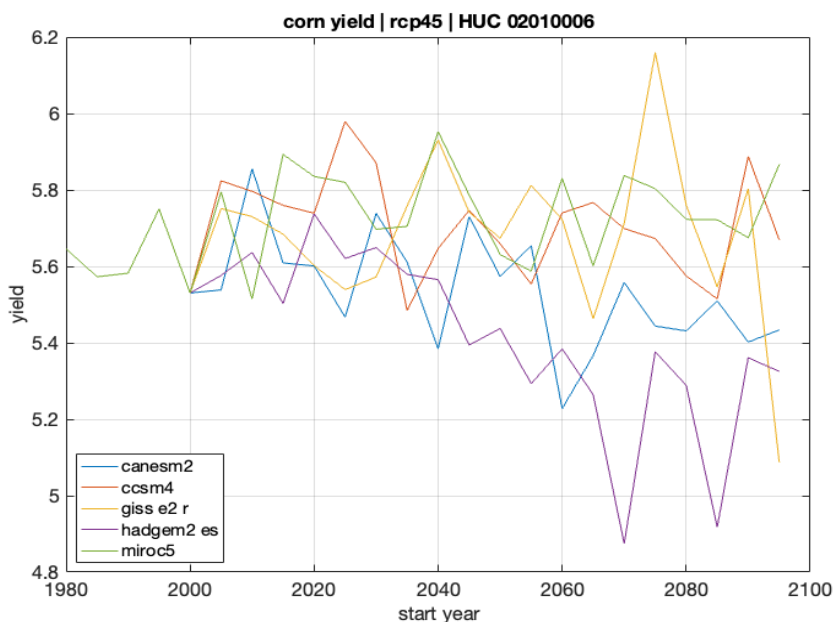
First, we took crop yield simulated output from the EPIC model for barley, corn, hay, potato, soybean, and wheat for historical and projected CMIP5 climate scenarios. EPIC has been applied in multiple settings to assess crop yields under alternative simulated climates. Yield potential is simulated for each crop for both rainfed and irrigated production with the exception of potatoes, which are assumed to be irrigated.

These simulations were performed for the EPA's Climate Impacts and Risk Assessment (CIRA) Project. The CIRA analysis was done over irrigated and rainfed land, but in this section, only rainfed data are used because estimates of water available for irrigating crops under future climate change scenarios is not yet available. The CIRA data was organized into hydro basin catchments labeled by 8-digit Hydrologic Unit Codes (HUCs) for the entire U.S., with data every 5 years from 1980 to 2099. The data was also available for five GCMs and two Representative Concentration Pathways (RCPs). We extracted the outputs for the HUCs in New York State. As an example, Figure B-2 shows simulated corn yield from EPIC for a sample HUC in New York State.

Figure B-2. Representative Simulated Yield over Time for Corn for a Sample Hydrologic Unit Codes

Yield data are available by crop, GCM, RCP, and HUC in 5-year intervals from 1980 to 2100.

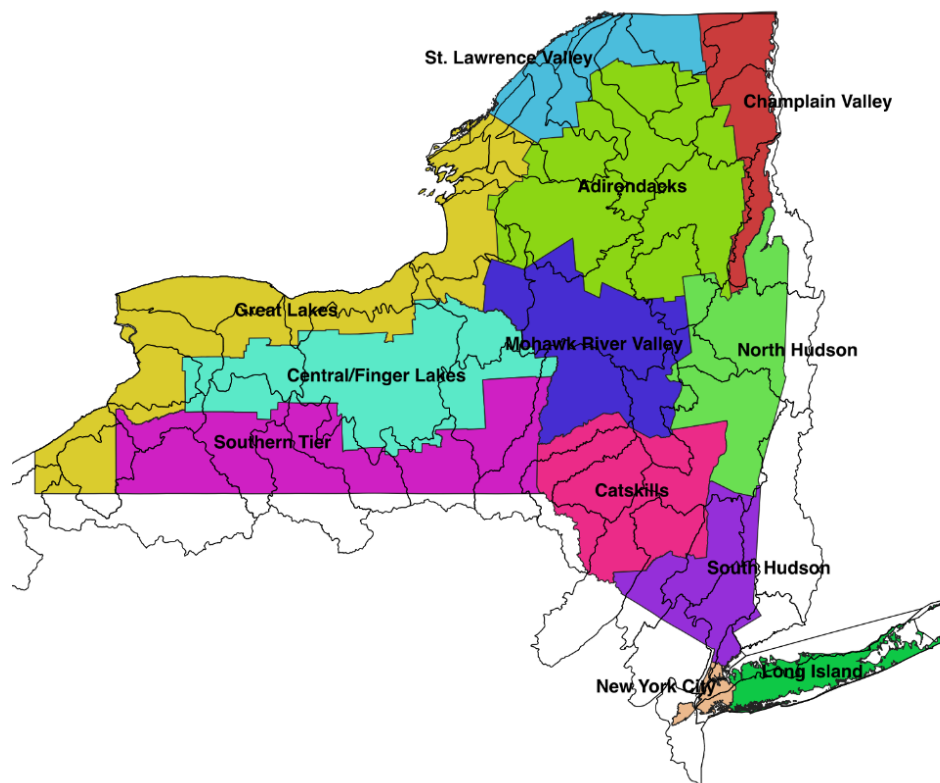
Source: Author's analysis based on Beach et al. (2015).



We then aggregated the data from HUCs to the 12 regions established for this analysis by area-weighted averaging the yield of the crop in each HUC in the region. The NYSCIA regions were used because they were developed as regions with similar combined temperature and precipitation climatic characteristics—temperature and precipitation jointly affect agricultural yields in the EPIC modeling we adapted for this work. Figure B-3 illustrates the spatial relationship among the 12 NYSCIA regions and 52 HUCs for New York State.

Figure B-3. Map of Climate Impacts Assessment Regions Overlaid with Hydrologic Basins

Map of the 12 NYSCIA regions labeled and filled with color over 52 HUCs, outlined in gray.



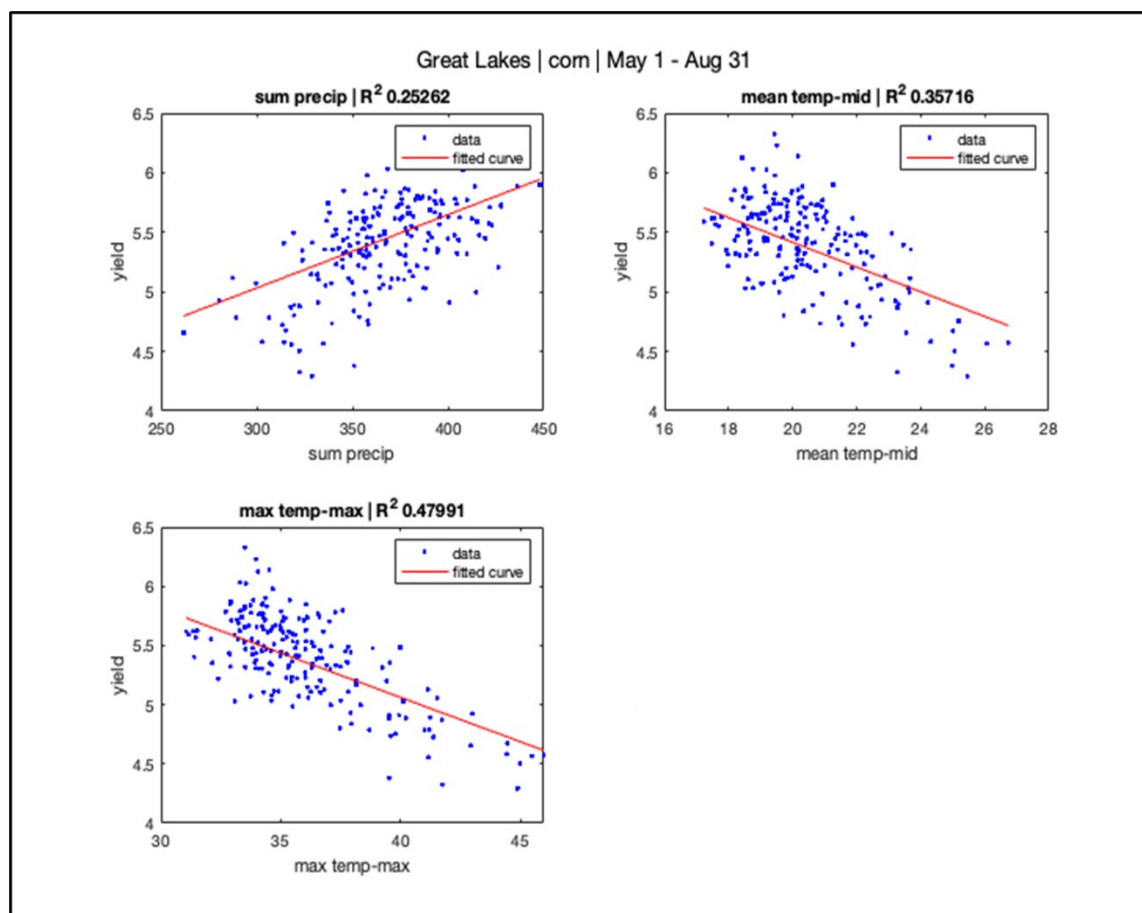
Next, we extracted relevant climate variables from the daily CMIP5 climate data used to create projected yields in Beach et al. (2015). We assumed that only the data over the growing season would be relevant and determined for New York State, defined the growing season to be from May 1 to August 31. Over these days, we extracted three variables from each year:

- Sum of the precipitation over the growing season
- Mean of the daily temperature midpoint (halfway between daily maximum and minimum) during the growing season
- Maximum of the daily temperature maximums during the growing season

We then calculated the mean over 5-year periods for each variable to match the 5-year intervals of crop-yield projections and convert the data from grid cells to regions by averaging area in each region, as was done with crop yields.

For each crop and region, we ran a multiple linear regression relating the three climate variables described above to crop yields. We determined that the two temperature-based variables were highly correlated, so we tested two separate models, each with precipitation and one of the temperature variables, and then chose the model with the highest individual R-squared for the model. Using the precipitation and temperature variables, we reran the multiple linear regression to find the coefficients for that crop that can be used to find yield from climate data. Figure B-4 illustrates this process for corn in the Great Lakes region.

Figure B-4. Illustrative Great Lakes Region Individual Variable Regressions Relating to Yield



For two of the crops, hay and wheat, this process resulted in a poor statistical fit, so other methods were used. For hay, we used observed yield, precipitation, and temperature data from Baral et al. (2022) for rainfed alfalfa in the Great Plains and Northeastern U.S., which included New York State. Alfalfa is one type of hay commonly grown in New York State—about one-third of the overall hay yield in the State is accounted for by rainfed alfalfa, with the other two-thirds including timothy and fescues among the more commonly harvested types. Climate change studies of agriculture sometimes use the modeled alfalfa response to represent the response of the broader hay category (Cho and McCarl 2017). Based on the data from Baral et al. (2022), we created a regression between alfalfa yield and growing-season mean temperature, which, although better performing than models we considered with precipitation as an explanatory variable, still has a low R-squared value (0.23), and results must therefore be treated as indicative only. This acknowledged, the regression indicates a positive relationship between mean temperature and yields, which is consistent with prior research suggesting positive effects of climate change on hay yields in the Northeastern U.S. (e.g., Rotz et al. 2016).

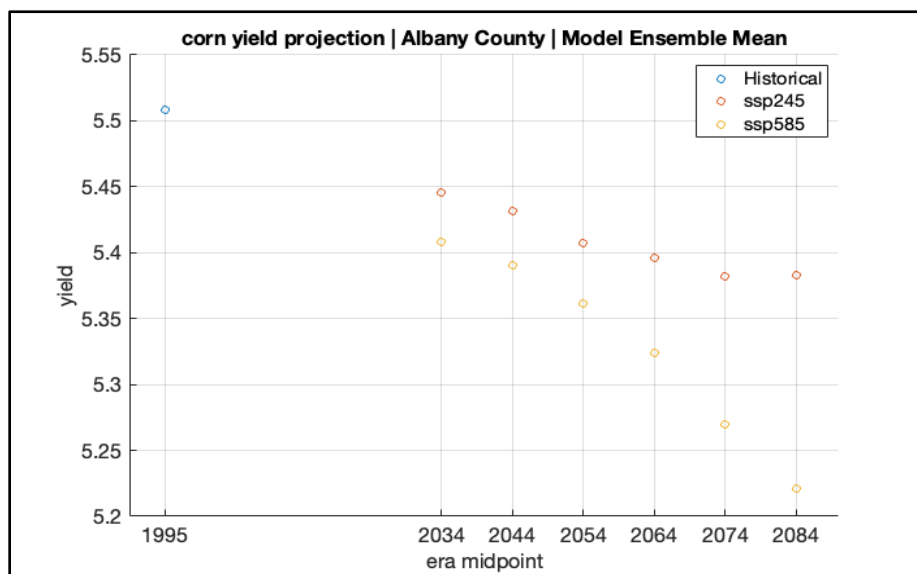
For wheat, New York State cultivates almost exclusively winter wheat, so the winter wheat results from Beach et al. (2015) are used here. We used data from the USDA's National Agricultural Statistics Service (NASS) for 1980 to 2022 and compared the wheat yield to the corn yield in New York State, finding a strong linear relationship between the two with an R-squared of 0.63. We used this relationship to forecast future wheat yields as a function of projected corn yields.

B2.2.2 Projecting New CMIP6 Crop Yield Model

Previously, we created county-level daily climate data from CMIP6 for New York State with 16 GCMs, 2 RCPs, and 6 different projected eras, plus historical data. Using this data, we created the same growing season variables as from the CMIP5 data for 30-year era averages. We then used the crop yield model developed above to project the crop yields for the CMIP6 era-level projections. Figure B-5 is a sample of projected yields for corn for the CMIP6 climates.

Figure B-5. Corn Yield Projection for Albany County Using CMIP6 Climate Data

Figure shows historical yield (far-left datapoint) and projections for SSP2-4.5 (top, red datapoints) and SSP5-8.5 (bottom, yellow datapoints).



Next, we took the ratio of the historical yield to the projected yield. We used NASS data on 2017 production amounts in 58 of the counties in New York State.⁸ We then used price data from the NASS New York State Agricultural Overview (USDA 2023) for 2021 to determine the total value of the production. We multiplied the value of the crops by the ratio found earlier to create projected values for production in each county.

Table B-10. Crop Analysis Data Sources

Data	Description	Source
Crop yield simulation	Basin Level Crop Yields	Beach et al. (2015)
CMIP5 climate data	2.5 x 2 degree, daily from 1976 to 2099	EPA, Office of Atmospheric Programs (2015)
CMIP6 climate data	County by Era from Stations	Bader and Horton (2023)
Baseline production by crop	Data by county for 1980 to 2022	USDA NASS (2023)
Price by crop	Data by county	USDA NASS (2017)

B3 Buildings

B3.1 Coastal Properties

This analysis employs the most recent version of the National Coastal Property Model (NCPM), from Neumann et al. (2021). The model allows for estimation of economic impact for two response scenarios, representing a range of impact response effort and adaptation cost, with higher levels of adaptation effort reflecting implementation of cost-effective measures in the time and location where the benefits of adaptation exceed the costs.

The NCPM simulates the rollout of property protection from both permanent inundation and storm surge using a set of decision rules that are governed by least-cost principles. Within the model, properties can be protected by hard structures like sea walls, which protect from sea-level inundation and storm surge up to the 100-year surge height (in the simulation, seawalls are built to the height of the 100-year flood at the time of construction); elevation of structures, which protects from storm surge only; and beach nourishment, which is similar to hard structures but is only effective up to a certain flood depth. Hard

⁸ For potatoes, the yield data and production came from separate NASS tables. Note that ideally, more than one year of NASS production data would be available to develop this ratio of historical to projected yield, but the 2022 NASS survey was not yet available at the time of this analysis, and the 2012 survey is too dated.

structures and nourishment protect not only the most vulnerable near-coastal properties but are also built to protect properties further inland.

The decision rules within the NCPM compare the cost of different adaptation options within each cell to the expected reduction in damages that would result from those adaptation options. This model assumes that armoring and elevation will be implemented for the 100-year flood—storm surge above that level overtops the flood protection and represents a post-adaptation residual risk, which is also quantified in the model.

The cost-benefit test compares an estimate of discounted avoided damages over the next 30 years with the cost of each adaptation option. This decision rule is based on an estimate of expected annual damages and expected annual benefits of adaptation.

The expected annual benefit is the avoided damages given the assumption that adaptation will prevent damages for events up to and including the current 100-year flood. The decision relies on the following:

- **Cost of adaptation:** Varies across cells and adaptation type. For abandonment, cost is equal to property value. For armoring and elevation, cost includes capital and present value of maintenance.
- **Expected annual damages over 30 years (discounted at 3%):** The calculation is based on the annual damage for a forward-looking 30-year period, at each point when a protection decision is evaluated, and updates each time a decision is made to forgo protection for that period.
- **Expected annual damages with adaptation in place:** Damages for events larger than the 100-year event at the time the protection was constructed.
- **Expected annual benefits of adaptation:** The difference between the expected annual damages without protection and the expected annual damages with protection.

For each adaptation decision, the NCPM looks ahead 30 years, using the prospective 30-year future expected annual damage as the approximation of baseline, pre-adaptation response risk. The NCPM discounts future expected annual damage to model adaptation decision-making, which has, for federal government-sponsored analyses, been the 3% (real) rate required by the Office of Management and Budget's Circular A-4, to obtain a present value of expected damages over 30 years.⁹ Expected damages are estimated with and without adaptation for the 100-year event in order to estimate the present value

⁹ In other parts of this report, we adopted NYSERDA's preferred 3.6% discount rate, however because most major coastal protection projects involve planning and major financing from the U.S. Army Corps of Engineers (the Corps), for the coastal properties analysis, we adopted a federal discount rate to better approximate the Corps project decision-making analysis.

of expected benefits of adaptation. In its simplest form, the decision rule implements the lowest-cost adaptation option if benefits for that option exceed the cost of protection. This represents a traditional benefit-cost test for optimal risk-reduction investment, emulating the protection decision often used by the U.S. Army Corps of Engineers or for flood mitigation assistance to municipal governments (through the Federal Emergency Management Agency, or FEMA). The costs of protection are estimated by site-specific characteristics, such as if the property is situated in the back bay or ocean-facing, which requires additional costs for seawalls to protect from wave action. The model chooses the protection type that is the most cost-effective for that grid cell.

The NCPM includes an initiation period that effectively determines existing protection. In order to estimate the incremental benefits of adaptation, it is important for the model to start from a common and stable state. Effectively, this means that the NCPM must use an economically optimal adaptation build simulation for existing protection, a likely overestimate of existing protection for all simulations, even one without adaptation. As a result, estimates from the NCPM can underestimate the incremental climate change damages.

It is important to note that many adaptation response decisions of this type in the coastal zone are not made with strict cost-benefit decision rules, particularly at the local level. Other factors may include local zoning bylaws, future land use plans, the presence of development-supporting infrastructure, or proximity to sites with high cultural value. However, the analytical framework of the NCPM provides a simple, benefit-cost decision-making framework that can be consistently applied for regional and national-scale analyses.

Table B-11. Coastal Properties Analysis Data Sources

Source: Author's summary based on Neumann et al. (2021).

Data	Description	Source
SLR and tide gauge levels	SLR projections by scenario	Bader and Horton (2023).
Storm surge heights, tide gauge levels	Storm surge heights and tide gauge levels used to develop storm surge heights and probabilities	NOAA (2017)
Infrastructure inventory data	Property value for each 150 m x 150 m coastal county grid cell is derived from compiled tax assessment values for land and structure, and addresses residential, commercial, industrial, institutional, and most categories of public land (excluding military installations)	Updates from Neumann et al. (2010) available by county at CIRA2.0 sectoral impact data repository (IEc 2017)
Elevation, land cover, land use, mean tidal levels	Various land and tidal characteristics for all coastal areas, including elevation, land cover, land use, MHHW historical levels, compiled for use in the NCPM	Neumann et al. (2021)

B3.2 Inland Flooding

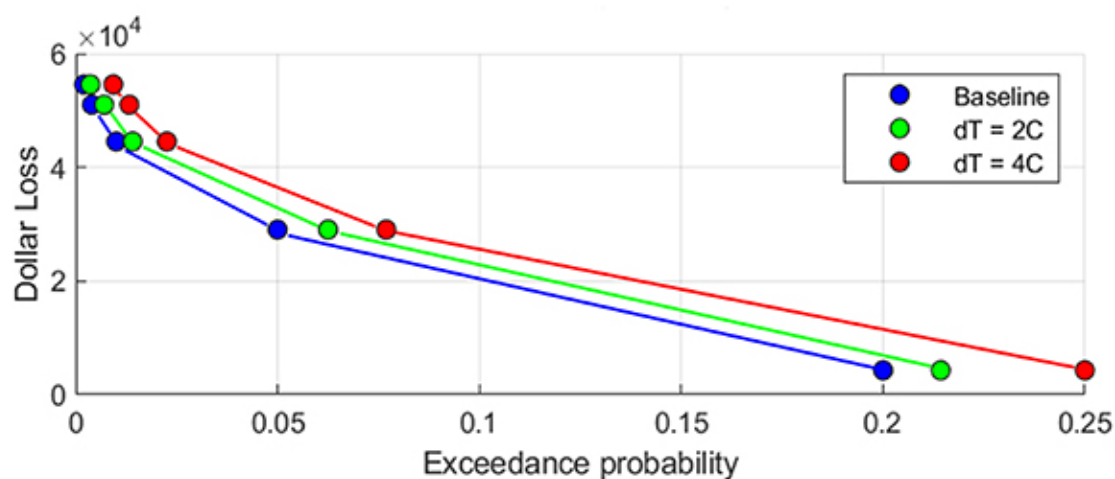
To assess the expected damages from riverine flooding, we rely on flood damage projections from First Street Foundation (2020) and Wobus et al. (2021), modified for the climate scenarios explored in this analysis. The First Street Foundation includes information on riverine flood depths for events with return intervals ranging from the 2-year to the 100-year event at each property in New York State. The First Street database also includes property details such as building type, total square footage, structure value, and other parameters.

Using this dataset and depth-damage functions for each property type, we calculated expected annual damage (EAD) at each property in the State under baseline conditions by numerically integrating under the damage-probability curve for each property. Figure B-6 shows an example of damage-probability curves for the baseline and two future climate scenarios. Each point identified on the baseline (bottom, blue) curve represents dollar losses associated with an event expected to occur with the stated exceedance probability. For example, an event with a 0.2 exceedance probability (20% chance of annual occurrence) in the baseline has relatively low associated dollar losses. A less frequent event (e.g., an event occurring with a 5% chance) has a higher associated dollar loss. The EAD is calculated as the area under the damage curve and therefore accounts for events of varied magnitude and probability of occurring.

Figure B-6. Illustration of Expected Annual Damage Calculation

Schematic illustrating the calculation of EAD for baseline (bottom blue) and future climate conditions (middle green and top red). Discrete dollar losses are calculated from flood depths with probabilities of 0.2, 0.05, 0.01, 0.004, and 0.002. Losses were interpolated between those intervals and total area under the curve was calculated between 0.1 and 0.001. Changing probabilities for future events increase or decrease the area under the curve and, therefore, the EAD. Vertical axis in millions USD for one New York State County. Change in temperature of 2°C (dt = 2c) corresponds roughly to the midcentury estimates for SSP5-8.5, or the late-century estimate for SSP2-45. A 4°C temperature change is roughly the late-century estimate for SSP5-8.5.

Source: Wobus et al. (2021).



The middle (green) and top (red) lines in Figure B-6 represent how under future climates, events of the same magnitude become more likely to occur in any given year (e.g., the same losses associated with an event that had a 5% chance of occurring in the baseline has a 7.5% change of occurrence in the scenario demonstrated by the top (red) line. As each event becomes more frequent, the damage-probability curves are pushed to the right, increasing the area under the curve and expected annual damage.

Flood factors derived from NYS precipitation projections and hydrological data are used to estimate projected EADs under each SSP and era. We calculate flood factors for each HUC (a spatial resolution commonly used in hydrological models) using the USDA's Soil Conservation Service Technical Release 20 (TR-20) flow model, which is an event-based, unit hydrograph rainfall runoff model.¹⁰ Flood factors are a function of the following:

¹⁰The original TR-20 approach was described in a 1983 USCA Soil Conservation Service technical release—while that work is no longer widely cited, the approach is incorporated in many types of hydrology software. A recent reference can be found in the online documentation for HydroCad (USDA Soil Conservation Service n.d.).

- 24-hour rainfalls from the climate projections developed for the NYS Climate Impacts Assessment (six GCMs and two SSPs). See Chapter 1, Methodology, of this report for more information.
- Soil types and land cover data (used to define a “curve number”).
- Slope, or elevation change.
- “K-factor,” a measure of soil erodibility.

TR-20 uses the above information to calculate peak flow for a given rainfall depth. The ratio of peak flow projected in future eras versus the baseline for each HUC (for each GCM-SSP combination) is the flood factor.

Next, we overlaid building locations with HUC-8s and modified the probabilities of the 2-year, 5-year, 20-year, and 100-year events for each property according to the appropriate flood factors. In all cases, the 100-year change factor was assumed to be the same as the 20-year change factor. We then reconstructed the damage-probability curves with these new flood probabilities, and numerically integrated under the curve as in the baseline condition to calculate a new EAD for each property. In general, increasing likelihoods of each flood event in New York State push the damage-probability curves to the right, increasing the area under the curve and expected annual damage. These changes in EAD are analogous to those depicted in Figure B-6.

Table B-12. Flooding Analysis Data Sources

Data	Description	Source
Station data	Precipitation, maximum and minimum temperature by station	Bader and Horton (2023)
PRISM data	Precipitation, maximum and minimum temperature by 1/24th degree	PRISM Group (n.d.)
Precipitation data	The 2-year and 100-year 24-hour precipitation frequency estimates (maximum) for the Western U.S. and the Ohio River Basin	PRISM Group (n.d.) and USDA TR-20 (n.d.)
Land cover data	The dataset is in raster format (200-meter resolution) and is classified into 21 classes of land cover	USGS Earth Explorer (n.d)
Soil data	Hydrologic soil group polygons	USDA Soil Data (n.d.)
Slope	Describes the maximum change in elevation between each cell and its neighbors	USGS EROS (n.d)
Flow direction	Defines the direction of flow from each cell to its steepest down-slope neighbor	

Table B-13 summarizes the climate models used for each scenario, along with the abbreviations used in the output files.

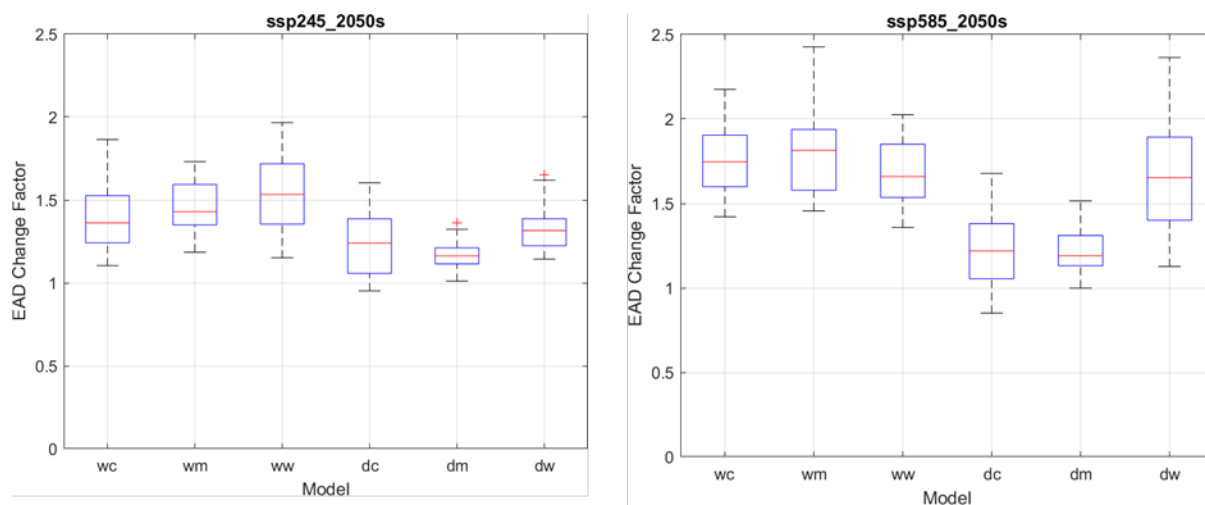
Table B-13. Scenarios, Climate Models, and Outputs

Scenario	Climate Model	Abbreviation Used in Figures
Wet, cool	CNRM-ESM2-1	wc
Wet, moderate	ACCESS-ESM1-5	wm
Wet, warm	UKESM1-0-LL	ww
Dry, cool	INM-CM4-8	dc
Dry, moderate	NorESM2-LM	dm
Dry, warm	HadGEM3-GC31-LL	dw

The two examples in Figure B-7 illustrate the general effects of climate change on riverine flood damages across New York State, at midcentury under moderate (SSP2-4.5) and more severe (SSP5-8.5) climate change scenarios. In each figure, the y-axis is the change factor on EAD, the x-axis is the model identification (i.e., wet, warm or dry, cool), and the box and whisker plots summarize EAD change factors from all of the HUC-8 watersheds in the State. As shown in this figure, by midcentury, the models suggest median EAD changes of ~25%–50% higher than baseline under the moderate climate change scenario, and 25%–75% higher than baseline under a more severe climate change scenario.

Figure B-7. Example Change Factors for Midcentury

Changes in EAD for riverine flooding in the 2050s era.



B4 Energy

B4.1 Electricity Transmission and Distribution Infrastructure

Table B-14 lists the impacts for New York State, and details follow. Table B-14 also summarizes the approach used to simulate adaptation to each stressor under two response scenarios: reactive response and proactive adaptation. These scenarios represent a range of potential responses and adaptation efforts, but they are not the only possible adaptation responses to climate hazards. Other adaptation options are also possible, and new strategies may evolve over time.

For the reactive and proactive strategies, utilities respond by “designing” infrastructure to either recent climate (reactive) or an expected future climate (proactive) based on climate projections. This is done by upgrading infrastructure until it meets the baseline performance or service level. For example, for wood pole lifespan reductions, upgrades are made until the historic aggregate baseline lifespan is achieved. Reactive and proactive responses are distinguished by designing to different climates, either reactive to the past climate or proactive to a projected future climate. Proactive adaptation designs to the future lifespan using an “expected” climate. Perfect foresight is not used, as it would be unrealistic. Instead, it is designed using the mean over all the climate projections to provide a projected change from current climate. In this way, proactive adaptation is forward-looking but does not design perfectly.¹¹

¹¹ Depending on the actual future climate that occurs, the infrastructure could be overdesigned and in others it could be under-designed, both causing undesirable outcomes. For this reason, and only in rare cases, the proactive approach can be more costly overall because the uncertainties in the projection related to the lifespan of the infrastructure are such that a reactive approach is more cost-effective. This approach does not take into account potential improvements in climate model projections over the next century.

Table B-14. Summary of Climate Change Damages and Response Assumptions for the Electric Grid Infrastructure Analysis

Source: Author's summary based on Fant et al. (2020).

Climate Hazard	Impact	Description	Reactive Response	Proactive Adaptation
Increased temperature	Reduced transformer lifespan and capacity (both substation and distribution)	Changes in air temperature cause changes in the lifespan and capacity of large power transformers	Build replacement transformers using recent climate	Build replacement transformers using projected climate
Increased temperature	Reduced transmission line capacity	High temperatures cause a reduction in transmission-line ampacity	Ampacity upgrade of existing lines using recent climate	Ampacity upgrade of existing lines using projected climate
Precipitation and temperature changes	Wood pole decay	Changes in precipitation and temperature alter the rate of decay at the base of the wood poles	Steel reinforcement as needed based on the recent climate	Steel reinforcement as needed based on projected climate
Precipitation and temperature changes (indexed to temperature changes)	Change in vegetation management needs	Changes in climate result in altered vegetation growth, which requires changes in vegetation management	No adaptation options considered	No adaptation options considered
SLR and storm surge	Substation damage from SLR and storm surge	SLR inundation or rising storm surge heights necessitate either relocating or repairing substations	Ancillary beach nourishment is intended to protect the beach and property	Ancillary beach nourishment and protection from engineered structures built to protect property

The following are additional details on the model approach for each of the impacts listed in Table B-15:

- Substations and distribution transformers:** Two types of transformers are considered, large power transformers within substations (substation transformers) and standalone transformers, either on the ground in a covered metal box or fixed on power poles (distribution transformers). As in Fant et al. (2020), transformers are modeled as being primarily impacted by changing ambient air temperature,¹² which affects transformer lifespan and capacity. Higher air temperatures affect the hot spot conductor temperature within the transformer, which in turn reduces the peak load capacity of the bank of transformers. Higher ambient air temperature

¹²Complete transformer failure due to high temperatures or lightning strikes is rare and poorly characterized historically, and is thus excluded from this analysis.

also reduces transformer lifespan by developing hot spots within the cooling system, which can damage the insulating paper that prevents short circuits. An established approach is applied to estimate reduced transformer lifespan for smaller transformers used in the distribution system and large power transformers, the primary components of substations. Changes in capacity are modeled with a linear relationship derived from existing literature. Both the reduction in capacity and lifespan result in more transformers needed or more frequent replacement. Under both the reactive and proactive scenarios, unit costs are higher for transformers with higher temperature thresholds, but replacement frequency is lower.

- **Change in summertime capacity of the high-voltage transmission system:** Rising ambient air temperature increases the resistance of conductors and thereby decreases the carrying capacity of cables (“ampacity”). These decreases in capacity may create a bottleneck in the grid if extremely hot days become more common. Bartos et al. (2016) developed a method for evaluating these impacts, which are applied here with only minor modifications as described in Fant et al. (2020). If planners ignore these capacity losses, lines may need to be shut off on hot days, potentially causing major outages. Typically, these lines are monitored closely, and as a result, outages on the transmission system¹³ are generally very rare. To maintain system capacity, an assumption is made that existing lines will have ampacity upgrades (i.e., replacement with higher capacity lines) during routine replacement of cables (reactive/proactive), at a higher cost per mile.
- **Wood pole decay:** The primary mechanism by which air temperature and precipitation impact wood poles is through degradation from fungal attack at the base. Following Fant et al. (2020), timber pole degradation is estimated using a general form of the relationship between climate and pole decay rate (caused by fungal attack). Decay reduces the diameter of the pole, which then reduces the pole strength to the point of requiring a replacement. Similar to transformers, a reduced wood pole lifespan means more frequent replacement. This is valued based on estimated unit costs for steel reinforcement under a reactive or proactive case.
- **Vegetation management:** In Fant et al. (2020), the impact of increased vegetation on the electricity transmission and distribution system is quantified in a simple way. With increased vegetation, the authors assume vegetation management costs will also increase and that this relationship is linear, while recognizing that in areas of the U.S. with more tree cover, vegetation management costs are higher than in regions that are drier (e.g., Arizona). Increased vegetation management costs under climate change are based on estimated costs per mile per tree density. In Fant et al., this was modeled for a specific set of climate projections that do not align with those modeled here. Here, a linear relationship between changes in vegetation growth and in county mean annual temperature is developed from Fant et al.’s projected results and applied to the changes in county annual temperature used in this New York State study. The reduced-form temperature indexing approach implicitly captures the effects of changes in precipitation or CO₂ fertilization, both of which are major drivers of vegetation change. It is

¹³The same effect may occur on distribution lines, but these often run well below capacity and so are not included here.

assumed that utility companies will increase vegetation management expenses to keep vegetation away from lines and other infrastructure, rather than neglecting the increased growth, which would be much more costly due to increased outages and infrastructure repair/replacement. Therefore, different adaptation options are not considered for vegetation management, i.e., all response scenarios are the same.

Table B-15. Electric Transmission and Distribution Infrastructure Analysis Data Sources

Source: Author's summary based on Fant et al. (2020).

Data	Description	Source
Substations, transmission lines, and electric retail services	Homeland Infrastructure Foundation Level Data; contains shapefile for substations, transmission lines, and ERSTs across the U.S.	HIFLD (2017)
FERC Form 1	FERC has annual reports on electric utilities across the U.S., which contain information on substation transformers	FERC Form 1 (n.d.)
Distribution line miles, distribution transformers	2017 Utility Data Institute <i>Directory of Electric Power Producers and Distributors</i> ; used to calculate number of distribution line miles and distribution transformers per county	Platts (2017)
Electricity sales and number of customers by state, utility, and sector	The EIA has yearly data on electricity sales and a number of customers by state, utility, and broken down by sector (industrial, residential, commercial)	USEIA (2018)
SLR and tide gauge levels	SLR projections and tide gauge levels used to develop storm surge heights and probabilities	NOAA (2017)
Changes in aboveground tree carbon	Changes in aboveground tree carbon are used as a proxy to project changes in vegetation management costs	EPA (2017a)

B4.2 Energy Supply and Demand

This assessment relies on hourly temperature projections from GCMs to examine the impacts of climate change on NYS's electrical system. There are a number of GCMs that vary in their sensitivity to different climate drivers which in turn impacts the degree of change that each GCM projects in New York State. In addition, GCMs can be run for multiple different Shared Socioeconomic Ppathways (SSPs) which contain different assumptions about future emissions and other inputs.

By combining 6 different GCMs with 2 different SSPs, 12 different climate projections were available for examination. However, to allow for a focused examination of energy system impacts, this analysis relies on three distinct GCMs that broadly capture a wide range of climate futures, and the corresponding range of potential impacts that climate change might have on the bulk electricity system. Although results from the 3 other GCMs would likely have provided useful insights into the impacts of climate change on New York State’s power system, the analysis team was unable to incorporate projections from these additional GCMs into the analysis due to resource constraints.

To determine the range of scenarios to use in assessment of low and high range of electric infrastructure impacts, this analysis focuses primarily—but not exclusively—on the seasonal extremes across the 12 climate projections considered for this study. The analysis referenced the hottest and coldest temperatures in each year of projected climate realizations and compared climate scenarios using median (“one occurrence in two years”) temperatures and outer quantiles (shown below). The median temperature is a particularly important metric because many system planners, including the New York Independent System Operator (NYISO), develop their planning requirements around the median system peak (see NYSERDA 2023 for details).

Prior work as part of the NYS Climate Action Council’s Scoping Plan process used a set of proxy assumptions for the impact of climate change on future demand, assuming that cooling demand would grow by 1% per year, and assuming no impact on future heating demand (see NYSERDA 2023 for details). Based on review of the range of GCMs available for this economic analysis, this assumption set aligns most closely with the INM-CM4-8 GCM in SSP2-4.5. This analysis therefore defines a “mild” scenario that continues the one 1% per year Scoping Plan assumption through 2050 and then uses levels of warming projected by INM-CM4-8 in the 2050—2100 period. This mild scenario serves as the energy planning baseline for this analysis, and economic impacts are measured as the difference between other climate scenarios and the mild scenario.

A maximum of two additional climate scenarios could be adopted in this work, owing to the computational and resource requirements of the modeling platform. One moderate scenario is intended to capture relatively higher levels of overall warming in the summer, with extreme summer temperatures on the hottest days, and more muted impacts of warming on cold winter temperatures, relative to other GCM projections. The second is a “severe” scenario which reflects some of the highest warming impacts both in the summer, leading to increased cooling demand across the entire summer and extreme hot days, as well as in the winter, with climate impacts leading to a substantial increase in winter minimum

temperatures and corresponding reductions in heating demand. Based on the climate realizations in Figure B-8, the analysis uses the ACCESS GCM under the SSP2-4.5 pathway as the moderate climate scenario, and the UKESM GCM under the SSP5-8.5 pathway as the severe climate scenario. Figures B-9 and B-10, respectively, show a more detailed comparison of the projected distributions of winter and summer extreme temperatures for each scenario. Changes in heating degree days (HDD) and cooling degree days (CDD), which impact annual heating and cooling demand projections, were also accounted for. The effective annual CDD growth rates from 2020–2100 are 0.52%, 1.29% and 2.52% in the mild, moderate, and severe scenarios, respectively. The HDD growth rates are -0.04%, -0.39% and -1.25%, respectively.

Figure B-8. Historical and Projected Minimum and Maximum Temperatures in New York State

Source: *Impacts of Climate Change on the New York Energy System (NYSERDA 2023)*.

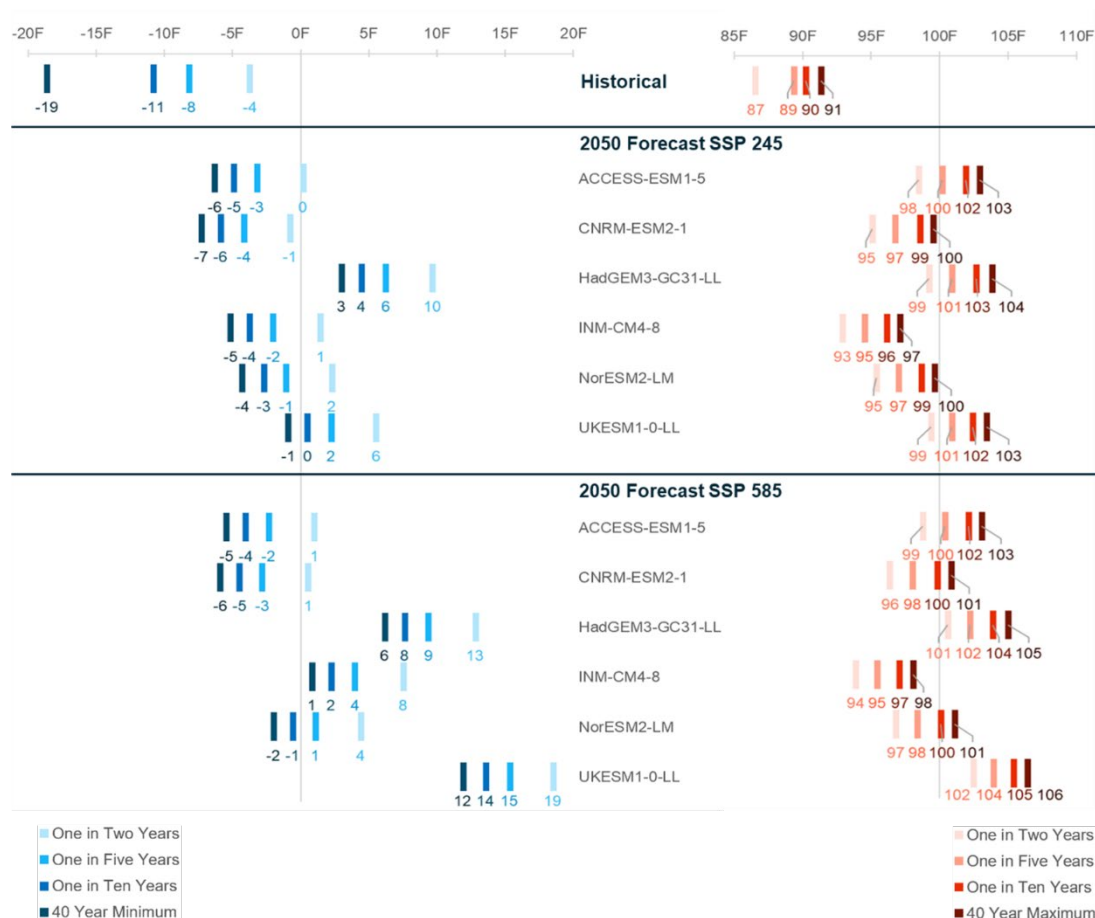


Figure B-9. Projected Winter Minimum Temperatures under Selected Scenarios

Source: *Impacts of Climate Change on the New York Energy System (NYSERDA 2023).*

Climate Change Scenarios

Quantiles of Annual Minimum Temperature (F)

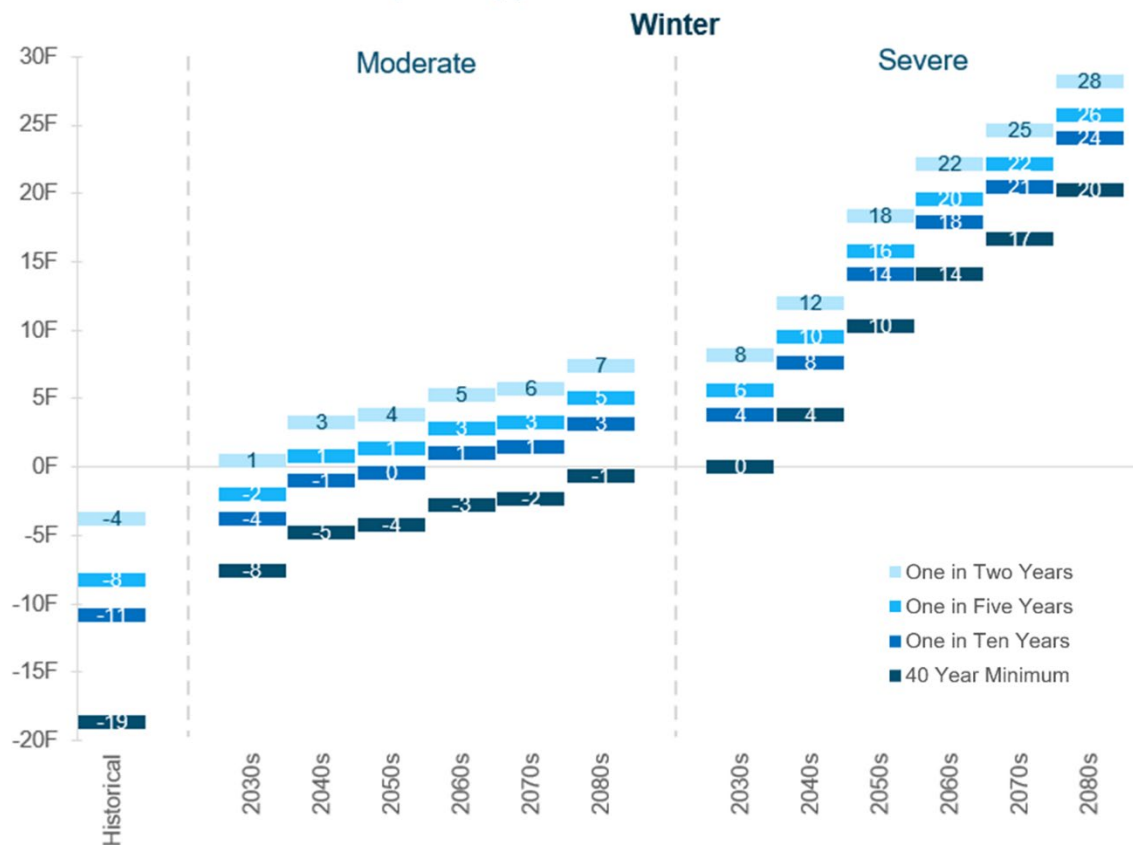
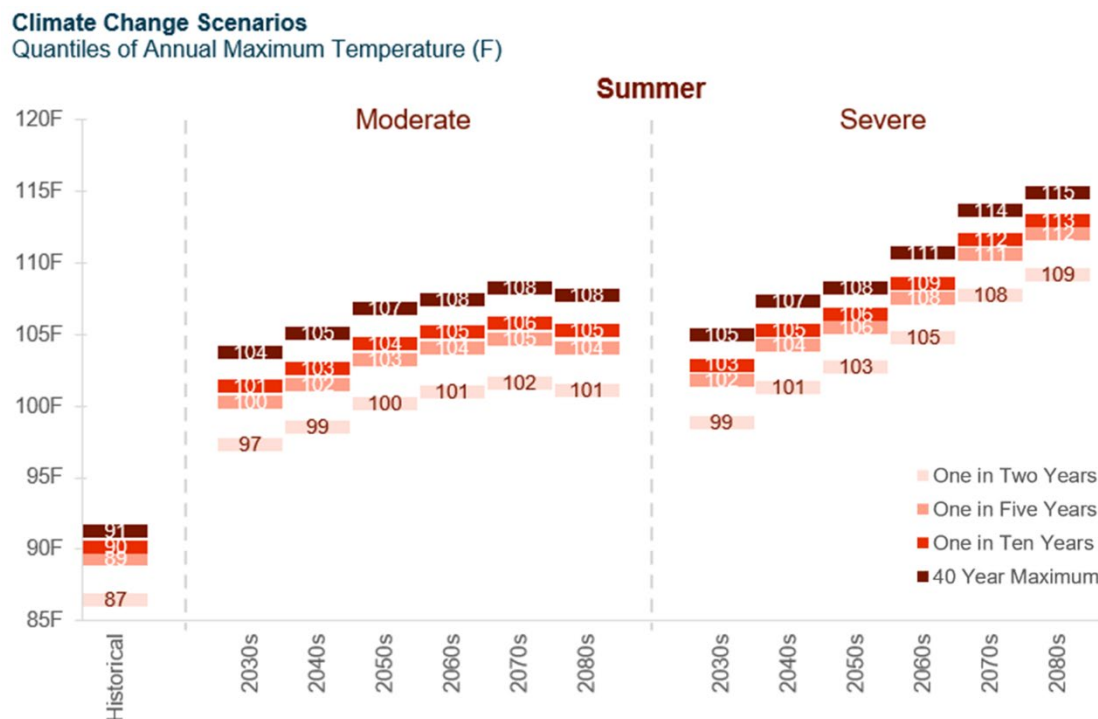


Figure B-10. Projected Summer Maximum Temperatures under Selected Scenarios

Source: *Impacts of Climate Change on the New York Energy System (NYSDERDA 2023).*



It should be noted that all GCMs evaluated in this analysis provide a clear signal of warming winter temperatures, including on extreme temperatures. However, severe winter storms and polar vortex events are likely to continue to be a significant risk to the reliability of the electricity system for years, if not decades, to come. The mild scenario represents a case in which the system continues to plan for a winter that resembles historical conditions, with no discernible impact on winter heating demand on either an annual or peak basis. While impacts of three different climate scenarios are presented in this section, the economic impacts presented in the broader climate impacts report, including the Executive Summary, used the moderate results to represent an SSP2-4.5 scenario and the severe results to represent an SSP5-8.5 scenario.

B4.2.1 Infrastructure Scenarios Overview

The assessment examined the impacts of climate change on two future infrastructure scenarios: a reference case and a decarbonization scenario.

The reference case is defined as a business-as-usual case that contains all implemented policies in New York State as of 2021 (the start of the Scoping Plan analytical work), including but not limited to energy efficiency achieved by funded programs, funded building electrification, a statewide zero-emission vehicle mandate, and a statewide Clean Energy Standard (CES) including technology carveouts.

The decarbonization scenario represents a scenario that is fully compliant with the Climate Act, using “Scenario 2: Strategic Use of Low Carbon Fuels” from the Final Scoping Plan Integration Analysis as the starting point. Both cases include the tax credits available to generators under the Inflation Reduction Act. The reference case includes only the 70% by 2030 CES, while the decarbonization scenario also includes the 100% by 2040 Zero-Carbon Electricity goal enroute to the net-zero economy-wide goal by 2050. a summary of infrastructure impacts assumed is presented below. While two infrastructure scenarios were considered, economic results referenced elsewhere in the economic assessment report, unless otherwise labeled, correspond to the decarbonization scenario.

Table B-16. Summary of Assumptions and Infrastructure Impacts between the Reference and Decarbonization Scenarios

Source: Impacts of Climate Change on the New York Energy System (NYSERDA 2023).

Description	Reference	Decarbonization
New sales of heat pumps	4% by 2025	77% by 2029, 100% by 2030/2035 (Single Family/Multifamily + Commercial)
Share of electrified buildings	7% by 2030 & 2050 0.6 million households by 2030 and 2050 0.6 billion commercial sq. ft. by 2030 and 2050	18% by 2030, 92% by 2050 1.5 million households by 2030, 7.8 Million by 2050 1.1 billion commercial sq. ft. by 2030, 5.3 billion by 2050
Residential efficient shell penetration	3% Deep Shell, 4% Basic Shell by 2030 5% Deep Shell, 10% Basic Shell by 2050	7% Deep Shell, 18% Basic Shell by 2030 26% Deep Shell, 66% Basic Shell by 2050
Zero-emission vehicles sales	LDVs: 30% by 2030, 50% by 2040, 63% by 2050 (50% vehicles charge flexibly) HDVs: 7% by 2030, 17% by 2040, 27% by 2050 Bus: 7% by 2030, 20% by 2040, 30% by 2050	LDV: 90% by 2030, 100% by 2035 [50% vehicles charge flexibly] HDV: 40% by 2030, 100% by 2045 Bus: 100% by 2030
Low carbon fuels	No advanced renewable fuels; existing federal ethanol blend (~7% by energy) and New York State (B20 heating oil blend by 2030)	9% RNG, 75% renewable distillate by 2030 100% RNG and renewable distillate by 2050

Table B-16. (continued)

Description	Reference	Decarbonization
Nonenergy (waste, agriculture, forestry and land sinks, negative emissions technologies)	Moderate increase in forest sequestration, no additional afforestation on marginal lands, no direct air capture or other NETs	Waste diversion and reduced methane leakage from existing and future landfills, anaerobic digesters in solid waste; abatement in manure, animal feeding, and soil management; forest sequestration returns to 1990 levels, additional afforestation on marginal agricultural lands; 11 MMT abatement from direct air capture or other NETs
Annual electricity demand in mild (GWh)	172 TWh in 2050, 206 TWh in 2100; based on adaptation of the NYS Integration Analysis framework to reflect the impact of temperature changes on electricity demand and load shape	304 TWh in 2050, 351 TWh in 2100; based on adaptation of NYS Integration Analysis framework to reflect impact of temperature changes on electricity demand and load shape
Median Peak Electricity Demand in Mild (not including PRM)	34 GW in 2050, 42 GW in 2100	47 GW in 2050, 56 GW in 2100 (winter peaking in mid-2030s and beyond)
Electric Sector Goals	70x30 CES, technology-specific targets (10 GW distributed solar by 2030, 6 GW storage by 2030, 9 GW OSW by 2035)	70x30 CES, technology-specific targets (10 GW distributed solar by 2030, 6 GW storage by 2030, 9 GW OSW by 2035), 100% zero emissions electricity by 2040

B4.2.2 Incorporation of the Temperature Impacts of Climate Change into Integration Analysis Framework

In this economic assessment, the Integration Analysis framework was adapted and extended to directly examine the impacts of climate change on the electricity system. Modeling improvements were made to the framework, including better representation of building heating demands to peak demands, reflecting heat pump performance improvements over time, and better representing the flexibility of electric vehicle (EV) demand. As a result of these improvements, the results presented in the mild climate scenario vary from the results published in the Scoping Plan but are similar in magnitude and key takeaways between infrastructure scenarios remain unchanged.

The impacts of warming temperatures on many aspects of the electricity system are well documented (e.g., heating and cooling demand, transmission ampacity, thermal generator output, and solar output), while for other components of the electricity system, the impacts are less well-known, or the relationships have not been thoroughly studied. Figure B-11 summarizes the modeled and non-modeled impacts of climate change.

Figure B-11. Matrix of Modeled and Non-Modeled Climate Change Impacts on New York State Electricity System

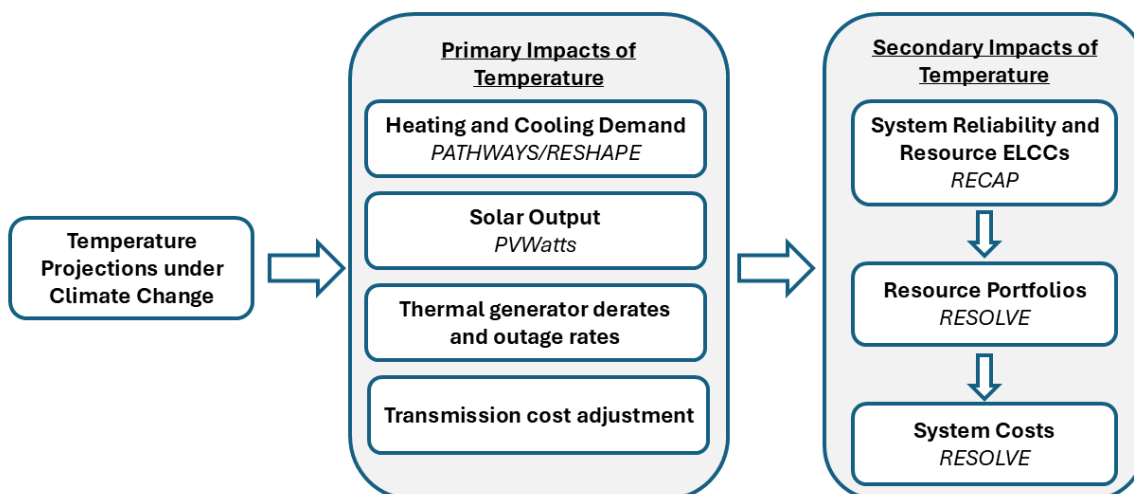
Source: *Impacts of Climate Change on the New York Energy System (NYSERDA 2023)*.

	Impact More Certain	Impact Less Certain
Modeled	 Heating and cooling demand  Transmission capacity derates  Thermal generation efficiency  Solar panel efficiency and output	 Thermal generation outage rates
Not Modeled	 Distribution capacity derates  Delivery of input fuels	 EV and bulk battery storage efficiency  Wind  Land use and resource potential  Hydropower potential

For each of the modeled impacts, the temperature outputs from each climate scenario served as inputs into the Integration Analysis framework, described in the following sections.

Figure B-12. Incorporation of Temperature into Integration Analysis Framework

Source: *Impacts of Climate Change on the New York Energy System (NYSERDA 2023)*.



B4.2.3 Impacts of Temperature on Heating, Ventilation, and Air Conditioning Demand

Heating, ventilation, and air conditioning (HVAC) demand simulations were performed using two tools: PATHWAYS and RESHAPE. PATHWAYS is an energy accounting model used to examine changes in energy demand across New York State at the end-use level, for example, by tracking the number of air-source heat pumps (ASHPs) with electric resistance (ER) backup installed in residential buildings over time. Demand from different types of heating and cooling equipment, including ASHPs with ER, ASHPs with fuel backup, ground-source heat pump (GSHPs), and air conditioners (ACs), is accounted for. PATHWAYS is used to estimate the impacts on annual heating and cooling demand as a result of climate change, using calculated changes in HDDs and CDDs under each climate scenario. RESHAPE is an HVAC energy-demand simulation tool used to model hourly demand of electrified end uses, including new heating and cooling equipment. The hourly temperatures of each GCM serve as inputs into RESHAPE, which is then used to develop a normalized hourly shape that captures changes in the distribution of heating and cooling demand over the course of the year.

Leveraging the projected annual changes in heating and cooling demand from PATHWAYS, coupled with hourly simulations of HVAC demands from RESHAPE under each set of temperature projections, provides a detailed picture of changes in both the magnitude and timing of HVAC demands as a result of climate change, which serve as inputs into both the electricity modeling as well as calculations of the impacts on heating fuel demand.

The temperature projections under each GCM were used to calculate CDD and HDD growth rates by decade and geographic region, using a standard reference temperature of 65 degrees Fahrenheit (°F). Table B-17 shows the projected changes in CDD and HDD.

Warming winters will also reduce fuel-based heating demand. The magnitude of impact on fuel requirement is contingent on how much of the heating demand stays nonelectrified. The HDD growth rates were also used to adjust the fuel demand that remains after electrification of heating is accounted for in each respective infrastructure scenario.

Table B-17. Impacts of Climate on Cooling and Heating Demand

Source: *Impacts of Climate Change on the New York Energy System (NYSERDA 2023)*.

CDD and HDD Change by Period, by Climate Scenario			
Period	Mild	Moderate	Severe
CDD Growth			
2020–2050	1%	2.52%	4.15%
2020–2100	0.52%	1.29%	2.52%
HDD Growth			
2020–2050	0%	-0.64%	-1.49%
2020–2100	-0.04%	-0.39%	-1.25%

B4.2.4 Impacts of Temperature on Solar PV Output

The output of solar photovoltaic (PV) panels has a direct relationship with the temperature of the panel; specifically, the available output is determined by the module’s short-circuit current (ISC) and open-circuit voltage (VOC), and as the temperature of the module increases, ISC increases slightly but VOC decreases substantially, leading to a net result of reduced power output.

The National Renewable Energy Lab’s PVWatts model was used to simulate solar output profiles. By feeding in historical temperatures and then temperature forecasts from the climate models in sequential model runs, it was found that solar output decreases by 0.22% per °F increase in temperature. This is consistent with the findings from other studies (Dubey et al. 2013, Segbefia et al. 2022, Tobnaghi et al. 2013).

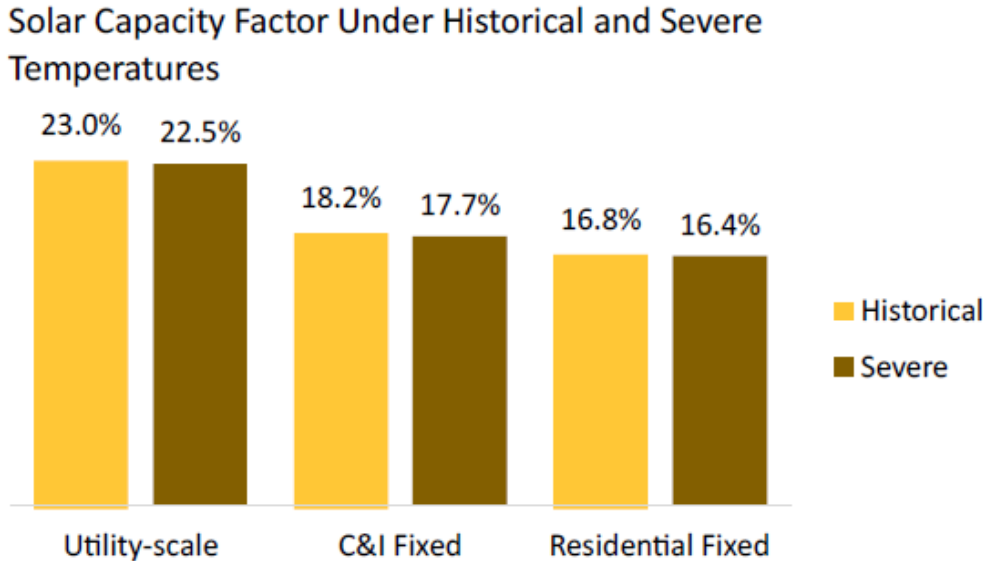
Solar profiles previously used in the Scoping Plan were kept unchanged for the mild scenario. Hourly temperature differences between the mild and moderate and the mild and severe scenarios in 2050 were then used to adjust the solar profiles for the moderate and severe scenarios, respectively. As shown in Figure B-13, the capacity factor of solar power decreased by 0.5% (absolute) in the severe scenario relative to the mild.

This assessment focused solely on the impacts of temperature on solar PV output, using projected air temperatures as a proxy for changes in the solar module’s temperature. However, climate change may impact other weather variables such as wind and cloud cover, and thus irradiation, reaching the module surface. These impacts were not accounted for.

Figure B-13. Modeled Impacts of Increased Temperatures on Solar PV Output

Changes in solar capacity factor under historical (left bars) and severe (right bars).

Source: *Impacts of Climate Change on the New York Energy System (NYSERDA 2023)*.



The changes in solar PV output profiles as a function of temperature served as inputs into the electricity sector modeling framework. A reliability model, RECAP, was used to assess the impacts that adjustments to solar output profiles have on the contributions of solar resources to overall system reliability. The solar profiles were also updated in RESOLVE, a capacity expansion model, such that the economic decision-making and resource selection under each climate scenario takes into account the impacts of warming temperatures on solar output.

B4.2.5 Impacts of Temperature on Thermal Power Plants

Thermal generators are weather-dependent in two ways:

- 1. Their output is a function of ambient temperature
- 2. Thermal units have historically performed worse under both extreme cold and extreme heat

Combustion turbines are impacted by ambient temperature because they rely on air recirculation for cooling. As a result, the larger the delta between the temperature of combustion and the temperature of ambient air, the higher the efficiency and rated output of the turbine. As temperatures increase, the rated output of the turbine declines nearly linearly.

Because fossil units are more likely to experience outages during extreme temperature conditions, this means that their availability also has a correlation with projected loads. Using historical data, a relationship between extreme temperatures and fossil outages can be determined using a probability function. Fossil outages were simulated using the hourly temperatures under each GCM, and RECAP was then used to examine the relationship between fossil outages and hours of potential loss of load. In combination with ambient-temperature derates, the reliability contributions of each generation technology can be developed.

The relationship between the probability of thermal outages and temperature was derived from a 2019 paper by Murphy et al. (2019) that examined historical data from the Pennsylvania-New Jersey-Maryland Interconnection (PJM).¹⁴ This empirical relationship is an area of emerging study and is one of increasing importance as recent winter storms have severely threatened grid reliability in Texas, PJM, and elsewhere (PJM 2023). During Winter Storm Elliot, PJM estimated that over 10 gigawatts (GW) of thermal capacity was unavailable due to fuel supply issues. Although it did not lead to severe loss of power like Winter Storm Uri did in Texas, Winter Storm Elliot provides another extreme case of correlated outages during extreme cold—out of 186 GW of unforced capacity (UCAP) in the PJM, 46 GW was unavailable during the storm, with plant equipment issues and fuel supply issues identified as the leading contributors of outages.

To date, no similar study has been conducted within New York State directly; instead, the results of the study conducted by Murphy et al. (2019) were extended to NYS generators for use in this analysis. However, differences between the two regions may complicate the applicability of the relationship, especially during extreme cold events. Many generating units in New York City are required to maintain on-site

fuel oil storage on site in order to remain available in case of gas pipeline outages, potentially mitigating one of the key contributors to thermal outages during extreme cold. Although there are not any direct requirements for on-site fuel storage in PJM, PJM's capacity market structure includes performance incentives and penalties that provide additional financial motivation for generators to be available during

¹⁴The PJM is a regional transmission organization (RTO) that coordinates the movement of wholesale electricity in all or parts of 13 states and Washington, DC, including New York State (Murphy et al. 2019).

challenging periods, known as a pay-for-performance model, which the NYISO does not have. Due to these differences between the two regions in the requirements and incentives for maintaining reliability during extreme cold, caution should be used when interpreting the load-carrying capacity findings for thermal generators in New York State, which are described below.

An additional area of uncertainty is presented in the decarbonization scenario, in which one or more emerging technologies may provide the estimated capacity in the zero-carbon firm resource category. This analysis adopts the Integration Analysis approach of modeling the zero-carbon firm resource as a hydrogen-fueled, combustion-based resource, which would be expected to be impacted by temperatures similarly to existing combustion-based resources. However, part of the impacts of extreme cold temperatures in particular on the availability of thermal units is intertwined with the reliance of those units on natural gas infrastructure that may also be constrained by fuel demands driven by building space heating needs; this may not be a factor for hydrogen infrastructure, which is not expected to play a meaningful role in building heating in the pathways modeled as part of the Scoping Plan. Alternatively, if other technologies such as long-duration battery storage provide zero-carbon firm capacity, the temperature-based relationship would not be applicable.

B4.2.6 Impacts of Temperature on Transmission Ampacity

The ampacity of transmission lines also declines as a function of increasing temperature, and as a result climate change is likely to lead to reductions in transfer capacity across transmission systems during the summer as temperatures continue to rise. Capturing the impacts of increasing temperature on transfer capacity in New York State is difficult within this modeling exercise due to the high-level topology used to represent the NYS transmission system, as well as factors that may require further study (for example, Central East, one of the most limiting interfaces in the State, is a voltage-limited interface that would not be impacted by temperature-driven changes in thermal transfer capacity).

As a proxy for the impacts of temperature on transmission, a multiplier was applied to the transmission deliverability costs for renewable builds. This approach captures the increased costs of renewables-driven transmission expansions that have already been identified in the mild case; however, the analysis does not consider additional upgrades that may be required in areas of the existing system that are not needed in the mild case but become necessary as a result of the more significant temperature rise in the moderate or severe cases. A much more granular representation of the transmission system and an assessment of areas that are already nearly constrained would be required for such an exercise.

Transmission derates in each hour were calculated corresponding to the hourly temperature in each of the three climate scenarios, adapted from the ampacity response functions used in Fonseca et al. (2021). The average of the derates in each climate scenario was then calculated over the hours from 12:00 p.m. to 7:00 p.m. in June, July, and August. The choice was informed by the finding that temperature, demand, and thus loss-of-load probability can be high during these hours. These hours are also aligned with the summer peak load window defined by NYISO and have previously been used for the accreditation of duration-limited resources (e.g. energy storage) in the capacity market. The average derates in the moderate and severe scenarios were then compared to the mild, to yield the transmission cost increases applicable in those scenarios, which are applied as a cost multiplier relative to the cost assumptions used in the Scoping Plan and the mild scenarios in this assessment. Exceptions were made for transmission upgrades expected to be underground (Zone J) and transmission lines expected to be underwater (offshore wind interconnected to Zones J and K); for these lines, costs were not increased to account for warming. For the remainder of the system, including the existing system, this assessment assumes that costs are incurred for upgrades to existing overhead lines with no change in underground versus overhead lines distribution in response to climate stressors; however, future hardening efforts may include an increased focus on building new lines underground.

Table B-18. Calculated Impacts of Temperature on Transmission Upgrade Costs

Source: Impacts of Climate Change on the New York Energy System (NYSERDA 2023).

NYISO Zones	Transmission Cost Increase under Moderate Scenario	Transmission Cost Increase under Severe Scenario
A-E	3.7%	7.9%
F	3.6%	8.5%
G-I	4.5%	8.6%
J	6.8%	9.3%
K	5.7%	7.4%

B4.2.7 Extension of Integration Analysis Framework to Late Century

For this economic assessment, the Integration Analysis framework has been extended to cover a longer time horizon, through the end of the century, in order to capture the impacts of climate change on the electricity system throughout the period for which climate projections are available.

Most energy modeling efforts use 2050 as an endpoint, including the Integration Analysis performed for the Scoping Plan, as well as notable, publicly available national sources such as the Energy Information Administration (EIA) and U.S. Department of Energy’s (DOE) National Renewable Energy Laboratory, which serve as foundational datasets for the Integration Analysis. As with any modeling effort, projections become more uncertain as a function of time relative to the year in which the modeling is being conducted; this effort is made more uncertain due to the lack of projections for future fuel prices, technology costs, and other underlying drivers past 2050. As a simplifying assumption, these variables are held constant after 2050.¹⁵

There are only two input variables that change between 2050-2100: (1) hourly temperatures, which are outputs of each GCM, and (2) population growth. Population growth assumptions came from the Cornell Program on Applied Demographics (PAD), which was focused on 2020–2040, but the rates of population growth (Table B-19) were assumed to be constant through 2100. These two variables have downstream effects because they lead to changes in electricity demand, which in turn lead to changes in required infrastructure, fuel consumption, and associated costs.

Table B-19. Assumed Population Growth Rate by Region

Source: Impacts of Climate Change on the New York Energy System (NYSERDA 2023).

Region	Annual Population Growth Rate
Upstate Zones A-E	-0.13%
Upstate Zone F	0.07%
Downstate Hudson Valley	0.24%
Downstate NYC	0.34%
Downstate Long Island	0.04%

B4.2.8 Nonmodeled Impacts

This assessment focused on the impacts of temperature change on key components of the energy system for which the relationship with temperature is well understood and well documented. However, there are many components of energy system planning that will be impacted by climate change which are currently

¹⁵In the decarbonization scenario, continued stock turnover has minimal impact of because modeling building heating and LDVs are nearly entirely electrified by 2050.

not well understood. These components are briefly summarized below, though this list is not intended to be exhaustive, future research may identify additional linkages between climate change and energy system investments and operators.

- **EV charging:** The Integration Analysis framework does not currently capture seasonal or temperature-driven changes in EV charging patterns. While it is well documented that colder temperatures lead to reduced range for EVs, the detailed relationship between temperature and resulting electricity demand has not been studied.
- **Wind and hydropower:** Unlike solar PV output, the quality of evidence and/or agreement among studies on the impact of climate change on wind and hydropower in New York State is not high (Craig et al. 2018). While climate change is projected to have significant impacts on hydropower in the Western U.S. due to increases in drought conditions, the impacts of climate change on rainfall and hydropower outputs in the Northeast are projected to be less significant and will be highly uncertain.
- **Electricity distribution and fuel delivery systems:** The distribution and fuel delivery systems are not represented in the Integration Analysis framework at the level of granularity that would be needed to perform for an examination of the impacts of climate change on these systems, and as a result, these systems are not included within the scope of this assessment. These nonquantified impacts include distribution system derates due to the impacts of temperature online ampacity, increasing cooling requirements for substations, impacts on fuel pipelines and storage, needs for storm hardening, and other factors. These impacts are discussed in NYSERDA (2023); Consolidated Edison, Inc., (ConEd 2019), also recently completed a comprehensive climate change vulnerability study for its system.
- **Land use and resource potential:** The Integration Analysis leveraged the CES Cost Study to develop estimates of the available land-based wind and solar PV potential in New York State. The study conducted a geospatial analysis of suitable land for renewable development (Sustainable Energy Advantage 2020). Climate change may have significant impacts on land use in New York State, including by impacting land use for agriculture and livestock grazing, climate-induced migration (both inter- and intrastate) and its impact on land use, and other factors. The impacts of climate change on the total available land for wind and solar development in New York State are highly uncertain and were not considered in this assessment.

B4.3 Additional Results

Analysis also included other aspects of demand, including peak demand and impacts of climate change on future resource portfolios.

B4.3.1 Peak Electricity Demands

In addition to a warming trend across both the winter and summer months, the underlying temperature data shows a more pronounced impact on temperature extremes, consistent with the broader climate literature. This analysis framework allows us to capture both the impacts on annual demand as well as the impacts on daily and hourly demand, providing a detailed examination of the impacts of climate change on summer and winter peak demands and associated reliability challenges. Systems are typically designed for the higher of the two peaks and sufficient “headroom” exists to meet the lower one. However, in some cases, both peaks may be similar in magnitude and thus of equal importance.

In the reference case, and in the absence of a major policy shift towards electrification of the buildings and transportation sectors, the NYS electricity system remains summer-peaking, and the impacts of climate change will place additional stress on summer peak demands over the forecast horizon. By the 2080s, severe climate change could drive up to a 10 GW difference in summer peaks relative to a more mild climate change scenario. Despite the cooling demand increasing by a higher amount in the reference case, as shown in Figure B-14, the *total* summer peak is generally lower than that in the decarbonization scenario, given the contribution of other electrified end-uses (e.g., LDVs) included in the latter. The exception to that is the severe scenario, where the increase in space cooling demand, driven by lower-efficiency ACs and the absence of other energy efficiency investments, is greater than demand growth driven by other electrified end uses. This leads to a summer peak of 50 GW and 55 GW in the reference scenario in 2080 and 2100, which is approximately 2 GW higher than the peaks in the decarbonization scenario in each respective year.

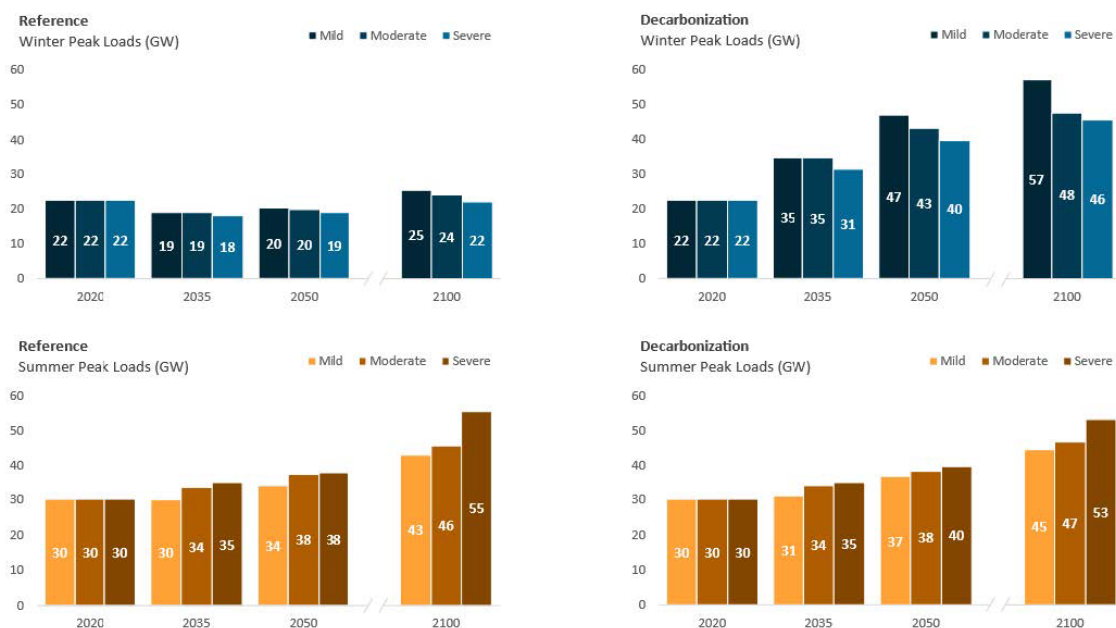
In the mild decarbonization scenario, New York State’s electricity system becomes winter-peaking by the mid-2030s due to the electrification of heating demand. By 2050, if winter extreme temperatures are relatively unaffected by climate change, as modeled in the mild scenario, winter peaks are projected to reach about 47 GW. In the severe climate scenario, winter extreme temperatures become significantly warmer due to climate change, leading to a lower winter peak demand than under the mild scenario. At the same time, summer extreme temperatures increase, leading to the severe decarbonization scenario becoming a dual-peaking system by 2050, and returning to a summer-peaking system in the 2080s.

In the reference case, the annual peak is 46 GW and 55 GW in the 2080s in the moderate and severe climate scenarios respectively. It is very comparable to the annual peaks of 48 GW and 53 GW in the decarbonization scenario in each corresponding climate scenario. Given the low heating electrification and low winter peak in the reference case, additional capacity is needed to simply meet the high cooling

demand driven by less efficient ACs and lack of other energy efficiency measures described above. The decarbonization scenario involves aggressive electrification of both heating and cooling, among other end-uses and investments in energy efficiency, which leads the system to a similar peak demand outcome as the reference in the long run. However, the decarbonization scenario results in more efficient use of generation and transmission infrastructure because this infrastructure is leveraged to support both summer and winter peak demand. Additionally, while both cases require incremental investment to meet a similarly sized later period peak under severe climate change, there are significant incremental carbon and health benefits associated with the adoption of energy efficiency, higher electrification, and reliance on carbon-free resources in the decarbonization scenario.

Figure B-14. Projected Summer and Winter Total Peak Demand by Policy and Climate Scenario

Source: *Impacts of Climate Change on the New York Energy System (NYSDERDA 2023)*.



B4.3.1.1 Impacts on Effective Load-Carrying Capability

The impact of warming and electrification policies on the load shape and the timing and magnitude of peak demand will also affect the contribution of different resource types toward the system's ability to reliably meet demand. Changes in the timing of system demand—both seasonally and daily—lead to shifts in how well the outputs of each generation resource align with peak demand. An effective load-carrying capability (ELCC) was calculated for all combinations of policy and climate scenarios,

for different generation types. These values then serve as inputs to the capacity expansion modeling to ensure that sufficient total capacity is built to meet median peak forecast plus the planned resource margin (PRM). Detailed results of the ELCC scenarios for both renewable and thermal electricity supply options are available from NYSERDA (2023).

B4.3.2 Impacts of Climate Change on Future Resource Portfolios

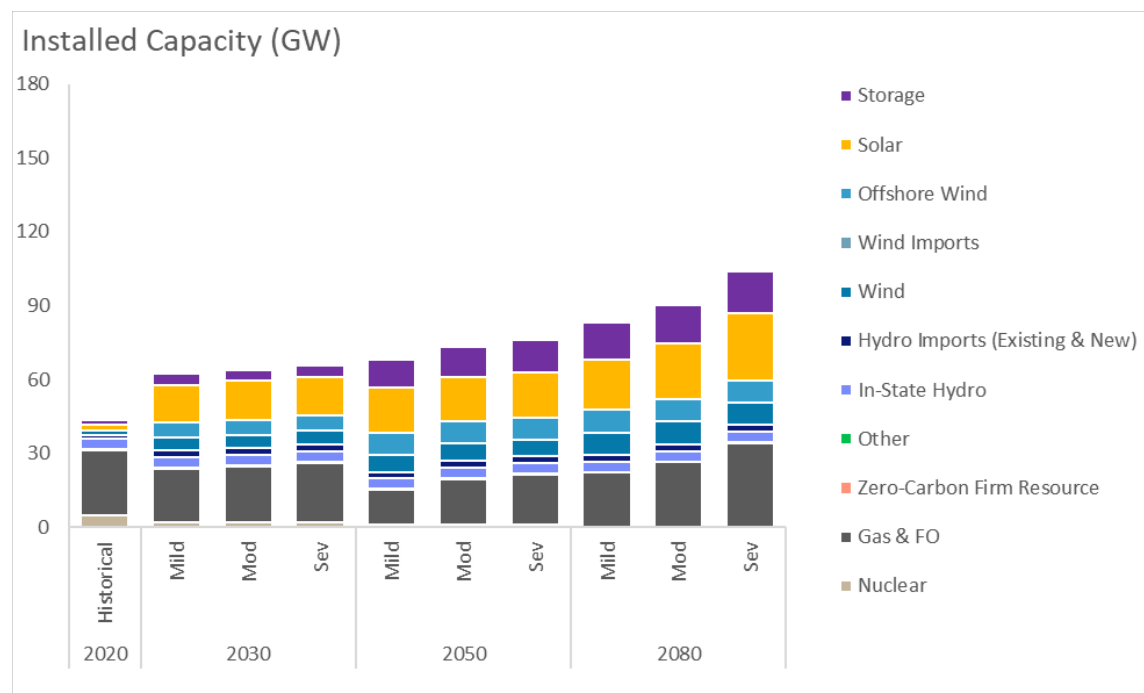
The results of the preceding sections, using temperature projections from the GCMs to simulate the impacts of climate change on hourly electricity system demands; transfer capacity of new local transmission; and the reliability contributions of wind, solar, storage, and thermal generators, serve as inputs into the capacity expansion modeling exercise. In this way, the resulting portfolios are optimized to meet electricity demand while maintaining reliability by taking directly into account the impacts of climate change on loads, resources, and transmission.

B4.3.2.1 Reference Case Portfolios

In the reference case, electrification of space heating is minimal, and the system remains summer peaking. As a result of increased warming in the moderate and severe scenarios, the increase in demand driven by rising summer temperatures results in a need for additional capacity to meet reliability needs, as well as additional renewable energy generation required by the 70% clean energy standard. To meet increasing reserve margin requirements, driven both by increases in system peaks as well as increases in load variability that lead to an increased PRM requirement, the system builds over 3 GW of additional gas-fired capacity and 1 GW of additional battery storage capacity by 2100 in the moderate reference case relative to the mild reference, and nearly 12 GW of gas-fired capacity and nearly 6 GW of battery storage capacity in the severe reference relative to the mild. Additionally, to meet the increased clean energy requirements driven by increases in annual load, solar capacity is the primary resource selected as an increasing proportion of load occurs in the summer and is most coincident with solar output. As a result, an additional 0.4 GW of solar capacity is built by 2100 in the moderate reference case, and nearly 8 GW of additional solar capacity is built by 2100 in the severe reference case, compared to the mild reference.

Figure B-15. Comparison of Climate Change Scenarios under the Reference Case

Source: *Impacts of Climate Change on the New York Energy System (NYSDERDA 2023)*.



B4.3.2.2 Decarbonization Scenario Portfolios

In the decarbonization scenario, winter demand increases substantially due to electrification of building space heating needs, and as a result New York State transitions to a winter-peaking system in the mid-2030s in the mild decarbonization scenario. However, under each climate scenario, increased warming leads to both a decrease in winter heating demand and a significant increase in summer cooling demand, which are largely offsetting on an annual demand basis but lead to significant declines in overall peak load compared to the mild decarbonization scenario. As a result, the two primary drivers of changes in the resource portfolio driven by climate change are:

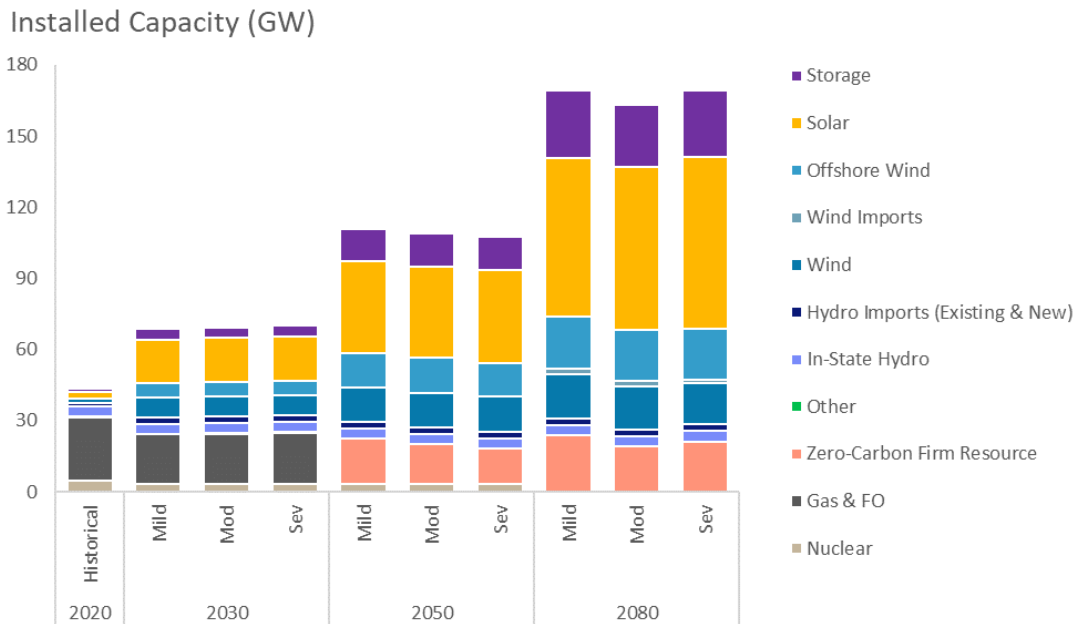
1. Declines in system reserve margin requirements, which lead to a lower build-out of zero-carbon firm capacity and battery storage
2. Changes in the timing of demand from winter to summer, which leads to more solar being cost-optimal and less wind

In the moderate decarbonization scenario, the primary shift occurs in the build-out of firm capacity and battery storage, with nearly 7 GW less zero-carbon firm capacity and 2 GW less battery storage by 2100, and impacts on the renewable resource mix are negligible relative to the mild decarbonization scenario. In the severe decarbonization scenario, there is a smaller decline in reserve margin requirements by 2100

relative to the mild because of significant increases in summer peak demand, and as a result there is a decline of 4 GW of zero-carbon firm capacity by 2100 relative to the mild decarbonization portfolio. In addition, the shift toward summer demand from an annual energy perspective is more pronounced in the severe decarbonization scenario, which leads to a significant shift in the renewable resource mix, with nearly 9 GW of additional solar capacity and 2 GW of lower land-based and offshore wind capacity relative to the portfolio in the mild decarbonization scenario.

Figure B-16. Comparison of Climate Change Scenarios under the Decarbonization Scenario

Source: Impacts of Climate Change on the New York Energy System (NYSERDA 2023).



B5 Human Health and Safety

B5.1 Extreme Temperature

The following sections describe more details on the extreme temperature analyses presented in Chapter 6, Human Health and Safety.

B5.1.1 Exposure Response Functions

Mortality: The relationship between daily mean temperature and relative risk (RR) of mortality is estimated from Figure 2 of Lay et al. (2021) though Lay et al. estimate temperature-related mortality among urban areas exclusively, additional research suggests that extreme heat-related health impacts in

the Northeastern U.S. are not limited to urban areas and may be of comparable magnitude in nonurban areas (Madrigano et al. 2015). Therefore, we apply two regional functions from Lay et al. across New York State. We apply a linear approximation of the trend for the Northeastern U.S. coastal region in Lay et al. (illustrated in Figure B-17) to counties that make up the Long Island, New York City, and South Hudson regions of New York State. We apply the linear approximation of the trend for the Northeast in Lay et al. (2021) for all other counties in New York State, based on the spatial distribution of cities included in the underlying analysis. For both regions, we consider the sum of lag 0 and 5-day moving average terms for the 1993–2002 time period (Figure B-17).

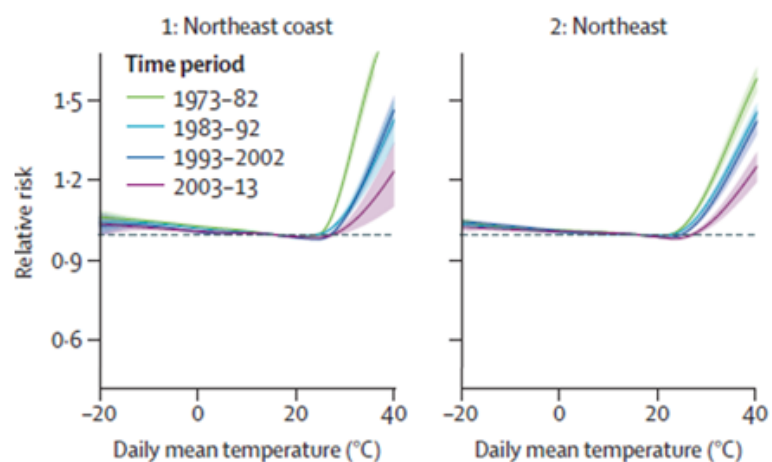
As shown in Figure B-17, the functions in Lay et al. (2021) are estimated for the temperature range from -20°C to 40°C (-4°F to 104°F). Historical data outside the range are sparser, as suggested by the broadening 90% confidence interval (shade areas), as the function estimation moves to the extremes. With climate change, however, temperature projections may fall outside this range. In this analysis, we do not attempt to extrapolate these functions but instead treat any daily mean temperature less than -20°C (-4°F) as having an equivalent effect as a -20°C day, and any daily mean temperature greater than 40°C (104°F) as having an equivalent effect as a 40°C day.

Figure B-17. Exposure Response Functions

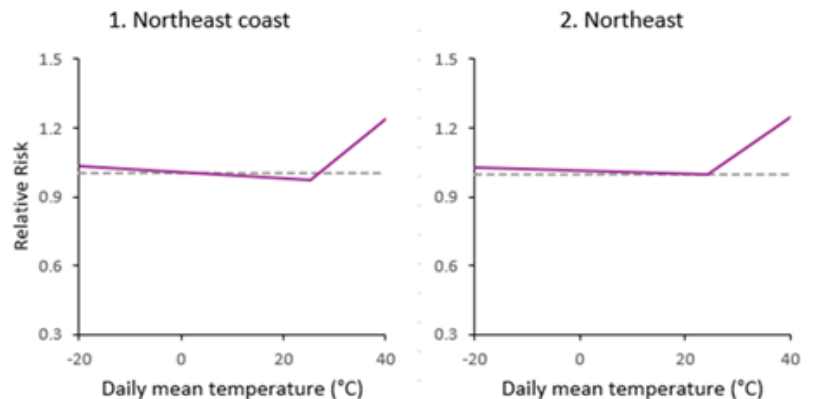
Exposure response functions for total relative risk from Lay et al. (2021) is shown in Panel A, and linear approximation used in this study is shown in Panel B.

Source: Lay et al. (2021).

Panel A: Regional-Scale Mortality Relative Risk Functions



Panel B: Linear Approximation of 2003-2013 Period Functions



Respiratory hospitalizations: The relationship between daily mean temperature in the summer and the RR of hospitalization for respiratory causes is calculated from Lin et al. (2012), which estimated percent change of hospitalization per degree above a threshold, for 14 NYS regions. Threshold temperatures for this analysis ranged from 71°F to 87°F.¹⁶

B5.1.2 Valuation

Mortality: Mortality attributed to extreme heat is valued using the value of statistical life (VSL) based on individual values for avoiding the risk of premature death. The baseline VSL is projected through the twenty-first century using national GDP and individual average income projections and a longitudinal income elasticity of 0.4. These estimates are consistent with current best practices for EPA analyses of air pollution impacts, as documented in EPA (2022).

Respiratory hospitalizations: Respiratory hospitalizations are valued using estimates of hospital charges and lengths of hospital stays based on discharge statistics provided by the Agency for Healthcare Research and Quality's Healthcare Utilization Project National Inpatient Sample Database (2016), available in the EPA BenMAP-CE tool (EPA 2022). The total value per hospitalization, accounting for hospital costs and lost wages, is \$9,646 (in 2021 USD).¹⁷

B5.1.3 Processing Steps

Mortality: We estimated daily RR of mortality by GCM and county through the end of the century using exposure response functions from Lay et al. (2021) and future daily mean temperature derived from the primary six downscaled climate models used in this report, as described in Chapter 1, Methodology. We averaged the RR values by year to estimate annual mortality attributable to extreme temperature. We multiplied the RR of mortality by baseline mortality incidence and population for each year and county

¹⁶The percent changes in Lin et al. (2012) are based on degrees of apparent temperature, or "real feel", which incorporates dew point into temperature estimates. Apparent temperature usually exceeds ambient temperature. For this analysis, we approximate apparent temperature using the difference between ambient and apparent temperature in the baseline period, in lieu of projections of dew point, which are not available for the CMIP6 scenarios.

¹⁷This valuation method offers a more recent alternative to the valuation used in Lin et al. (2012). Lin et al. values hospitalizations on a region-by-region basis, with costs ranging from \$3,792 to \$8,003 per admission. The valuation estimates in the paper is not published, so it is assumed to be 2012. Adjusted to 2021 USD, this range is equivalent to between \$4,340 and \$9,160 per admission.

for the six CMIP6 GCMs and the baseline. Finally, we averaged annual mortality risk across GCMs for three future eras (2030s, 2050s, and 2080s) under two SSPs (SSP2-4.5 and SSP5-8.5) and subtracted baseline mortality (1981–2010) to isolate the effect of changes in heat events attributable to climate change. We allocated impacts to the 12 NYS regions based on population.

Respiratory hospitalizations: We used the relationships between change in risk and temperature from Lin et al. (2012) to develop temperature response functions for each region in the underlying analysis, and then attributed these functions to the counties that fall within each region. We estimated daily RR for all summer days using future mean temperature derived from the primary six downscaled climate models used in this report, as described in Chapter 1, Methodology. We averaged RR values by year to estimate the annual number of hospitalizations attributable to extreme heat. We multiplied the RR of respiratory hospitalization by baseline respiratory hospitalization incidence and population for each year and county for the six CMIP6 GCMs and the baseline. Finally, we averaged the annual risk of respiratory hospitalization across GCMs for three future eras (2030s, 2050s, and 2080s), under two SSPs (SSP2-4.5 and SSP5-8.5), and subtracted the baseline (1981–2010). We allocated impacts to the 12 NYS regions based on population.

Table B-20 presents the data sources referenced in this analysis.

Table B-20. Extreme Temperature Mortality and Morbidity Analysis Data Sources

Data	Description	Source
Mortality exposure response functions	Functions for total RR associated with daily mean temperature	Lay et al. (2021)
Respiratory hospitalization exposure response functions	Functions for total RR associated with daily mean summer temperature above threshold	Lin et al. (2012)
Baseline mortality incidence	2010–2060, by county in 5-year eras	CDC Wonder (n.d.)
Baseline respiratory hospitalization incidence	2014, by county	EPA (2022)
Population projections	2010–2095, by county in 5-year eras	ICLUS ver. 2.0 (EPA 2017b)
Value of statistical life	All-cause mortality VSL based on 26 value-of-life studies	EPA (2022)
Cost of respiratory hospitalization	Cost-of-illness, incorporating hospital costs and lost wages	Agency for Healthcare Research and Quality (2016)

B5.1.4 Impact of Population Forecasts and Baseline Mortality on Results

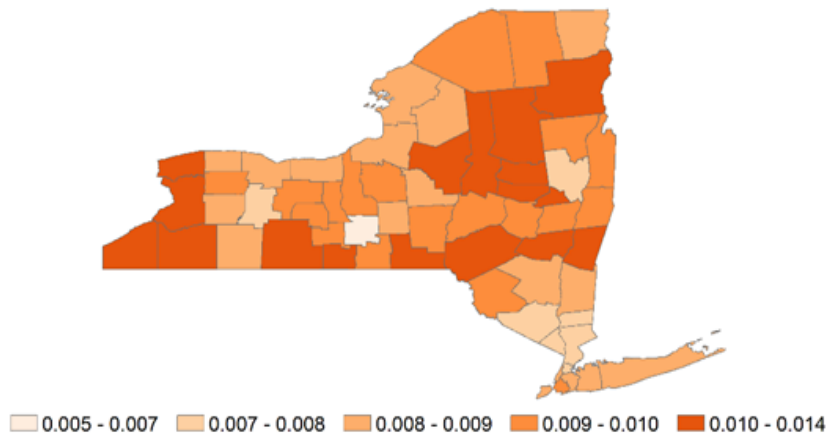
Drivers to mortality impacts include baseline mortality incidence and population change. Baseline incidence is an estimate of the average number of people who die in a given population over a given period of time. The baseline mortality incidence used in this analysis comes from CDC WONDER (n.d.). Projections are based on U.S. Census Bureau (N.d) projected life tables. Figure B-18 shows mortality incidence in the baseline period, as well as change in mortality incidence in the 2050s era relative to the baseline. Across the nation on average, baseline mortality decreases over time due to medical advances and other adaptation measures designed to reduce the risk of mortality. Many NYS counties reflect this trend, with increases in baseline mortality incidence projected for numerous counties in the eastern and northwestern portions of the State. Generally, increasing and decreasing mortality risk over time contributes to the patterns in extreme temperature-related deaths with climate change expected throughout the State.

Figure B-19 shows population by county in the baseline period, as well as the percentage change in population in the 2050s era. Population projections used in this analysis come from the Integrated Climate and Land-Use Scenarios (ICLUS) ver. 2.0, as noted in Chapter 1, Methodology. ICLUS projects a decrease in population across much of the State in the 2050s compared to the current population, while counties that include urban areas of New York City, Albany, Rochester, Buffalo, and Binghamton are expected to grow in population. This analysis estimates mortality impacts for a growing and moving population as modeled in ICLUS. In order to isolate the impact of population migration, Table B-21 presents mortality impacts for a static (2020) population.

Figure B-18. Change in Baseline Mortality Incidence in the 2050s Relative to the Baseline

Mortality incidence in the baseline period is shown in Panel A. Change in mortality incidence in the 2050s relative to baseline incidence is displayed in Panel B.

Panel A: Baseline Mortality Incidence, Baseline Period



Panel B: Change in Baseline Mortality Incidence, 2050s

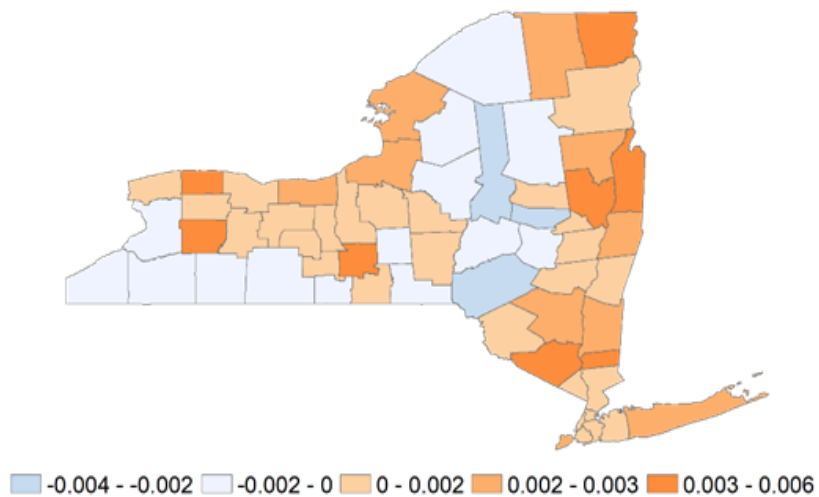
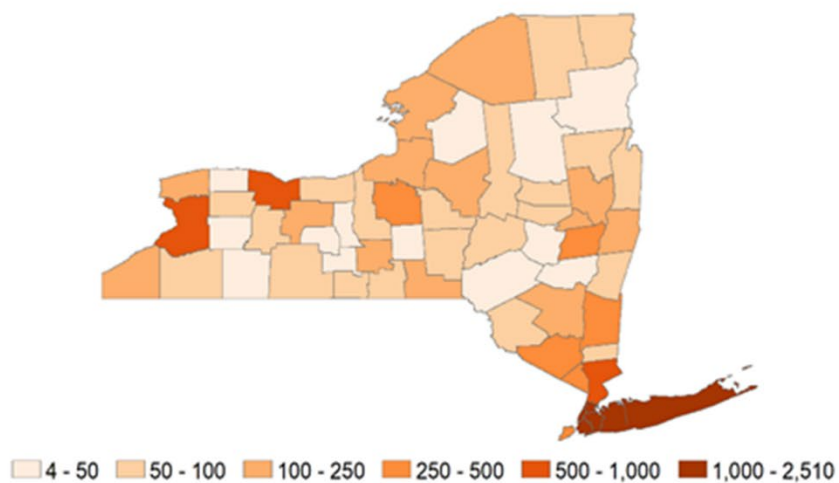


Figure B-19. Change in Population in the 2050s Relative to the Baseline

County-level population in the baseline period, in thousands, is shown in Panel A. The percent change in population in the 2050s era relative to the baseline period is displayed in Panel B.

Panel A: Total Population, Baseline Period (in thousands)



Panel B: Percent Change in Population, 2050s

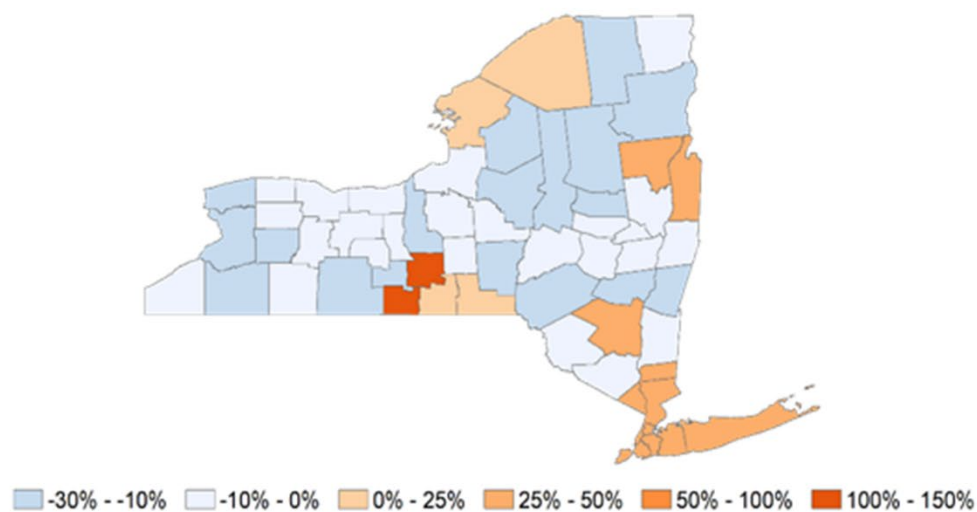


Table B-21. Additional Annual Premature Deaths Associated with Extreme Temperature Due to Climate Change, Static Population

Change from baseline. Additional premature deaths (birth to age 99) attributable to climate change, assuming a static 2020 population. Future impacts presented for three time periods (near century, midcentury, and late century). Negative values represent projected benefits of climate change due to reduced extreme cold. Values may not sum due to rounding.

Region	Baseline (All Deaths)	Near Century (2030s)		Midcentury (2050s)		Late Century (2080s)	
		SSP2-4.5	SSP5-8.5	SSP2-4.5	SSP5-8.5	SSP2-4.5	SSP5-8.5
Adirondacks	1,200	0.1	0.1	1.1	2.2	1.3	9.2
Catskills	3,500	4.4	4.7	8.8	13	10	38
Central/ Finger Lakes	9,100	11	12	28	42	36	120
Champlain Valley	1,300	3.0	3.1	6.0	7.8	7.0	19
Great Lakes	24,000	36	39	77	110	93	310
Long Island	24,000	-8.7	-7.8	28	73	75	310
Mohawk River Valley	5,200	-3.5	-3.2	-1.7	3.3	-0.2	33
New York City	70,000	200	210	370	590	560	1,500
North Hudson	9,000	14	15	33	47	40	120
South Hudson	16,000	-14	-13	5.4	31	32	190
Southern Tier	6,300	-2.8	-2.3	-0.8	5.9	0.7	45
St. Lawrence Valley	1,200	0.3	0.4	2.5	4.1	3.7	14
Statewide	170,000	240	260	550	930	860	2,800

Changes in temperature, RR, baseline mortality risk, and population all contribute to the estimate of extreme temperature-related premature deaths presented in this analysis, and these impacts vary over space and time, making it difficult to isolate drivers of specific impacts. However, the trends related to RR, baseline incidence, and population shown in Chapter 6, Human Health and Safety, Figure B-18, and Figure B-19 help to explain the spatial distribution and magnitude of mortality impacts described in Chapter 6.

B5.2 Air Quality

The following sections describe more details on the air quality analyses presented in Chapter 6, Human Health and Safety.

B5.2.1 Climate Data

This analysis is based on Fann et al. (2021), who estimated the mortality risk associated with changing air quality; specifically, ground-level ozone (O₃) and PM_{2.5} concentrations. Fann et al. modeled future pollutant concentrations in response to changes in meteorology and emissions (i.e., air quality surfaces) using two GCMs (CanESM2 and GFDL-CM3) and two alternative simulated air pollutant emissions scenarios, one which uses a 2011 inventory that estimates pollution burden from all sources as of that year, and an alternative 2040 dataset that accounts for the implementation of a suite of regulatory policies on stationary and mobile emissions sources. This analysis uses modified air-quality surfaces under the 2040 emissions scenario from Fann et al. to quantify health effects attributable to PM_{2.5} and O₃ exposure. The Fann et al. study is limited in its ability to capture projected reductions in conventional air pollutant emissions resulting from New York's Climate Leadership and Community Protections Act (CLCPA). Although it is difficult to determine with certainty the Fann et al. study likely excludes these important benefits of the CLCPA. Consideration of CLCPA air pollutant emission co-benefits would likely lead to a lower health risks to New York State residents than those shown in this chapter.

The air-quality surfaces were modified to account for updated CMIP6 temperature projections used in this economic assessment.

B5.2.2 Epidemiological Studies

Numerous epidemiological studies document the relationship between degraded air quality and human mortality and morbidity. This analysis draws on evidence from three studies that have been parameterized for use with the EPA's Environmental Benefits Mapping and Analysis Program (BenMAP), a tool that estimates the human health impacts of air quality changes at a refined spatial scale.¹⁸

Di et al. (2017) estimated the relationship between mortality among the Medicare population (aged 65 and older) and long-term exposure to PM_{2.5}. The authors modeled PM_{2.5} exposure across the contiguous U.S. using a hybrid methodology including land-use regression, satellite data, and monitoring data, and used Cox proportional hazards models with a generalized estimating equation to relate pollutant exposure and mortality.

¹⁸For more information on the BenMAP program, see EPA (2022).

Zanobetti and Schwartz (2008) evaluated the relationship between short-term ozone exposure and all-cause mortality across 48 U.S. cities. The National Center for Health Statistics reported 6.9 million total deaths. The authors ran conditional logistic regression models by season, month, and age group, controlling for temperature, dew point, and day of the week.

Tetreault et al. (2016) investigated the relationship between the onset of childhood asthma (from birth to age 17) and long-term exposure to PM_{2.5} and O₃. The authors followed a cohort of 1 million children in Quebec, Canada, and mapped asthma incidence with residential exposure to air pollutants. They used Cox proportional hazards models to estimate the association between asthma onset and exposure to pollution, controlling for demographics and socioeconomic status.

B5.2.3 Impact of Population Forecasts on Results

A key driver for the mortality impacts is the projection of population change by county. These projections have a first-order influence on the mortality results, but because the projection reflects trends in rural-to-urban migration in New York State, population changes can influence results in the opposite direction of the climate stressor, giving the appearance of a mitigated impact in rural areas. This limitation is acknowledged in the main text and is explored quantitatively as a sensitivity analysis in greater depth in the previous section on extreme heat.

B5.2.4 Valuation

The direct medical and indirect lost income cost of a new diagnosis of asthma is estimated to be \$49,600 and includes lifetime medical costs and productivity losses. Mortality attributed to air pollution is valued using the VSL based on individual values for avoiding the risk of premature death. The baseline VSL is projected through the twenty-first century using national GDP projections and a longitudinal income elasticity of 0.4; these estimates are consistent with current best practices for EPA analyses of air pollution impacts, as documented in EPA (2022).

B5.2.5 Processing Steps

It wasn't feasible to rerun the Fann et al. (2021) air quality models for the temperature projections and suite of GCMs used in this analysis due to the analytical and time constraints associated with simulating air quality concentrations. Instead, we estimated future PM_{2.5} and O₃ concentrations for six CMIP6 GCMs using the relationship between air quality and temperature described in Fann et al. by the two CMIP5 GCMs. First, we plotted temperature and pollutant concentration by era for each county-GCM scenario

using PM_{2.5} and O₃ concentrations from Fann et al. Then, we interpolated across the linear splines of the resulting piecewise function to estimate the pollutant concentrations associated with the average CMIP6 temperature for three future eras (2030s, 2050s, and 2080s) for six GCMs by NYS county. We estimated health impacts based on these future pollutant concentrations.

This analysis uses BenMAP to estimate health impacts resulting from changes in air pollution concentrations. First, we modified the air quality concentrations from Fann et al. (2021) to represent updated climate scenarios for two SSPs and two RCPs (SSP2-4.5; SSP5-8.5). We then quantified and valued health impacts at the county level for each GCM-SSP/RCP scenario using BenMAP for the baseline period (1981–2010) and three projected eras (2030s, 2025–2044; 2050s, 2045–2064; and 2080s, 2075–2094). Finally, we averaged impacts across the 6 climate models and allocated them to 12 New York State regions based on population. Table B-22 presents the data sources referenced in this analysis.

Table B-22. Air Quality Analysis Data Sources

Data	Description	Source
Pollutant concentrations	County-level concentrations of PM _{2.5} and O ₃ for four eras: 2000 (baseline), 2030s, 2050s, and 2080s	Modified from Fann et al. (2021)
Baseline mortality incidence	2015 to 2060, by county in 5-year eras	CDC WONDER (n.d.)
Baseline asthma incidence	2012, national value	Winer et al. (2012)
Asthma prevalence	2010, national value	American Lung Association (2010)
Population projections	2010 to 2095, by county in 5-year eras	ICLUS ver. 2.0. (EPA 2017b)
Cost of illness, asthma incidence	Includes lifetime medical costs and lifetime productivity loss	Belova et al. (2020)
Value of statistical life	All-cause mortality VSL based on 26 value-of-life studies	BenMAP, projected using NYS GDP Projections (EPA 2022)

B5.3 Aeroallergens

The following sections describe more details on the aeroallergen analyses presented in Chapter 6, Human Health and Safety.

B5.3.1 Climate Data

This analysis relies on methods originally developed by Neumann et al. (2019) to estimate future changes in pollen-induced asthma ED visits due to climate change. The Neumann et al. analysis uses the Localized Constructed Analogs (LOCA) dataset to generate model-specific downscaled climate projections for the contiguous U.S. (CONUS) for five CMIP5 GCMs (CanESM2, CCSM4, GISS-E2-R, HadGEM2-ES, and MIROC5) and two different climate scenarios. The temperature response functions linking ED visits to these climate projections were modified for this analysis to account for updated CMIP6 temperature projections.

B5.3.2 Exposure Response Functions

Neumann et al. (2019) assessed the climate effects on pollen-induced asthma ED visits for three pollen types (birch, grass, and oak) and two age groups (birth–17, 18–99), with a different health impact function (HIF) or pooled set of HIFs drawn from the literature for each combination:

- **Birch, birth–age 17:** Estimates rely on a regression model for all age groups developed by Ito et al. (2015).
- **Birch, aged 18–99:** We adopt the same Ito et al. regression model for this age group.
- **Grass, birth–age 17:** Results represent a pooled estimate drawn from Gleason et al. (2014), Heguy et al. (2008), Babin et al. (2007), and Darrow et al. (2012).
- **Grass, aged 18–99:** Darrow et al. is the only one of the four grass pollen studies that assesses impacts for a group aged 18 and older, so we use that response function here.
- **Oak, birth–age 17:** Projections use a pooled effect estimate based on Zhong et al. (2006), Darrow et al., and Ito et al.
- **Oak, aged 18–99:** Results are calculated using a pooled approach based on Darrow et al. and Ito et al.

Exposure-response functions from the studies listed here are pooled in order to comprehensively estimate pollen-induced asthma ED visits across all ages, for three of the most harmful aeroallergens.

B5.3.3 Impact of Population Forecasts on Results

A key driver for the health incidence impacts is the projection of county-level population change. These projections have a first-order influence on the health effect estimates, but because the projection reflects trends in rural-to-urban migration in New York State, population changes can influence results in the opposite direction of the climate stressor, giving the appearance of a mitigated impact in rural areas. This limitation is acknowledged in the main text and is explored quantitatively as a sensitivity analysis in greater depth in the previous section on extreme heat.

B5.3.4 Valuation

Additional pollen-induced asthma ED visits are valued using an average of direct medical cost estimates from two studies, Stanford et al. (1999) and Smith et al. (1997). These estimates are consistent with current best practices for EPA analyses involving asthma-related ED visits (see, e.g., EPA 2022). The per-visit cost used is \$641.

B5.3.5 Processing Steps

Using the approach of Neumann et al. (2019) and the health impact functions described earlier, we projected future asthma ED visits attributable to pollen exposure for each of the five CMIP5 GCMs, three pollen types, and two age groups listed previously and calculated results for 2030, 2050, 2070, and 2090. Using these data points, we constructed piecewise linear temperature-response functions for each county and GCM. For each of the 12 updated climate scenarios used in this analysis (six CMIP6 GCMs and two SSP-RCP combinations), we generated projected annual values for the 20-year intervals representing the projection periods in this analysis using these response functions. We then calculated era averages by taking the mean across years in each interval. Finally, we averaged impacts for each era across the six CMIP6 GCMs and allocated these county-level results to 12 NYS regions based on population. Table B-23 presents the data sources referenced in this analysis.

Table B-23. Aeroallergens Analysis Data Sources

Data	Description	Source
Baseline asthma ED visits	County-level, for the 2018–2020 period	New York State Department of Health Asthma County Dashboard (DOH n.d.)
Projected pollen-induced asthma ED visits	County- and GCM-specific projected ED visits for five CMIP5 GCMs, three pollen types, and two age groups	Neumann et al. (2019)
Population projections	2010–2095, by county in 5-year increments	ICLUS ver. 2.0 (EPA 2017b)
Cost of an asthma ED visit	Direct medical costs	Stanford (1999) and Smith et al. (1997)

B5.4 Infectious Disease

The following sections describe more details on the infectious disease analyses presented in Chapter 6, Human Health and Safety.

B5.4.1 Climate Data

The primary research underlying these projections estimated future changes in disease incidence due to climate change using modeled climate data from the CMIP5 suite of GCMs. The exposure-response functions linking impacts to climate projections were modified for this analysis to account for updated CMIP6 temperature and precipitation projections.

B5.4.2 Exposure Response Functions

Lyme disease: This analysis relies on functions developed by Couper et al. (2020) to project Lyme disease incidence in six U.S. regions in response to climate change. The model for the Northeast region, which includes New York State, estimates future incidence as a function of average spring temperature, number of hot/dry days, cumulative temperature, total annual precipitation, and daily temperature variability. The Couper et al. study includes land-cover controls, and the effect of that control is that areas with low forest and vegetation coverage would be expected to show lower levels of Lyme disease. Because future land-cover projections were not available, this control was omitted in this application. One concern with this omission is that areas such as New York City, with lower forest cover, might erroneously show large increases in Lyme disease. While baseline rates of Lyme disease are low in New York County (Manhattan), rates in Staten Island, Queens, and the Bronx are higher and nearly comparable to rates in other parts of New York State. In addition, we found that another recent study (Yang et al. 2024) found increases in Lyme disease in the five counties that make up New York City that are roughly comparable to the results presented here.

West Nile virus: These results were drawn from health impact functions specified by Belova et al. (2017), which modeled the association between West Nile virus (WNV) neuroinvasive disease incidence and temperature in historical data based on previous work by Hahn et al. (2015). Belova et al. parameterized health impact functions at the county level using historic observational data and then projected them to 2050 and 2090. As noted in that study, above-normal temperatures have been among the most consistent predictors of outbreaks, due in part to the acceleration of viral incubation in mosquitoes and increased mosquito reproduction rates at higher temperatures.

Vibriosis: This analysis is based on an EPA-sponsored study by Sheahan et al. (2022), which constructed logistic regression models using historic vibriosis incidence and sea-surface temperature data at the county level for each of four *Vibrio* species groups. The study traces infections reported to the CDC to likely locations of exposure and estimates the influence of environmental factors such as sea surface temperature on infection rates. The model of infection rates is then used to develop estimates of projected cases of vibriosis for future climate change scenarios. While the route of exposure is limited to marine coastal environments, the transport of seafood across the country means that infections can occur almost anywhere. Regional results reported here are based on coastal exposure locations, not locations where seafood might be consumed.

B5.4.3 Impact of Population Forecasts Results

A key driver for the health effect impacts is the projection of county-level population change. These projections have a first-order influence on the health effect impact results, but because the projection reflects trends in rural-to-urban migration in New York State, population changes can influence results in the opposite direction of the climate stressor, giving the appearance of a mitigated impact in rural areas. This limitation is acknowledged in the main text and is explored quantitatively as a sensitivity analysis in greater depth in the previous section on extreme heat.

B5.4.4 Valuation

Lyme disease: Impacts are valued using a single cost-of-illness estimate of \$12,859 from Zhang et al. (2006), adjusted to 2021 USD, representing both direct medical costs and indirect costs (e.g., productivity losses).

West Nile virus: Additional cases are valued using a weighted average of costs for fatal and nonfatal outcomes of WNV. Impacts from nonfatal cases are valued using a combination of medical cost-of-illness estimates for treating the disease and lost productivity. Impacts from fatal cases are valued using the VSL, a number derived from individual willingness to pay (WTP) for a marginal reduction in mortality risk. The baseline VSL is projected through the twenty-first century using national GDP projections and a longitudinal income elasticity of 0.4; these estimates are consistent with current best practices for EPA analyses involving climate-related mortality (see, e.g., EPA 2022). Approximately 6.5% of cases in the historical period resulted in death, which is assumed to remain constant throughout the century.

Vibriosis: Additional cases are valued using species-specific weighted averages of costs for fatal and nonfatal outcomes based on the relative proportions of different health outcomes by species. Costs for specific health outcomes are described in Sheahan et al. (2022) and include both direct medical costs and lost productivity due to illness. Fatal cases are valued using the VSL used throughout this report.

B5.4.5 Processing Steps

Lyme disease: We estimated future Lyme disease incidence using county-level baseline data from the New York State Department of Health (DOH n.d., Communicable Disease),¹⁹ the exposure-response functions detailed earlier, and climate variable data for each of the 12 updated climate scenarios used in this analysis (six CMIP6 GCMs and two SSP–RCP combinations).

West Nile virus: We projected future WNV incidence using state-level data from Belova et al. (2017) disaggregated to the county level using baseline data from DOH and the CDC.²⁰ The original study modeled future incidence for each of five CMIP5 GCMs (CanESM2, CCSM4, GISS-E2-R, HadGEM2-ES, and MIROC5) and provided results at the era level for 2010, 2050, and 2090.²¹ Using the Localized Constructed Analogs (LOCA) dataset to generate model-specific county-level downscaled climate projections, we constructed piecewise linear temperature response functions for each county and for each GCM. For each of the 12 updated climate scenarios used in this analysis (six CMIP6 GCMs and two SSP–RCP combinations), we generated projected annual values for the 20-year intervals representing the projection periods in this analysis using these response functions. We then calculated era averages by taking the mean across years in each interval. Finally, we averaged impacts for each era across the 6 CMIP6 GCMs and allocated these county-level results to 12 New York State regions based on population.

¹⁹County-level incidence is available for 1994–2010 from the Communicable Disease Annual Reports (DOH n.d.) for all counties outside of the New York City region, for which an aggregated value is reported. We use 2018–2020 Community Health Indicator Report data (DOH n.d.), which are reported at the county level, even for counties in the New York City region, to disaggregate the reported regional values to the county level.

²⁰County-level incidence is available for 2003–2010 from the Communicable Disease Annual Reports (DOH n.d.) for all counties outside of the New York City region, for which an aggregated value is reported. We use 2003–2010 data from CDC ArboNET’s National Arbovirus Surveillance System (CDC 2024), which reports at the county level, including counties in the New York City region, to disaggregate the reported regional values to the county level. CDC-reported values generally exceed state-reported values at the county level. This may be due to differences in the methods used to record WNV cases, which might be contracted in one county but reported in another.

²¹We use the 2010 value provided in Belova et al. (2017) for constructing the temperature response functions, but the baseline period results we present in this analysis are drawn from the DOH and CDC as described earlier.

Vibriosis: We estimated annual vibriosis incidence for each of six CMIP5 GCMs (CanESM2, CCSM4, GFDL-CM3, GISS-E2-R, HadGEM2-ES, and MIROC5) using the exposure-response functions from Sheahan et al. (2022) detailed earlier. For this analysis, we adopted that study’s baseline impact period (1986–2005) and modeled baseline data. As for WNV, we constructed temperature response functions using localized constructed analogs (LOCA) climate data for the six CMIP5 GCMs (CanESM2, CCSM4, GFDL-CM3, GISS-E2-R, HadGEM2-ES, and MIROC5) used in the original modeling. We then used these functions to project annual values for the 20-year intervals representing the projection periods for each of the updated climate scenario. Lastly, we averaged across eras and GCMs and allocated results to 12 NYS regions by population.

Table B-24 presents the data sources referenced in these analyses.

Table B-24. Infectious Disease Analysis Data Sources

Data	Description	Source
Baseline Lyme disease incidence	County level, for the 1994–2010 period	Data from the <i>Communicable Disease Annual Reports</i> (DOH n.d.) for counties outside of the NYC region, for which an aggregated value is reported. 2018–2020 “Community Health Indicator Report” data (DOH n.d.), used to disaggregate values for the NYC region to the county level
Projected Lyme exposure response functions	CONUS region-specific functions	Couper et al. (2021)
Baseline West Nile virus incidence	County-level, for the 2003–2010 period	Data from the <i>Communicable Disease Annual Reports</i> (DOH n.d.) for counties outside of the NYC region, for which an aggregated value is reported. 2003–2010 data from ArboNET: National Arbovirus Surveillance System–Historic Data (CDC 2024), used to disaggregate values for NYC region to the county level
Projected West Nile virus incidence	State-level, GCM-specific projected WNV incidence for three eras and five CMIP5 GCMs	Data provided by Belova et al. (2017)
Baseline Vibriosis incidence	County-level, modeled for 1986–2005	Data provided by the authors of Sheahan et al. (2022)
Projected vibriosis incidence	County-level annual trajectory through 2099	Data provided by the authors of Sheahan et al. (2022)
Population projections	2010–2095, by county in 5-year increments	ICLUS ver. 2.0 (EPA 2017b)

Table B-24. (continued)

Data	Description	Source
Lyme disease cost of illness	Direct and indirect costs of illness	Zhang et al. (2006)
West Nile virus cost of illness	Direct and indirect costs of illness	Staples et al. (2014)
West Nile virus mortality rate	Mortality rate	Lindsey et al. (2015)
Value of statistical life	All-cause mortality VSL based on 26 value-of-life studies	BenMAP (EPA 2022), projected using NYS GDP Projections
Vibriosis cost of illness	Direct and indirect costs of illness by <i>Vibrio</i> species	Sheahan et al. (2022)

B6 Society and Economy

B6.1 Labor

This analysis estimates reductions in work time in New York State resulting from increased outdoor heat exposure associated with climate change. The underlying data sources and processing steps are outlined in the following sections.

Step 1: Determine the number of affected weather-exposed workers.

Step 2: Predict future heat under various climate models.

Step 3: Estimate the potential reduction in work time by applying the relationship from Neidell et al. (2021).

Step 4: Value the reduction in work time in terms of lost future wages.

Step 1. Weather-exposed workers: We calculate the number of weather-exposed workers (that is, workers in the agriculture, construction, and manufacturing sectors, as defined by Neidell et al. (2021) at the county level using data from the U.S. Census Bureau’s American Community Survey centered around 2010 (2008–2012) 5-year estimates, which aligns with the end of the baseline period considered for the climate data described in the following section. This analysis holds constant the number of workers expected to experience these effects given mixed historical trends on the change in employment across the industries included in this analysis.²² Table B-25 summarizes the total number of workers by climate region and statewide. As shown, nearly 1.7 million workers may experience these effects throughout New York State.

²² For instance, the manufacturing and utilities sectors are projected to experience a decline in overall employment between 2021 and 2031, whereas the mining, construction, and agricultural sectors are expected to employ more workers over the same timeframe (BLS 2021).

Table B-25. Total Number of Weather-Exposed Workers by Region in New York State

Source: Author calculations using data from the U.S. Census Bureau (n.d.).

Region	Number of Weather-Exposed Workers
Adirondacks	13,504
Catskills	35,591
Central/Finger Lakes	111,529
Champlain Valley	15,544
Great Lakes	264,186
Long Island	257,868
Mohawk River Valley	49,306
New York City	572,986
North Hudson	87,156
South Hudson	170,487
Southern Tier	75,910
St. Lawrence Valley	10,124
Statewide	1,664,192

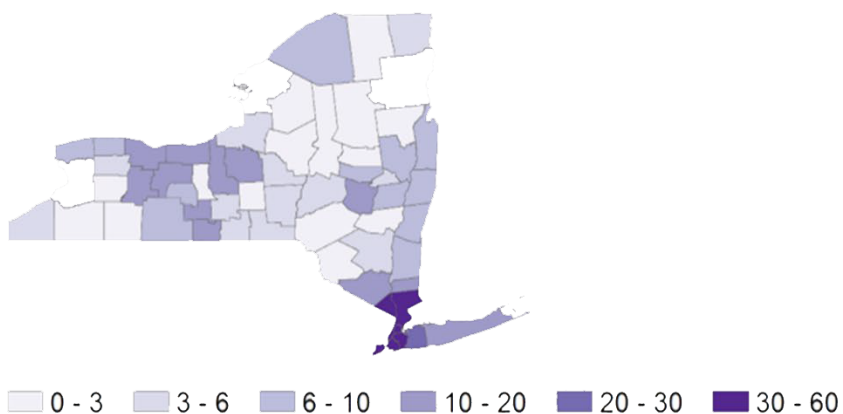
Step 2. Future heat: Future heat conditions are derived from the six primary downscaled climate models used in this report, as described in Chapter 1, Methodology. The main results reported in the main text are averaged across the six GCMs for each SSP. GCM-level results are presented as uncertainty bands in the summary graphics at the end of each section in the main text. In this section, we provide an illustration of this process at the GCM-level, using SSP5-8.5 results; the same process was also applied to the SSP2-4.5 results for each GCM, with the main results reflecting the six GCM averages.

For each climate model and year, this analysis calculates the number of degree days over 90°F in each future year by summing across all day-degrees above 90°F by year for each NYS county, following the approach in Neidell et al. (2021). The calculation relies on daily maximum temperature projections developed for the Climate Impact Assessment. For example, for 3 days that reach 91°F, 93°F, and 98°F, the number of degree days over 90°F would be $(91 - 90) + (93 - 90) + (98 - 90) = 12$. Figure B-20 displays baseline average annual heat by county across New York State, as well as the change in temperatures in the 2050s era by GCM relative to the baseline for each GCM included in this analysis under SSP5-8.5. As shown, the number of degree days over 90°F is expected to increase in 2050 relative to baseline (1981–2010), but results vary widely by GCM, with the INM-CM4-8 model showing the smallest changes from baseline by the 2050s era, mostly in the NYC region, and the UKESM1-0-LL model showing the largest changes.

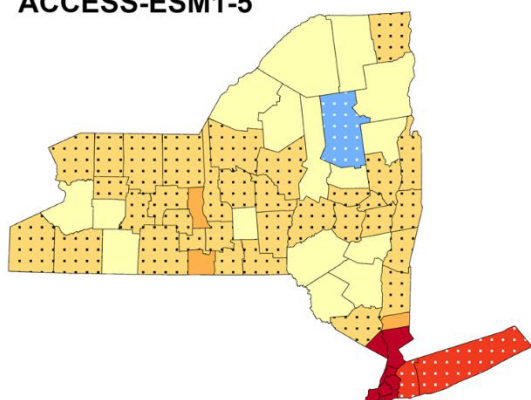
Figure B-20. Degree Days above 90°F in 2050 Era Relative to Baseline, by Climate Model

Baseline degree days above 90°F are displayed in the top panel. Change in degree days above 90°F in the 2050s era by GCM relative to baseline is shown in the six bottom panels for the SSP5-8.5 scenario.

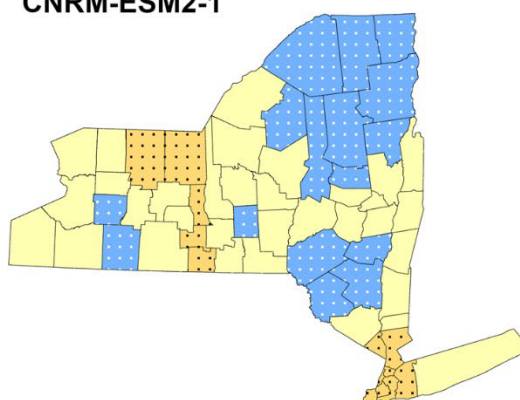
Baseline



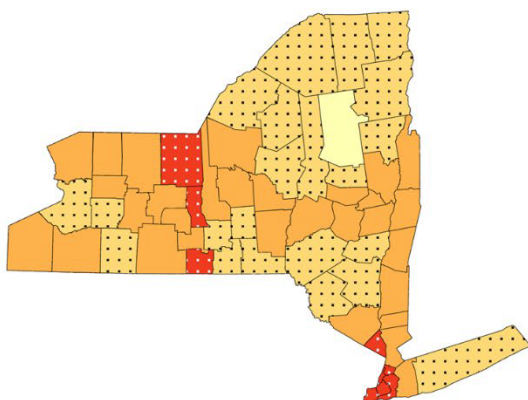
ACCESS-ESM1-5



CNRM-ESM2-1



HadGEM3-GC31-LL



INM-CM4-8

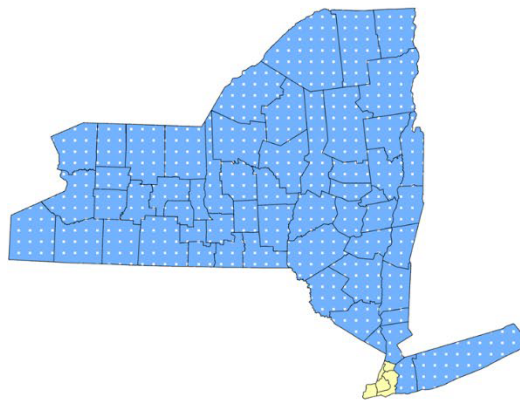
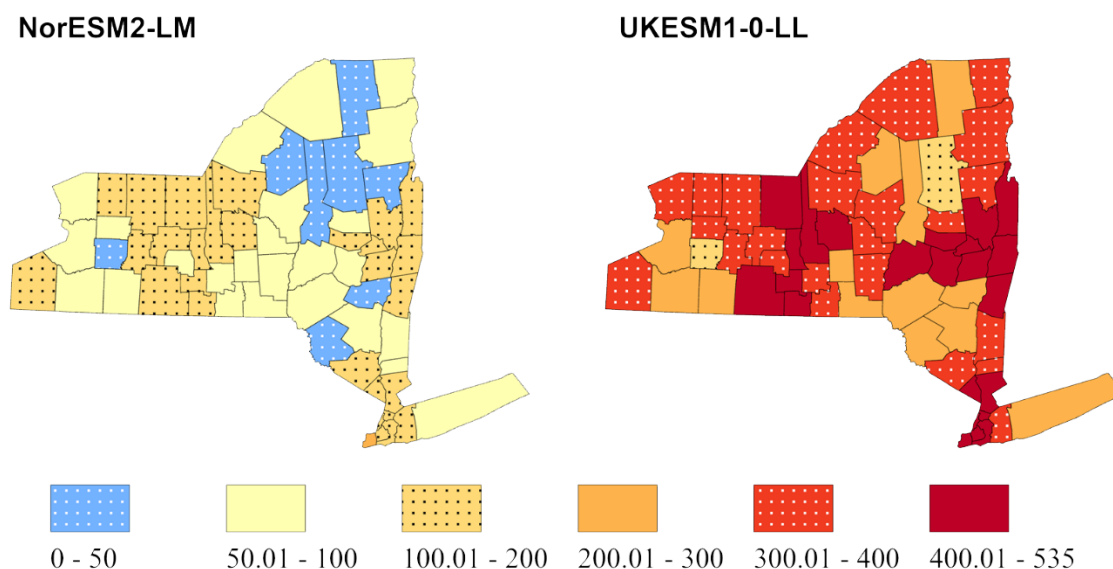


Figure B-20. (continued)



Step 3. Relationship between heat and work time: This analysis relies on the estimates from Neidell et al. (2021) to calculate the future labor-allocation impacts of heat. Neidell et al. provide the most recently available and nationally representative estimate of time lost on account of high temperature days and are therefore the most appropriate study to transfer for this analysis (Neidell et al.). Using data from the American Time Use Survey (ATUS) (information available at BLS (n.d.)), the authors estimate a reduction in work time of 2.6 minutes per worker for each degree over 90°F during periods of economic expansion. Using the years from the twentieth-century as guidance, the authors find an 86% probability of expansion in any given year. To calculate the impacts per worker per year on account of HDDs, this analysis multiplies the total number of degree days over 90°F by 2.6 minutes of lost work time as well as 0.86 to account for the probability of economic expansion. For example, for the 12 degree-days over 90°F estimated in the example from Step 2, the lost work time is $12 \times 2.6 \times 0.86 = 26.8$ minutes. To calculate the total impacts, we multiply the lost time per worker by the number of weather-exposed workers identified in Step 1.

Step 4. Lost wages: Lost time devoted to work is valued using wage rates for the relevant weather-exposed industries in New York State using data from the U.S. Bureau of Labor Statistics' (BLS) State Occupational Employment and Wage Estimates (OEWS). This data source assembles gross compensation information from a survey of businesses across industries. Table B-26 presents mean hourly wages by industry among categories of weather-exposed workers; the percent of weather-exposed workers that fall

into each occupation category, and the weighted average wage derived from this information. The result is a wage rate which can be applied for weather-exposed workers. Historical and future wage rates are adjusted using a per-capita GDP adjustment factor.²³ Continuing the example from Step 3, this valuation result would be used in the following calculation: 26.9 minutes/60 minutes per hour x \$25.24 = \$11.32 per affected worker.

Table B-26. Wage Rates among Weather-Exposed Workers in New York State

Reported in 2021 USD.

Source: *State Occupational Employment and Wage Estimates (BLS 2021)*.

Occupation Type	Percent of Weather-Exposed Workers in NYS	Mean Hourly Wage
Building and grounds cleaning and maintenance	14.8%	\$19.49
Farming, fishing, and forestry	0.3%	\$18.92
Construction and extraction	17.6%	\$33.69
Installation, maintenance, and repair	18.2%	\$28.56
Production	16.1%	\$22.14
Transportation and material moving	33.0%	\$23.02
Weighted average hourly wage	—	\$25.24

B6.2 Recreational Freshwater Fishing

This analysis estimates the change in participation in cold-water and all freshwater fishing associated with climate change, based on an existing study for the 48 contiguous states (Lane et al. 2015). Economic losses are calculated as the value of lost cold-water fishing trips and the net lost value across all freshwater fishing types. The underlying data sources and processing steps to apply the Lane et al. (2015) approach to New York State are outlined in the following sections.

²³ Projections of future gross domestic product come from the Emissions Predictions and Policy Analysis (EPAA, v6) model (Chen et al. 2015). The projection of GDP growth through 2040 comes from the 2016 Annual Energy Outlook Reference case (EIA 2016). We further note that if wages during periods of expansion grow faster than the projected GDP/capita, then the method used here may underestimate the lost wages. This point is referenced in the limitations section.

B6.2.1 Fisheries Habitat Shifts and Participation Projection Data

Lane et al. (2015) build on Jones et al. (2013) to estimate changes in freshwater fishing trips and associated lost values from a 1995 baseline driven by shifts in fisheries habitats (i.e., cold-water, warmwater, and rough fisheries) as air, and therefore water, temperatures rise. The authors model changes in habitat at the HUC-8 watershed level and estimate the resulting changes in fishing trips based on habitat availability, catch rates, and state-level demographic variables. Modeled habitats and changes in the value of fishing trips (cold-water and all freshwater) are available for four time periods (2030, 2050, 2070, and 2090) for two RCPs (RCP4.5 and RCP8.5) and five CMIP5 GCMs. Values per trip vary by habitat: cold-water trips, \$82.35; warmwater trips, \$54.20; and rough-water trips, \$42.79 (2021 USD, converted from 2015 values in Lane et al. using the Consumer Price Index). The change in the recreational value of cold-water fishing is a function of lost cold-water fishing days as fisheries convert to warm-water and rough fisheries. The change in all freshwater fishing recreational value reflects the net value change of shifts from cold-water trips to warmwater and rough trips and an overall decline in participation as waters warm. Habitat changes are available by HUC-8, and change in recreation value is available at the region level used in the Fourth National Climate Assessment (NCA).²⁴

B6.2.2 Processing Steps

To estimate lost fishing values for New York State from the Northeast regional totals available in the underlying study, we estimate future available habitats by HUC for six CMIP6 GCMs using the relationship between habitat types and maximum annual temperature described by the five CMIP5 GCMs and identify the proportion of change occurring in New York State compared to the rest of the Northeast region.

²⁴ New York State is in the Northeast NCA region, along with 11 other states and Washington, DC.

Table B-27. Freshwater Fishing Analysis Data Sources

Data	Description	Source
Habitat projections	HUC-8-level projections of freshwater fisheries habitats for four eras: 1995, 2030, 2050, 2070, and 2090 for five CMIP5 GCMs	Modified from Lane et al. (2015) and Jones et al. (2013)
Recreation fishing value projections	NCA region projections of freshwater and cold-water fishing valuation for four eras: 1995, 2030, 2050, 2070, and 2090 for five CMIP5 GCMs	Modified from Lane et al. (2015) and Jones et al. (2013)
U.S. rivers and streams	GIS shapefile of linear water features in the U.S.	USGS Earth Explorer n.d.)

Attribution of regional recreational value projections to New York State (and its regions) depends on the change in habitat distribution and baseline freshwater fishing participation relative to the rest of the Northeast NCA region (e.g., how many of the baseline cold-water trips that are converted to warmwater trips in the future in the Northeast region occur in New York State?). We perform the following steps to attribute regional value to New York State.

1. **Estimate the share of regional miles of rivers and streams per HUC-8:** In the absence of comprehensive and spatially refined data on baseline freshwater fishing participation, we use miles of rivers and streams USGS Earth Explorer n.d.) in each HUC-8 relative to the total number of miles in the Northeast NCA region as a proxy for the share of freshwater fishing participation. Note that socioeconomic factors also impact baseline participation, but due to data limitations, mileage of rivers and streams provides a reasonable basis for this estimate.

As an illustrative example, imagine that HUC-1 was a cold-water fishery in the baseline and contains 20% of the cold-water river and streams mileage in the Northeast region. We would then assume the HUC contains 20% of the baseline cold-water trips.

2. **Calculate the share of lost cold-water miles in each HUC and attribute the total lost cold-water fishing value in the Northeast to HUCs based on the calculated shares.** Using the modeled future habitats by HUC-8 from Lane et al. (2015), we calculate the total share of miles of rivers and streams converting out of cold-water habitats (i.e., sum of trips across all HUCs in the Northeast region that convert) for each future time period and GCM. We then calculate the share of the lost cold-water miles in the Northeast region per HUC-8 and apply the share to the regional total lost cold-water fishing value to get lost value per HUC-8 for each time period and GCM.

Following our example, in the first projection era, HUC-1 converted to a warmwater fishery along with several other HUCs, which in total represented 60% of the baseline cold-water fishery miles in the Northeast. In this step, we would then calculate the share of lost cold-water miles in HUC-1 as 30% of the lost cold-water fishery miles (20%/60%).²⁵ If total lost cold-water fishing value in the Northeast was \$100, HUC-1 would have an estimated \$30 loss (\$100 x 30%).

3. **Estimate a fishing value per HUC-8 for the baseline and projections.** Using miles per HUC-8 in each habitat assignment from Lane et al., and values per trip by habitat type, also from Lane et al. (2015), we calculate the value of trips per HUC-8 for the baseline and projections based on habitat assignments by era and GCM, and subtract the baseline from future values.

Following the example of HUC-1, assuming HUC-1 had 20 miles of cold-water fishing in the baseline (valued at \$82.35 per trip) and it converted to warmwater in the future (valued at \$54.20 per trip), the lost value for this HUC is \$28.15 (\$82.35 - \$54.20).

4. **Calculate the share of lost freshwater fishing value in each HUC and attribute the lost freshwater fishing value in the Northeast based on the calculated shares.** We multiply the lost value per HUC-8 by the miles per HUC-8 and calculate the share of total lost value by HUC-8. We then multiply the share of lost value per HUC by the total loss for the Northeast region in the underlying study to estimate total loss per HUC.

HUC-1 has a change in weighted fishing value of -5.7. The total change in weighted fishing value across all HUCs in the Northeast is -20; therefore, the share of lost value for HUC-1 is 28.3% (-6.1/-20). If the total lost fishing value in the Northeast were \$50, HUC-1 would have an estimated \$14.15 loss (\$50 x 28.3%).

The result of this process is lost cold-water fishing value and lost all freshwater fishing value for HUC-8 for five CMIP5 GCMs and four future eras. To estimate projected valuation under the six CMIP6 scenarios, we plot temperature²⁶ and lost value (cold-water and freshwater fishing) for each HUC-8 and CMIP5 GCM pair. Then, we interpolated across the linear splines of the resulting piecewise function to estimate the lost value associated with the CMIP6 temperature in three future eras (2030s, 2050s, and 2080s) for six GCMs at the HUC-8 scale. HUC-8 results are converted to the 12 analysis regions using spatial area weights.

²⁵Values are rounded for simplicity in this example.

²⁶The specific temperature variable used in this process is the lowest maximum monthly average temperature across half-degree grid cells per HUC-8, following Jones et al. (2013).

B6.3 Winter Recreation

This analysis estimates reduced visits to ski areas for downhill skiing, cross-country skiing, and snowmobiling, and the associated revenue loss for resorts attributable to climate change. Wobus et al. (2017) estimated changes in season length from a 2011 baseline at 247 ski locations across the U.S., including 15 NYS locations, documented below. The authors applied changes in season length to estimate changes in winter recreation visits in 2050 and 2090, incorporating snowmaking for downhill ski season lengths.

Visits were valued in the underlying model using the National Ski Areas Association (NSAA) average adult weekend ticket price for each snow sport. Table B-28 presents these values, adjusted to 2021 USD. Note that these values represent revenue to resorts, not willingness to pay of participants—willingness to pay of participants may be substantially higher than revenue of the applicable venues.

Table B-28. Value of Winter Recreation Activities per Visit

Reported in 2021 USD

Activity	Value per Visit
Downhill Skiing	\$90.55
Cross Country Skiing	\$11.11
Snowmobiling	\$4.45

To estimate winter recreation impacts, we isolated the winter season length (in days per year) by era and GCM for 15 ski areas in New York State from Wobus et al. (2017). Importantly, Wobus et al. incorporate a “modeled” baseline for the current winter season length, using available weather data; therefore, the estimates for some ski areas may not match other data sources. We then developed site-specific impact functions relating the number of recreation days to county-level LOCA temperature. We applied these functions to each of the six CMIP6 GCMs and two SSPs-specific temperature results for the eras included in this analysis (2030s, 2050s, and 2080s). Finally, we averaged the season lengths across CMIP6 GCMs, resulting in the number of days per ski area for each era and SSP. Table B-28 presents a list of included ski areas and their adjusted season lengths, each area as described earlier.

To estimate baseline and projected site-level visitation and revenue, we divided the statewide baseline of the number of visits and revenue from Wobus et al. (2017) by the winter recreation season length (in days). We used the resulting visits/day and cost/visit to estimate changes in visitation and revenue for the

projected season lengths by site. We allocated ski areas to the regions in which they fall. None of the ski areas from the underlying study fall within the Long Island, Mohawk River Valley, New York City, or South Hudson Valley regions; therefore, we do not estimate impacts to winter recreation in these regions. Table B-29 presents the data sources referenced in this analysis.

Table B-29. Winter Recreation Analysis Data Sources

Data	Description	Source
Baseline season length	Number of days, for downhill skiing, cross-country skiing, and snowmobiling in 2011 by resort	Modified from Wobus et al. (2017)
Projected season length	Number of days, projected using six GCMs, for 2050 and 2090 eras, by resort	Modified from Wobus et al. (2017)
Number of visits	Statewide number of visits in the baseline (2011)	Wobus et al. (2017), based on NSAA projected alpine snow sport average visits by state from 2006–2007 to 2015–2016
Value of visits	Statewide value of total visits in the baseline (2011)	Wobus et al. (2017), drawing from NSAA average adult weekend ticket prices from 2014–2015 to 2015–2016

B6.4 Other Outdoor Recreation

This analysis estimates the change in outdoor recreation trips in New York State resulting from changes in temperature and precipitation patterns associated with climate change. The underlying data sources and processing steps are outlined in the following sections.

- Step 1:** Calculate the baseline number of outdoor recreation trips in New York State using the ATUS.
- Step 2:** Project future temperature and precipitation under various climate models (CMIP6).
- Step 3:** Estimate the potential change in outdoor recreation trips by applying regression models from Willwerth et al. (2023).
- Step 4:** Value the change in number of trips using willingness to pay estimates from a recent application of the Recreation Use Value Database (RUVD).

Step 1. Baseline outdoor recreation participation: Following the approach of Willwerth et al. (2023), we assemble historical outdoor recreation trip data for New York State using the ATUS for the 17-year period between 2003 and 2019 (BLS ATUS n.d.). ATUS is a nationally representative cross-sectional survey of Americans aged 15 and older that asks respondents to report a detailed diary of how they

allocated the preceding 24 hours by activity, location, and length of time via a telephone interview. Table B-30 summarizes the number of outdoor recreation trips observed for the 10,707 respondents residing in New York State by activity type. The table splits the many activities into two overarching categories:

- **Limited recreation types**, which include major recreation activities and have direct matches in the valuation database introduced below.
- **Nonlimited recreation types**, which include sports and other recreation activities that may occur during scheduled event times and have less flexibility. This category also includes—and is dominated by—recreational walking, as distinct from walking for commuting purposes.

These data identify over 546 million outdoor recreation trips per year in the State, equivalent to nearly 35 trips per person aged 15 and older. The activities with the highest participation include walking (for recreational purposes), running, and participating in water sports.

Table B-30. Number of Outdoor Recreation Trips in New York State (2003–2019)

Source: Author calculations using data from the BLS ATUS (n.d.), 2003–2019 and 2010 U.S. Census Bureau (n.d.) data for population aged 15 and older.

Outdoor Recreation Type ^a	Total Number of Trips per Year ^b	Number of Trips per Year per Capita
Limited Recreation Types		
Running	67,058,824	4.3
Participating in water sports	58,294,118	3.7
Biking	28,470,588	1.8
Hunting	13,705,882	0.9
Fishing	9,352,941	0.6
Boating	8,470,588	0.5
Hiking	5,758,824	0.4
Skiing, ice skating, snowboarding	3,364,706	0.2
Non-Limited Recreation Types		
Walking	272,352,941	17.4
Playing basketball	39,882,353	2.5
Other	28,764,706	1.8
Golfing	22,117,647	1.4
Playing racquet sports	10,647,059	0.7
Playing football	10,176,471	0.7
Playing soccer	6,529,412	0.4
Playing baseball	5,941,176	0.4

Table B-30. (continued)

Outdoor Recreation Type^a	Total Number of Trips per Year^b	Number of Trips per Year per Capita
Playing softball	4,111,765	0.3
Rollerblading	3,029,412	0.2
Participating in equestrian sports	905,882	0.1
Climbing, spelunking, caving	259,899	0.0
Participating in rodeo competitions	0	0.0
Playing rugby	0	0.0
All outdoor recreation	546,470,588	34.9

^a See main text for definitions of “limited” and “nonlimited” recreation types.

^b Outdoor recreation activities are determined based on six-digit ATUS activity codes (with descriptions above) as well as location code (all activities not tagged as “gym or health club” are assumed to take place outdoors). Calculations are weighted using survey weights published with the data.

Step 2. Future temperature and precipitation: Future temperature and precipitation conditions are derived from the six primary downscaled climate models used in this report, as described in Chapter 1, Methodology. For each climate model and year, this analysis calculates the number of days with maximum daily temperatures that fall into specific 5°F bins as well as the number of days projected to receive precipitation of particular magnitudes (in inches), following the approach of Willwerth et al. (2023).

Figure B-21 displays the change in number of days in each temperature bin by era relative to baseline (1981–2010) on average across New York State. As shown, the number of cold days is projected to decrease, while the number of days 80°F and greater is expected to increase. Figure B-22 provides an analogous presentation for future precipitation. Both SSP2-4.5 and SSP5-8.5 project increases in days with less than 0.01 inch of rain only through the 2030s, then a reduction in days in that bin the remainder of the century. Days with 0.01 to 0.25 inches are projected to decrease, while days with 0.25 inches or greater precipitation are projected to increase.

Figure B-21. Number of Future Days by Temperature Bin by Era Relative to Baseline

Change in number of days on average in New York State in each temperature bin, annually, relative to baseline.

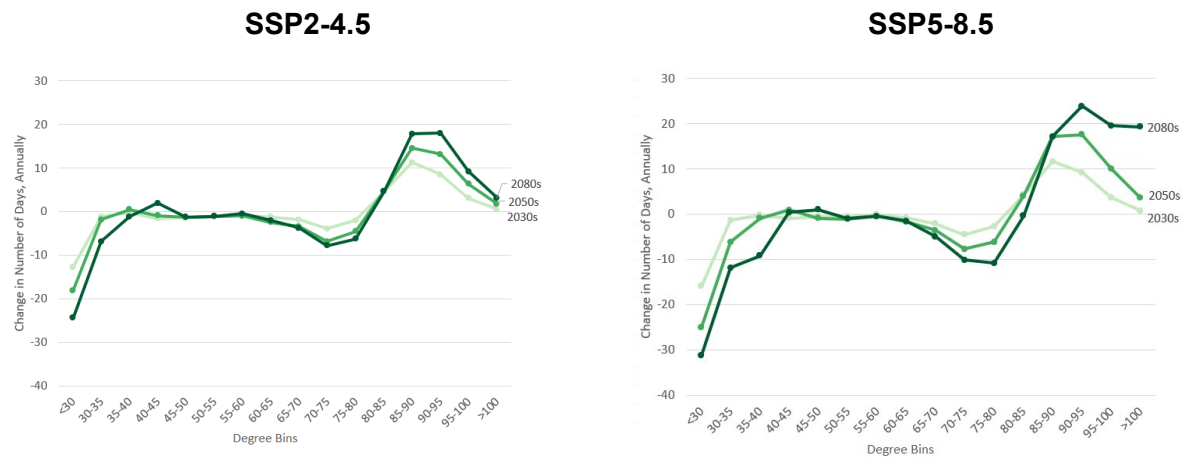


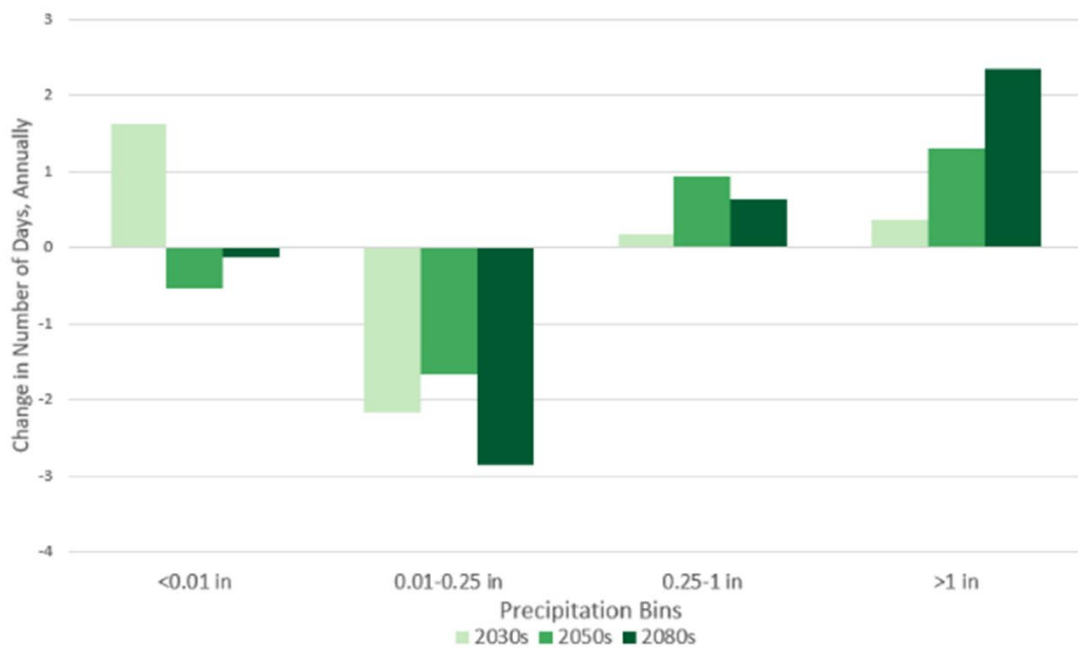
Figure B-22. Number of Future Days by Precipitation Bin by Era Relative to Baseline

Change in number of days on average in New York State in each precipitation bin, annually, relative to baseline. The top chart shows results for SSP2-4.5, and the bottom chart shows SSP5-8.5.

SSP2-4.5



SSP5-8.5



Step 3. Relationship between temperature, precipitation, and outdoor recreation: This analysis relies on the estimates from Willwerth et al. (2023) to project the change in future outdoor recreation trips related to changes in temperature and precipitation levels. While several other studies investigate the relationship between climate and specific recreation types, Willwerth et al. provide the only nationally representative and northern-region-specific projection across all outdoor recreation types. Using data from the ATUS, the authors estimate several regression models that predict the change in the probability of a trip for each 5°F temperature bin and precipitation bin. These models are disaggregated by activity type and aggregated across outdoor recreation categories in ATUS.

Willwerth et al. (2023) explore several scenarios that correspond with potential ways recreators may respond to changes in temperature and precipitation in the future. For this analysis, we employ the model results from Willwerth et al., consistent with how ATUS respondents in northern regions of the U.S. make choices about recreation participation under different climatic conditions. Table B-31 presents the marginal effects estimates for two of the models—all recreation and the limited recreation subset. As shown, participation in outdoor recreation significantly decreases at lower temperature levels relative to a 70°F–75°F day. Participation increases between 80°F and 100°F, but then decreases on days above 100°F. Relative to a day with <0.01 inch of rainfall, recreational trips are reduced at each of the three included precipitation levels, with participation decreasing at higher rainfall levels.

We employ the marginal effects estimates by for the models that describe all outdoor recreation, the limited recreation set, and by activity within the limited recreation set. These models predict the number of future recreation trips by type at the individual level. Finally, we scale the trip estimates using the total population aged 15 and older by New York State county using ICLUS ver. 2.0.

Table B-31. Marginal Effects for Weather Variables, Predicting Outdoor Recreation Participation

The northern regions are defined consistent with the NCA regions of the U.S. Global Change Research Program and include the Northeast, Northwest, Midwest, and Northern Great Plains. Each column describes a separate model run where the outcome variable describes a subset of outdoor recreation activities (see Willwerth et al. 2023 or Table B-30 for descriptions).

Source: Reproduced from Table 4 of Willwerth et al. (2023), results from northern regions specifically.

Model Variable ^b	All Recreation Model ^a Estimates	Limited Recreation Model ^a Estimates
Temp <30 (°F)	-0.0383***	-0.0083**
Temp <30 (°F)	(0.0073)	(0.0039)
Temp 30–35	-0.0402***	-0.0017
Temp 30–35	(0.0071)	(0.0048)

Table B-31. (continued)

Model Variable^b	All Recreation Model^a Estimates	Limited Recreation Model^a Estimates
Temp 35–40	-0.0319***	-0.0020
Temp 35–40	(0.0076)	(0.0048)
Temp 40–45	-0.0265***	-0.0066**
Temp 40–45	(0.0071)	(0.0031)
Temp 45–50	-0.0095	-0.0034
Temp 45–50	(0.0080)	(0.0039)
Temp 50–55	-0.0137*	-0.0020
Temp 50–55	(0.0079)	(0.0036)
Temp 55–60	-0.0108	-0.0029
Temp 55–60	(0.0075)	(0.0036)
Temp 60–65	-0.0060	-0.0025
Temp 60–65	(0.0079)	(0.0034)
Temp 65–70	0.0034	0.0044
Temp 65–70	(0.0081)	(0.0043)
Temp 75–80	0.0079	0.0063
Temp 75–80	(0.0070)	(0.0039)
Temp 80–85	0.0111	0.0090**
Temp 80–85	(0.0079)	(0.0042)
Temp 85–90	0.0173*	0.0186***
Temp 85–90	(0.0103)	(0.0058)
Temp 90–95	0.0122	0.0189**
Temp 90–95	(0.0122)	(0.0075)
Temp 95–100	0.0130	0.0147*
Temp 95–100	(0.0168)	(0.0086)
Temp >100	-0.0211	-0.0164**
Temp >100	(0.0359)	(0.0066)
Prcp 0.01–0.25 (inch)	-0.0129***	-0.0036**
Prcp 0.01–0.25 (inch)	(0.0030)	(0.0015)
Prcp 0.25–1	-0.0227***	-0.0052***
Prcp 0.25–1	(0.0040)	(0.0016)
Prcp >1	-0.0287***	-0.0083**
Prcp >1	(0.0073)	(0.0040)

^a For each model variable, the top line presents the coefficient while the bottom line presents the standard error (in parentheses). One asterisk (*) denotes statistical significance at the 90th confidence level, two (**) at the 95th confidence level, and three (***) at the 99th confidence level.

^b For the temperature variables (expressed in degrees Fahrenheit), all coefficients are relative to the 70°–75° degree omitted category. For the precipitation variables (expressed in inches), all coefficients are relative to the <0.01-inch omitted category.

Step 4. Value of outdoor recreation trips: The change in the number of outdoor recreation trips is valued using welfare estimates per trip from the Oregon Statewide Comprehensive Outdoor Recreation Plan (SCORP), an application of the Oregon State University’s RUVD (Rosenberger 2018). The RUVD

is a collection of outdoor recreation valuation studies coded for characteristics such as location, activity, valuation method, and year. Some estimates provided reflect NYS-specific or regional values and are preferentially applied in this analysis when available. In cases where no New York State or Northeast regional values are available, U.S. average values are used.

The SCORP reported average values per trip by activity from the RUVD after eliminating estimates for Canada and removing outlier estimates. Table B-32 matches the values provided in SCORP with the outdoor recreation activities reported in ATUS. Coverage in SCORP across outdoor recreation types in the nonlimited category is incomplete. To apply these values, we take a several-step approach that considers the variation in number of trips and values across recreation types:

- **For limited recreation types:** We first calculate the total change in trips by activity, then multiply those totals by the activity-specific value from SCORPS (Table B-32). We then sum the welfare estimates across limited activities and divide by the total change in activity days to calculate a weighted average dollar-per-trip for each degree. At the state level, the weighted average per-trip value is \$45.81 (2021 USD). The value per trip is applied to the net change in limited recreation trips at the county level.
- **For nonlimited recreation types:** We do not estimate activity-specific changes in nonlimited recreation trips. Instead, we subtract the change in total limited activity trips from the change in all outdoor activities estimate to arrive at the total change in nonlimited activities. We value the nonlimited activity trips using the SCORP value for walking, equivalent to \$14.59.

Table B-32. Welfare Values per Outdoor Recreation Trip

Adjustment to 2021 USD, Section 1, Table 1.1.9 of *National Data: National Income and Product Accounts* (U.S. Bureau of Economic Analysis 2022). Reported in 2021 USD.

Source per-trip values: Rosenberger (2018).

Outdoor Recreation Type	Value per Trip
Limited Recreation Types	
Participating in water sports	\$32.38
Running	\$68.01
Biking	\$105.00
Boating	\$74.72
Fishing	\$87.19
Hiking	\$91.30
Hunting	\$86.30
Skiing, ice skating, snowboarding	\$64.48
Nonlimited Recreation Types	
Walking	\$14.59

B7 Transportation

B7.1 Roads

The Reactive Response and Proactive Adaptation scenarios rely on U.S. Department of Transportation (DOT) productivity rates to estimate delays from the time required to complete climate-hazard-induced road maintenance. We accounted for the potential for vehicles to avoid damaged roads or road maintenance by rerouting through an index that represents redundancy in the road network. The application of the redundancy index is further described in the supplemental material for Neumann et al. (2021). Finally, to quantify delay costs for passenger vehicle travel, we used the value-of-travel-time-savings estimates from DOT (2016). For freight vehicle travel, we use data from the National Cooperative Highway Research Program (NCHRP) from its Truck Freight Reliability Valuation Model (NCHRP 2016).

The summary of costs included in the two roadway response scenarios (Reactive and Proactive) can be found in Table B-33. For more detailed information on each of the response scenarios, see the supplementary material from Neumann et al. (2021).

Table B-33. Summary of Costs Included in the Two Road Response Scenarios

Source: Neumann et al. (2021).

Reactive Response Scenario	Proactive Adaptation Scenario
Repair costs	Upfront capital costs of proactive strengthening
Costs of delays due to repairs	Repair costs
—	Costs of delays due to proactive strengthening and repairs
Routine (non-climate-driven) maintenance costs	Routine (non-climate-driven) maintenance costs

Table B-34. Road Infrastructure Analysis Data Sources

Data	Description	Source
Road data	Road stock inventory, by ownership category, including AADT and speed limit for each road (relevant to estimating travel time delay)	Road stock, traffic, and speed limit input data were compiled from the NYS GIS Clearinghouse (n.d.)
Speed reductions	The effect of roughness on free-flow travel speed	California Department of Transportation study by Wang et al. (2013) describes the relationship between PSR and free-flow speed, and research by Al-Omari and Darter (1994) describes the conversion from IRI to PSR, see additional details in Neumann et al. (2021) supplement
Estimation of delay times and valuation	Calculating VOCs from damages to road infrastructure associated with climate change	Research from Qiao et al. (2013) describes the change in IRI because of temperature changes, and IRI is linked to VOCs through research from Barnes and Langworthy (2004), additional details in Neumann et al. (2021) supplement
Delay costs per unit of time	To assign a dollar value to delays, we use DOT's 2016 guidance for estimating the valuation of travel time delay for economic analysis	DOT, Office of the Transportation Secretary (2016)

B7.2 Rail

The details of the response scenarios are described in the supplemental material of Neumann et al. (2021), with the term “damage” defined as the physical manifestation of climate effects, and the term “cost” as the economic implication of either repairing damage or, in the case of user and indirect costs, of failing to repair the damage. In the reactive response scenario, decision-makers respond to climate-related impacts using current practices (i.e., with reduced speed orders) which reduces the risk of buckling events. Delays and buckling events do occur under the reactive scenario, however, and increased ambient temperature increases the risk of those events. In the proactive adaptation scenario, decision-makers implement a heat sensor technology that allows train operators to more directly assess the risk of buckling during high heat events, and more precisely target the implementation of speed orders to situations where the track is at greatest risk of buckling (i.e., speed orders without sensors incorporate a safety margin based on indirect measures, such as ambient temperature readings rather than track temperature readings). These actions involve trading some upfront expenditures/investment to install the sensors, in exchange for the ability to conduct more precise climate risk management.

This analysis does not model derailments because of track buckling or associated costs and damages due to the low percentage of derailments that are caused by buckled track, which may result in an underestimate of costs overall. Table B-35 summarizes of costs included in the two rail response scenarios (reactive response and proactive adaptation). For more detailed information on each of the response scenarios, see the supplementary material from Neumann et al. (2021).

Table B-35. Summary of Costs Included in the Two Rail Response Scenarios

Source: Neumann et al. (2021).

Reactive Response Scenario	Proactive Adaptation Scenario
• Costs of replacing track to repair lateral alignment defects in the buckling zone, and costs of re-aligning rail in adjoining zones • Costs of delays that occur due to track buckling and repair, as well as delays associated with blanket speed reductions • Costs of derailment that may result from track buckling • Costs of developing and implementing the speed orders • Costs of routine (non-climate-driven) track maintenance	• Costs of purchasing, installing, and maintaining the track temperature sensors and related software infrastructure • Costs of delays associated with risk-based speed reductions • Costs of routine (non-climate-driven) track maintenance • Downtime during sensor installation (believed to be minimal)

Table B-36. Rail Infrastructure Analysis Data Sources

Data	Description	Source
Rail stock data	Rail stock data were compiled from the NYS GIS Clearinghouse; data is now only available in a viewer and not as a download	NYS GIS (n.d.)
Rail traffic	Rail traffic was compiled from the Federal Railroad Administration (FRA) highway-rail crossing database files and reports	DOT FRA (n.d.)
Stressor-response functions	Detailed descriptions of stressor-response functions in this analysis are primarily associated with track buckling	Probabilistic track buckling function from Kish and Samavedam (2013), see additional details in Neumann et al. (2021) supplement
Economic parameters for repair cost	Direct costs for buckling damage repair to rail infrastructure associated with climate change	Repair cost of \$21,000 per event (and 14-hour repair time) from Gordian (2017), additional details in Neumann et al. (2021)
Delay costs per unit of time	To assign a dollar value to delays, we use DOT's 2016 guidance for estimating the valuation of travel time delay for economic analysis	DOT Office of the Transportation Secretary (2016)

This analysis does not model derailments because of track buckling or associated costs and damages due to the low percentage of derailments that are caused by buckled track, which may result in an underestimate of costs overall. Table B-35 summarizes of costs included in the two rail response scenarios (reactive response and proactive adaptation). For more detailed information on each of the response scenarios, see the supplementary material from Neumann et al. (2021).

Table B-35. Summary of Costs Included in the Two Rail Response Scenarios

Source: Neumann et al. (2021).

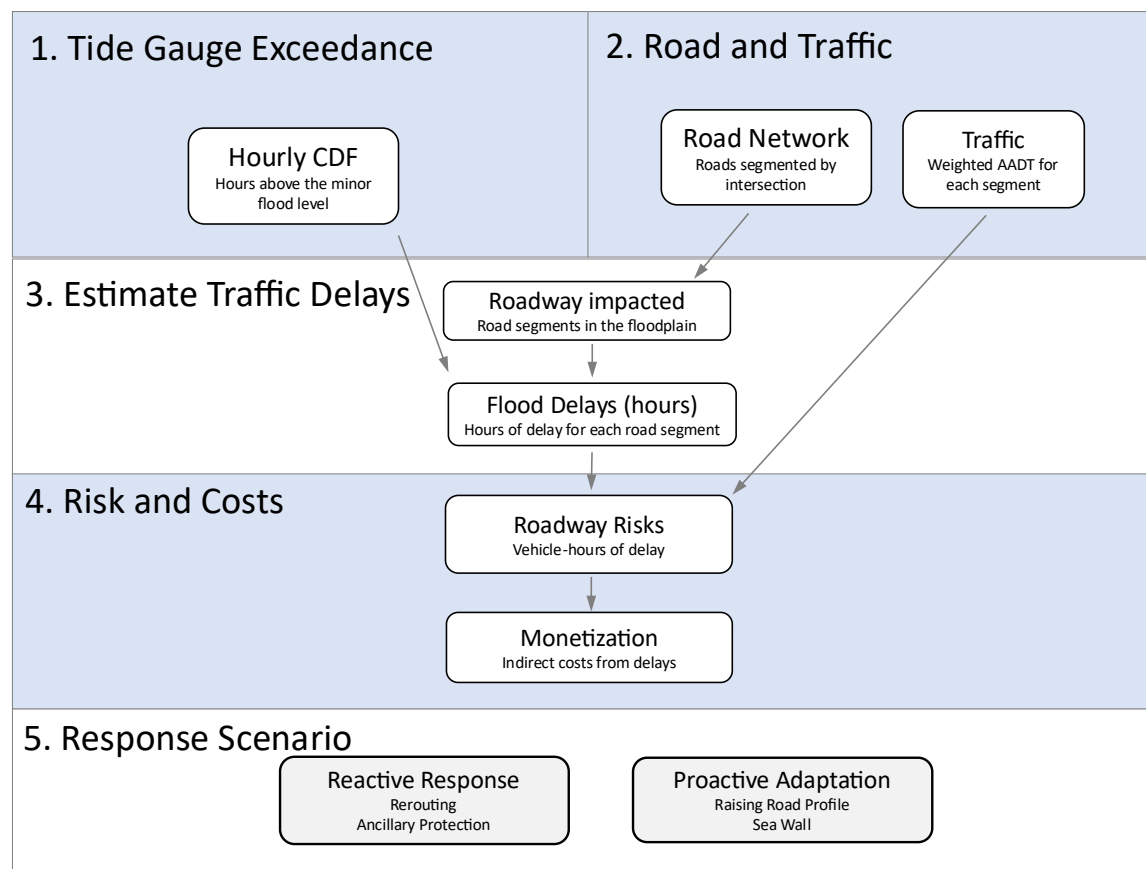
Reactive Response Scenario	Proactive Adaptation Scenario
• Costs of replacing track to repair lateral alignment defects in the buckling zone, and costs of re-aligning rail in adjoining zones • Costs of delays that occur due to track buckling and repair, as well as delays associated with blanket speed reductions • Costs of derailment that may result from track buckling • Costs of developing and implementing the speed orders • Costs of routine (non-climate-driven) track maintenance	• Costs of purchasing, installing, and maintaining the track temperature sensors and related software infrastructure • Costs of delays associated with risk-based speed reductions • Costs of routine (non-climate-driven) track maintenance • Downtime during sensor installation (believed to be minimal)

Table B-36. Rail Infrastructure Analysis Data Sources

Data	Description	Source
Rail stock data	Rail stock data were compiled from the NYS GIS Clearinghouse; data is now only available in a viewer and not as a download	NYS GIS (n.d.)
Rail traffic	Rail traffic was compiled from the Federal Railroad Administration (FRA) highway-rail crossing database files and reports	DOT FRA (n.d.)
Stressor-response functions	Detailed descriptions of stressor-response functions in this analysis are primarily associated with track buckling	Probabilistic track buckling function from Kish and Samavedam (2013), see additional details in Neumann et al. (2021) supplement
Economic parameters for repair cost	Direct costs for buckling damage repair to rail infrastructure associated with climate change	Repair cost of \$21,000 per event (and 14-hour repair time) from Gordian (2017), additional details in Neumann et al. (2021)
Delay costs per unit of time	To assign a dollar value to delays, we use DOT's 2016 guidance for estimating the valuation of travel time delay for economic analysis	DOT Office of the Transportation Secretary (2016)

Figure B-23. Framework for Estimating Traffic Delay from High-Tide Flooding Events

Source: Adapted from Fant et al. (2021).



The method adopts recently developed “minor” flood levels developed by NOAA as thresholds for HTF events. Using 19 years of hourly water levels spanning 1999 to 2017, flooded hours are estimated using the approach described in Jacobs et al. (2018). First, the hourly water-level record is detrended and brought to the common sea-level rise (SLR) baseline year, 2000. Using an empirical CDF, hours above the HTF threshold level provide the number of flooded hours for the baseline. These flooded hours are then estimated over time by adding the differences from the sea level in 2000 to the six local SLR projections from Sweet et al. (2018) to the water-level CDF. This approach is limited to tide gauge measurements and does not consider situations where flooding is intensified or induced by precipitation. NOAA’s flood maps, derived from 30-centimeter (cm) resolution light detection and ranging (LIDAR) digital elevation data using a modified bathtub approach, delineate the flood extent at specified levels

(NOAA n.d.a). Road segments within the NOAA flood extent are designated as road segments vulnerable to HTF. Using the NOAA flood map extents limits the analysis to the roads that are currently vulnerable to HTF. With rising sea levels, flood extents are expected to increase, and additional roads could become vulnerable.

A nontrivial step of the process involves developing road segments, divided at intersections using road network data provided by state DOTs (including NYSDOT). The number of segments flooded at intersections is the basis for understanding how traffic delays are estimated, as intersections provide on- and off-points for vehicles and allow for more accurate use of traffic data. The number of vehicles that would travel on these flooded segments, but find an alternative route due to flooding, are summed for the hours the road is inundated from HTF events, depending on how often the road is flooded and for how long.

B7.3.1 Reactive Response

This base traffic delay risk is reduced by factors that should occur independently of decisions made by road maintainers, processes termed “reasonably anticipated adaptation” in Fant et al. (2021), but characterized as a reactive response here. The method considers two responses to reduce traffic delay risk:

1. Driver-initiated or official detour rerouting that directs drivers around the inundated road
2. Ancillary protection, where high-tide flooding (HTF) is prevented using protective strategies, such as seawalls and beach nourishment that are built to protect nearby land and structures, but also prevent flooding on roadways

These actions, which are each discussed in the following paragraphs, form the basis of the traffic delay risk metric described in the next section, which is the traffic delay expected without direct adaptation.

Alternative routes take advantage of route redundancy in the road network, the effectiveness of which varies by location. In this study, route redundancy uses a slightly modified version of the traffic intensity indicator to reduce delays where the road network is extensive and more likely to provide reasonable alternative routes. in Fant et al. (2021) describes the details of this approach.

In addition to road redundancy, the method also considers avoided flooding and delays that result from actions that are taken to protect coastal property. The NCPM estimates damage from storm surge and inundation losses and compares these to various adaptation options, including seawalls and beach

nourishment, indicating the areas protected behind these improvements. Because these strategies are designed to protect against storm surge water levels around the 100-year event, it is reasonable to expect they will also prevent roadway flooding during HTF events.

B7.3.2 Proactive Adaptation

The proactive adaptation scenario (referred to as “direct adaptation” in Fant et al. 2021) considers the alleviation of HTF induced traffic delays through the implementation of adaptation strategies. While there are many conceivable ways to adapt to HTF, the model adopts two well-established options:

1. Build a seawall to hold back the floodwater
2. Raise the road profile above the effective threshold

For each road, the simulated decision to adapt using one of these two options depends on the ratio of benefits to costs. Lorie et al. (2020), among others, points out that in many cases, the benefits need to be significantly higher than the costs to trigger action. This work uses a benefit cost ratio of 4 as a requirement to trigger direct adaptation. The benefits of adaptation are the avoided traffic delay costs, and the cost of adaptation is the construction material and labor costs to raise the elevation of the road or build a sea wall to hold back the flood. While the adaptation costs include estimates of material, labor, and construction delays, actual costs will include additional factors not included in the estimates reported in this chapter. For example, omitted costs include those associated with management, design, easements, and land acquisition. In addition, this framework implies that protection will be built without design or construction errors or schedule and permitting delays due to sociopolitical or budgetary issues. It is important to note that while construction of either of these protection types would divert flood waters away from the road, flooding may occur elsewhere as a result, and additional costs would be incurred that are not captured in this analysis. Furthermore, these protections may have environmental impacts, such as preventing wetland migration.

Table B-37. Coastal Roads Analysis Data Sources

Source: Author's summary based on Fant et al. (2021).

Data	Description	Source
SLR and tide-gauge levels	SLR projections by scenario.	Bader et al. (2023)
Storm-surge heights tide-gauge levels	Storm-surge heights and tide-gauge levels are used to derive storm surge heights and probabilities.	NOAA (2017), Sweet et al. (2018)
Infrastructure roads data	We used HPMS shapefile data from 2016, and where noted in the report, 2015, for the roads and bridge locations. We processed the road data for each coastal state using methods outlined by Jacobs et al. (2018). Separate analyses were performed for functional classes 1, 2, and 3–7.	HPMS shapefile data were downloaded from the HPMS Public Release of Geospatial Data website for each state (DOT 2018), Jacobs et al. (2018)
Traffic and ridership data	The HPMS spatial data included in the AADT, lane width, and surface type. These data are used in various parts of the analysis, including traffic delay estimation, road redundancy calculation, and direct costs, respectively.	DOT FHWA (2016)
National Coastal Property Model	The NCPM was developed in estimate coastal flood damage in the U.S. as a result of different SLR and storm surge scenarios. The model estimates flood and inundation damages, as well as the cost of investments in coastal protection. The model was used to designate roads protected from property-related actions (ancillary protection).	Neumann et al. (2010, 2015), Lorie (2020)
Coastal flood exposure map	NOAA provided raster datasets containing the extent of minor-level flooding for each state, which were used to determine which road segments are vulnerable to tidal flooding.	NOAA (2019)
Tide gauge data	Hourly water levels from tide gauge stations were obtained from NOAA's Center for Operational Oceanographic Products and Services (NOS 2019) and methods for analysis are described in Sweet et al. (2018). 83 tide gauges from this set are in CONUS and we use 19-years of hourly water levels spanning from 1999 to 2017.	NOAA NOS (2019), Sweet et al. (2018)
Welfare economic cost of traffic delays	Different sources were used for passenger and freight vehicles. For passenger vehicles, the approach follows that recommended in U.S. DOT (2016) To quantify the cost of delay for freight vehicle travel, we rely on data from the NCHRP that are used as inputs to its Truck Freight Reliability Valuation Model (NCHRP 2016).	For passenger vehicles, DOT's "Revised Departmental Guidance on Valuation of Travel Time in Economic Analysis" (2016); for freight vehicles, NCHRP (2016)

B8 Water Resources

B8.1 Water Quality and Harmful Algal Blooms

Changes in precipitation patterns and air temperature affect water quality. Increases in precipitation, particularly heavy rainfall, carry agricultural pollution to water bodies, potentially altering ecosystem balance. Dry conditions can also impact water quality since the constituents—particularly nitrogen, phosphorus, and carbon levels—are less diluted by fresher rainwater. In addition, warmer temperatures increase chemical reaction rates, lower dissolved oxygen (DO) saturation levels, and adversely affect algal competition, increasing the chance of harmful algal blooms (HABs).

This analysis transfers results from two analyses conducted for the EPA on the economic consequences of climate change on water quality: a model of general water quality impacts and a model that focuses on the risks of HABs. The water quality model builds on the structure of the water systems model previously described and is also run across over 2,000 8-digit HUCs (Hydrologic Unit Code) of the contiguous U.S. except that the rivers within each 8-digit HUC are split into a number of river segments ranging from around 5 to about 30. Although the analysis is evaluated for the 8-digit HUC, we reaggregate to the county level to estimate economic impacts (willingness-to-pay described below) and aggregate to the 4-digit HUC to evaluate changes in the occurrence of HABs, also described below.

The analyses evaluate how changing temperature and precipitation patterns would affect nutrient concentrations, water temperature, and DO concentrations, and includes the impacts of changes in climate as well as changes in socioeconomic growth. To isolate the impact of climate change from socioeconomic growth, we develop a “control” scenario that includes socioeconomic growth impacts but uses historical climate. The control scenario acts as the counterfactual scenario from which future climate change scenarios are compared.

An adaptation action to improve water quality in freshwater systems is possible through actions such as reducing excess nutrient runoff into water bodies, but these are not considered in this analysis.

Table B-38 summarizes the data used in this analysis.

Table B-38. Data Sources

Data	Description	Source
General water quality model data and structure	Physical and management characteristics by basin; water demands; initial conditions; rivers, lakes, and reservoirs, and other data included in the water management and quality model. Boehlert et al. describe the original model with modifications described in Fant et al.	Boehlert et al (2015), Fant et al. (2017)
Data for modeling harmful algal blooms	Various parameters for the growth of four phytoplankton species groups: greens, diatoms, cyanobacteria N-fixers, cyanobacteria nonfixers and existing conditions.	Chapra et al. (2017)
Willingness to pay for water quality improvements	User and nonuser WTP for water quality improvements based on 131 estimates from 18 studies that were used to construct a meta-regression analysis nationwide.	Van Houtven et al. (2007)

Temperature is tracked using a heat budget model approach, that simulates the surface heat exchange of a body of water as well as water sources / sinks through inflows from upstream basins, outflows downstream, small tributaries, and groundwater. The equation in its simplest form is as follows.

Equation 4.
$$V\rho C_p \frac{dT}{dt} = A_s J + Q_{in}\rho C_p T_{in} - Q_{out}\rho C_p T$$

where:

- V = volume
- ρ = water density
- C_p = specific heat
- T = temperature
- t = time
- A_s = surface area of the water body
- J = the total heat exchange through the air-water interface
- Q_{in} and Q_{out} = the flows into and out of the system, respectively
- T_{in} = the temperature of Q_{in}

We assume that each riverbed is parabolic, which helps to derive a relationship of flow with surface area and velocity.

In the summer, as temperature warms and solar radiation increases, stratification in temperate reservoirs occurs. Temperature during the season of stratification is modeled differently for reservoirs, where a two-layer model is used, representing both the epilimnion (top) and the hypolimnion (bottom) layers. For example, if the reservoir is bottom-releasing (i.e., outflow is occurring in the Hypolimnion), then the following is used to model the reservoir temperature.

Equation 5.
$$V_e \rho C_p \frac{dT_e}{dt} = A_s J + Q_{in} \rho C_p T_{in} + v_t A_t \rho C_p (T_h - T_e)$$

Equation 6.
$$V_h \rho C_p \frac{dT_h}{dt} = -Q_{out} \rho C_p T_e + v_t A_t \rho C_p (T_e - T_h)$$

where:

- subscripts e and h = the epilimnion and hypolimnion, respectively
- v_t = the thermocline heat transfer coefficient
- A_t = the thermocline area

Within each waterbody (reservoir, lake, or river segment), the model tracks the following state variables (or constituents) shown in Table B-39 and Figure B-24.

Table B-39. Model State Variables

Variable	Symbol	Units ^a
Particulate organic carbon ^b	cp	mgC/L
Dissolved organic carbon	cd	mgC/L
Organic nitrogen ^b	no	µgN/L
Ammonia nitrogen	na	µgN/L
Nitrate nitrogen	nn	µgN/L
Organic phosphorus ^b	po	µgP/L
Inorganic phosphorus	pi	µgP/L
Phytoplankton biomass	ca	mgC/L
Dissolved oxygen	o	mgO2/L

^a mg/L ≡ g/m³ and µg/L ≡ mg/m³; In addition, the terms C, N, P, and A refer to carbon, nitrogen, phosphorus, and chlorophyll a, respectively.

^b Excluding phytoplankton organic carbon.

A general mass balance for a constituent in an element is written as follows:

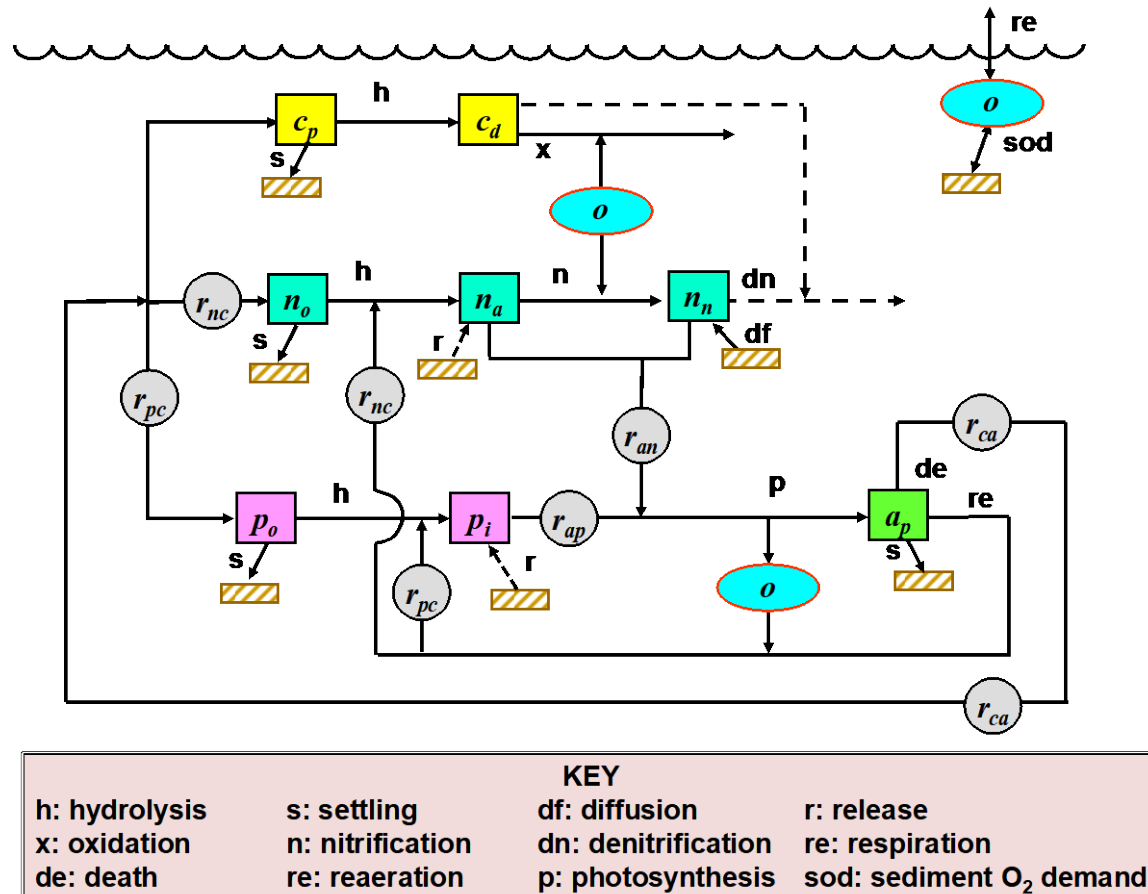
Equation 7.
$$\frac{dc_i}{dt} = \pm(\text{transport}) + \frac{W_i}{V_i} + S_i$$

where:

- c_i = concentration of element i [mg/L or $\mu\text{g/L}$]
- t = time (d)
- W_i = the external loading of the constituent to element i [g/d or mg/d]
- V_i = element volume (m^3)
- S_i = sources and sinks of the constituent due to reactions and mass transfer mechanisms [g/ m^3/d or mg/ m^3/d]

Figure B-24. Conceptual Framework for the Water Quality Model System

Source: Chapra et al. (2017).



Changes in these constituents are used to estimate changes in a water quality index (WQI) that was linked to a WTP to maintain historical water quality levels (from Van Houtven et al. 2007; see Boehlert et al. 2015 and Fant et al. 2017 for more details). Outputs from the model are reported at the HUC-level which are aggregated to New York State counties for this report.

The economic impacts of changes in water quality measures are estimated using a valuation of changes in the WQI, described in detail in McClelland (1974) and used in Van Houtven et al. (2007) among many others. The process is as follows:

1. Convert each measurement (e.g., concentration, temperature) into a subindex using water quality curves
2. Aggregate the subindex values multiplicatively into the WQI using weights

The four measures used here are DO, total nitrogen concentration, total phosphorus concentration, and temperature. Although quality curves can vary by location, we use the arithmetic mean for all basins.

Changes in WQI are translated to WTP using the reported values from the full linear meta-regression transfer function from Van Houtven et al. (2007) to develop a piecewise linear function for both users and nonusers. We use state-level data from the U.S. Census Bureau on persons per household to convert WTP per household to WTP per person and use the population projections to estimate municipal and industrial water demands to develop a State WTP across scenarios and eras. Constituent values in each segment are averaged, weighting by segment surface area. Consequently, we are assuming that each unit area is of equal importance.

Although red tides were among the first HABs to draw public attention to HABs, the phenomenon is much broader. For example, cyanobacterial HABs (cyanoHABs) in the world's freshwater systems are far more ubiquitous. Chapra et al. (2017) added a module to the above water quality model to simulate competition between algal groups, with a focus on cyanobacterial growth and the likelihood of cyanoHABs in freshwater systems.

In order to model competition between algae, the phytoplankton assemblage is divided into four functional groups consisting of a pair of beneficial algae (Diatoms and Greens) and a pair of harmful algae (N₂-fixing and non-N₂-fixing cyanobacteria). In most lakes and impoundments, a typical successional pattern evolves during the growing season with the spring beginning with diatoms, progressing to greens and "others," and finally leading to the development of blue-green algae in later summer and fall. The relative magnitude of each of these groups as well as their total biomass

is influenced by the system's trophic state. Nutrient-poor lakes tend to be dominated by diatoms, greens, and other non-harmful phytoplankton. In contrast, when lakes become over-enriched, blue-green algae predominate, especially during the late summer and early fall. It is known that the growth of each phytoplankton species has a different temperature tolerance. In lakes, cold-adapted diatoms and flagellates often are the first algae to exhibit growth in the early spring. In the summer, greens and cyanobacteria make up more of the algal assemblage, and during the warmest times of the year, with the latter particularly dominant in eutrophic systems (Paerl et al. 2011; Paerl and Huisman 2009). Harmful cyanobacteria have been found to have an optimal temperature for growth and photosynthesis at, or above, 25°C (Reynolds 2006, Jöhnk et al. 2008, Paerl and Huisman 2009). Chapra et al. (2017) offer more details on how cyanobacteria are simulated.

When cyanoHABs release toxins, it can have a variety of health impacts to people and other mammals, like pets. The impacts on recreational activity are based on thresholds defined by the World Health Organization (WHO) guidelines for evaluating recreational restrictions attributable to HABs (WHO 1999). The WHO recommendations establish 20,000 cells/ml as a threshold for which allergenic effects might be expected in some populations, and 100,000 cells/ml as a threshold where recreational restrictions would be advised as a result of the increased risk for adverse health effects resulting from exposure for the general population. Although the impacts of cyanoHABs are not included in the valuation, we use the above-mentioned thresholds to map the occurrences of cyanoHAB blooms for the projected climate, compared to the baseline.

B8.2 Municipal and Industrial Water Supply

This analysis estimates the welfare loss to consumers of water associated with unmet municipal and industrial (M&I) water demand, or consumer surplus loss. In other words, if, because of climate-induced shortages, water is unavailable for a category, such as municipal outdoor use (one of the lower valued uses), the economic loss is measured by consumers' inability to enjoy what the water provides—in the case of municipal outdoor use, this is usually a green and healthy lawn and gardens. Municipal indoor use tends to have a highest value, and industrial water use is valued between municipal indoor and outdoor water. We use consumer surplus, rather than price, because often the uses of water provide greater benefit to consumers than is captured by the price (if the value of water to consumers were less than the price, consumers would not choose to purchase the water).

To develop these estimates, the analysis defines water use demand functions for three categories of demand: municipal indoor use, municipal outdoor use, and industrial use. Each demand is defined by a constant elasticity of demand where elasticity varies by category, and lower absolute values for elasticity represent greater hardships of water shortages (outdoor water use elasticity = -0.6; indoor water use elasticity = -0.2; industrial water use elasticity = -0.4).^{27, 28}

Surface water demand data are derived using 2005 data from the U.S. Geological Survey (USGS) on annual water withdrawals and consumptive use in various sectors, including M&I. These data are originally available at the 3,109 counties of the continental U.S. and spatially averaged to 8-digit HUC resolution using the same approach taken by the U.S. Forest Service in their development of the Water Supply Stress Index (WaSSI). Note that the U.S. is divided and subdivided into successively smaller hydrologic units which are classified into four levels: regions, subregions, accounting units, and cataloging units. The hydrologic units are arranged or nested within each other, from the largest geographic area (regions) to the smallest geographic area (cataloging units). Each hydrologic unit is identified by a unique hydrologic unit code (HUC) consisting of two to eight digits based on the four levels of classification in the hydrologic unit system. HUC-8 maps the subbasin level—there are about 2,400 HUC-8 watershed units in the U.S. In New York State, there are 17 major watersheds (HUC-4) (DEC N.d), and within these, 52 HUC-8 watersheds (Cornell 1994).

These data are used for baseline water demand, as well as proportions used for allocating future demand among use categories. Return flow fractions from the WaSSI Ecosystem Services Model from the USDA's Climate Change Resource Center are used to assign unmet demand to each HUC based on consumptive use (NCSU 2012). All projected demands are scaled using population projections from EPA's Integrated Climate and Land-Use Scenarios (ICLUS) Ver. 2.0 model. Shortages (technically, unmet demands) at the HUC-8 level are distributed among the three categories of demand based on a prioritization scheme where shortages are first expected to be absorbed by outdoor use. If the shortage volume is greater than landscape demand, the remaining shortage is absorbed by industry. Finally, any remaining unmet demand after both outdoor and industry uses have been exhausted is taken from indoor municipal demand.

²⁷The function is $\ln(Q) = \alpha - \epsilon \times \ln(P)$. For examples of previous uses of this demand function for water see Henderson et al. (2015) and Cai et al. (2006).

²⁸Elasticities derived from ranges provided in Renzetti (1992), Espey et al. (1997), and Dalhuisen et al. (2003).

Before calculating economic welfare loss, several HUC-8s are removed from consideration in the analysis because the underlying model calculating unmet demand is unable to effectively simulate complexities of the water system supplies in those locations, either due to water connections (that is, interbasin transfers) that are not modeled or to storage and groundwater access contingency plans for water supply in densely populated areas. In addition, the underlying USGS surface water withdrawal is reported at the point of withdrawal, rather than the point of use, which is further complicated in areas with significant urban withdrawal. These include the HUC-8s nearest the Great Lakes and those with over half their area in a large Metropolitan Statistical Area (MSA),²⁹ consistent with the approach used in EPA (2017a).

Surface water supply estimates and the water balance of supply and demand for all sectors are generated using the USBasins model. USBasins characterizes the effects of climate change and water infrastructure on flow volumes, as well as water balance across demand sectors at the HUC-8 level. The USBasins system employs GCM projections of precipitation and temperature as inputs to a rainfall-runoff model, which is used to simulate monthly runoff in each of the HUC-8 basins, and a water demand model which projects the water requirements of the M&I and agriculture sectors. With these runoff and demand projections, the USBasins water resources systems model produces a time series of reservoir storage, release, and allocation to the various demands in the system, which include M&I, agriculture, environmental flows, transboundary flows, hydropower, and others. Boehlert et al. (2015) describes USBasins more fully, and it is also compared with another model in Fant et al. (2017). The USBasins system has been applied by the U.S. EPA in several assessments of climate impacts on water availability and water quality, including a recent assessment for the U.S. Global Climate Research Program's National Climate Assessment (EPA 2017a).

Welfare change is estimated using M&I water-supply prices from various utilities that match the HUC-4s statewide.³⁰ Welfare losses are therefore calculated at the HUC-4 level for each of the six GCMs and two RCPs, a historical scenario, which repeats 1981–2010 conditions, and a control scenario, which is the same as the historical scenario with socioeconomic growth included. Due to the asymptotic nature of the demand curves (that is, WTP is unreasonably high at very low levels of supply approaching zero), a willingness-to-pay cap is set at five times the price. This ensures that the estimated cost of unmet demand

²⁹ Limiting metropolitan statistical areas were those with a population >1,000,000 and include the following: New York-Newark-Jersey City, NY-NJ-CT-PA; Buffalo-Niagara Falls, NY; Rochester, NY.

³⁰ Water prices from: "2014 Water and Wastewater Rate Survey." Adjusted to 2021 USD values. (American Water Works Association and Raftelis Financial Consultants, Inc. 2015).

remains within reasonable bounds and is consistent with the approach used in EPA (2017a). Final welfare loss estimates due to climate change for each scenario are calculated as the difference in consumer surplus loss associated with unmet consumer demand, between the control and climate scenarios summed across the three demand categories.³¹

Table B-40. Water Supply Analysis Data Sources

Data	Description	Source
Baseline water supply and demand	1981–2010, by HUC-8	Kenny et al. (2009)
Water utility prices	Price of water utilities related to each HUC-8	American Water Works Association and Raftelis Financial Consultants, Inc. (2015)
Elasticities	A constant elasticity of demand for the water demand nodes	Renzetti (1992), Espey et al. (1997), and Dalhuisen et al. (2003)

B8.3 Urban Drainage

This analysis estimates the effect of climate change on urban drainage management costs for the 50 largest cities in New York State (see Table B-41), using estimates of adaptation costs for the State’s urban drainage systems by applying the methodology from Price et al. (2016). For each city, this analysis estimates urban drainage adaptation costs based on projected changes in three frequency-duration storm events: the 10-year, 24-hour storm; the 25-year, 24-hour storm; and the 50-year, 24-hour storm. This range of storm events is examined due to uncertainty regarding the design capacity of urban drainage systems. Some systems (or even portions of some systems) are designed to accommodate storms with a relatively short return period, while others are designed to manage runoff from less frequent but more significant rainfall events.

The assessment of adaptation costs for New York State’s urban drainage systems presented here applies the methodology from Price et al. (2016). To enable analysis of climate change-related urban drainage costs on a broad spatial scale, this study derived a regression-based approach for estimating changes in normalized flood depth (the volume of flooding normalized by the area of a drainage area or catchment).

³¹ A flat supply curve is assumed; therefore, no producer surplus is lost due to supply shortages.

These estimates, when coupled with a catchment's surface area, approximate the additional capacity required by an urban drainage system to prevent an increase in flooding. Unit cost values for stormwater infrastructure are then applied to this additional capacity to estimate the costs of expanding a city's urban drainage system.

Table B-41. Fifty Largest Cities in New York State

Source: Author's analysis, developed from data available in the Multi-Resolution Land Characteristics National Land Cover Database (USGS Earth Explorer n.d.), applying techniques from Maidment (1993).

City	Land Area (sq miles)	Population	% Impervious
Albany	21.4	98,617	44%
Amherst	53.2	129,299	25%
Babylon	52.3	218,296	24%
Binghamton	10.5	47,566	13%
Brookhaven	259.4	485,430	10%
Buffalo	40.4	276,807	47%
Cheektowaga	25.4	89,234	41%
Clarkstown	38.5	86,631	20%
Clay	48.0	60,490	14%
Clifton Park	48.2	38,153	9%
Colonie	56.0	85,461	26%
Cortlandt	39.3	42,092	11%
Greece	47.5	96,231	20%
Greenburgh	30.3	94,014	21%
Hamburg	41.3	60,156	19%
Haverstraw	22.2	38,976	12%
Hempstead	118.7	790,982	32%
Henrietta	35.4	46,634	20%
Huntington	94.0	204,197	15%
Irondequoit	15.0	50,548	26%
Islip	103.8	339,949	24%
Lancaster	37.7	45,110	15%
Mount Pleasant	27.5	45,300	16%
Mount Vernon	4.4	72,581	57%
New Rochelle	10.3	81,587	30%
New York	300.5	8,467,513	43%
Niagara Falls	14.1	48,360	40%
North Hempstead	53.5	237,433	27%
Orangetown	24.1	48,508	14%
Ossining	3.2	39,742	20%
Oyster Bay	103.7	299,583	19%
Penfield	37.2	39,341	9%

Table B-41. (continued)

City	Land Area (sq miles)	Population	% Impervious
Perinton	34.2	47,138	11%
Poughkeepsie	28.5	45,811	27%
Ramapo	61.1	150,344	14%
Rochester	35.8	210,606	15%
Rye	6.9	48,845	27%
Schenectady	10.8	66,990	45%
Smithtown	53.7	116,305	12%
Southampton	139.2	69,325	7%
Syracuse	25.1	146,103	48%
Tonawanda	18.7	72,084	41%
Troy	10.4	50,394	44%
Union	35.5	55,620	17%
Utica	16.7	64,501	34%
Webster	33.5	45,324	13%
West Seneca	21.4	45,281	25%
White Plains	9.7	59,526	33%
Yonkers	18.0	209,530	42%
Yorktown	36.7	35,953	11%

Consistent with Price et al., the present analysis begins with the estimation of the rainfall depth associated with each frequency-duration event under the baseline (no climate change) scenario and under each climate scenario and year. Baseline frequency-duration values for each city were obtained from NOAA Atlas 14 (NOAA n.d.b). To generate frequency-duration rainfall values for each climate change scenario, the analysis scales NOAA Atlas 14 values based on the proportional change in frequency-duration rainfall implied by daily precipitation projections from the GCMs described in Chapter 1, Methodology. Frequency-duration intensities were derived from GCM projections by fitting them to the Gumbel distribution, a commonly used distribution for estimating low-frequency precipitation intensities.

Using these frequency-duration values as a starting point, the analysis estimates the change in normalized flood depth for each scenario following the approach described in Price et al. (2016). Under this approach, the change in normalized flood depth is first calculated as a function of the frequency-duration rainfall amount and the imperviousness of each city's land cover. These estimates are then calibrated using the statistical model specified in Price et al., which adjusts the uncalibrated estimates of normalized flood depth based on the following variables:

1. The ratio of 24-hour to 6-hour storm rainfall amounts for each storm frequency
2. Combined sewer dummy variable
3. Imperviousness
4. Proportional change in frequency-duration rainfall events
5. Magnitude of the 6-hour storm event for each storm frequency

Applying this calibration approach yields adjusted estimates of normalized flood depth.

To estimate the costs associated with the calibrated increase in normalized flood depth for each city, this analysis converts the change in flood depth to a volumetric measure of flood water and calculates the cost of managing this volume. Following Price et al. (2016), these costs are estimated based on EPA unit-cost values for retention and detention basins and infiltration basins. These lump-sum capital costs are annualized over a useful life of 35 years using a discount rate/cost of capital of 3.6%.

B9 References

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