Technical Documentation on The Framework for Evaluating Damages and Impacts (FrEDI)

July 2023
(Updated)

EPA 430-R-21-004

FRONT MATTER

Acknowledgements

This technical documentation was developed by the U.S. Environmental Protection Agency's (EPA) Office of Atmospheric Protection. As described herein, components of this Framework for Evaluating Damages and Impacts (FrEDI) are derived from sectoral impact modeling studies produced by many external academic experts, consultants, and Federal agencies, including the Department of Energy (DOE) and the National Ocean and Atmospheric Administration (NOAA). Support for the technical documentation's production was provided by Industrial Economics, Inc. EPA gratefully acknowledges these contributions.

The FrEDI Technical Documentation was subject to a public review comment period and an independent, external expert peer review, in a process independently coordinated by ICF International and documented at EPA's Science Inventory. EPA gratefully acknowledges the following peer reviewers for their constructive comments and suggestions: Robert Kopp, Shubhra Misra, Frances Moore, James Rising, and Benjamin Sanderson. The information and views expressed in this report do not necessarily represent those of the peer reviewers, who also bear no responsibility for any remaining errors or omissions. The objective of the reviews was to ensure that the information developed by EPA was technically supported, competently performed, properly documented, consistent with established quality criteria, and clearly communicated. Upon completion of both reviews, the initial version of this Technical Documentation was published on October 15, 2021. Appendix A provides more information about the peer review.

Since publication of the original documentation in October 2021, additional sector impacts have been added to the peer-reviewed Framework and new functionality added to the FrEDI R code and data. This Technical Documentation has been updated accordingly, with changes summarized in Appendix H: Revision Log. As described herein, all sectoral impact models underlying the Framework described in this Technical Documentation have also been previously peer reviewed and published in the research literature.

Recommended Citation

EPA. 2021. Technical Documentation for the Framework for Evaluating Damages and Impacts (Updated). U.S. Environmental Protection Agency, EPA 430-R-21-004. www.epa.gov/cira/FrEDI

Data Availability

R-code and input/output data for FrEDI are publicly available at the following site:

https://github.com/USEPA/FrEDI

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CONTENTS

ONE | INTRODUCTION

The Framework for Evaluating Damages and Impacts (FrEDI) provides a method of utilizing existing climate change sectoral impact models and analyses to create estimates of the physical and economic impacts of climate change by degree of warming. These relationships between temperature and impacts in the United States (U.S.) can then be applied to custom scenarios to efficiently estimate impacts and damages under different emission or policy pathways. This technical document outlines the underlying theory, design, and structure of FrEDI. The Framework is implemented by application of open-source code referred to as the FrEDI code.

1.1 Objective of the Framework

FrEDI builds on approaches demonstrated in numerous previously published studies to produce physical and economic estimates of climate change impacts in the contiguous United States (CONUS), for a broad range of the most economically important impact sectors (e.g., impacts across human health, infrastructure, and water resource). FrEDI utilizes a "temperature binning" method and is based on a recently published conceptual paper and demonstration of the method (Sarofim et al., 2021a), and builds on previous analyses which have established strong relationships between the effects of warming in CONUS and monetized damages (U.S. EPA 2017; Hsiang et al., 2017; Martinich and Crimmins 2019; and Neumann et al., 2020).

The term "temperature binning" refers to a concept of synthesizing results of climate model-specific sectoral impact results by temperature change (sometimes using integer degree bins), described more fully in Sarofim et al. (2021a). The basic concept is to identify the arrival years of a given quantity of warming from a common baseline period (e.g., 1986 to 2005) for a particular climate model used in a sectoral impact study and extract associated impact estimates using a broader period (e.g., 11-year bin) centered around the arrival year. Impacts can then be compared across climate models, or general circulation models (GCM)s, by quantity of warming. Temperature binning aids comparability of independent analyses by using estimates of physical impacts without consideration of when that warming occurred or which scenario was used (other authors have used the nomenclature "time-slice" or "time-shift" for similar analyses) to drive estimations of economic impacts. For sectors where impacts are primarily driven by changes in sea level, a similar "binning" approach is followed, however in these cases bins are defined by global mean sea level (GMSL) rise in a given time period, as defined by the six sea level rise scenarios from Sweet et al. (2017) rather than temperature increments. References to "Temperature Binning" in this report intend to include both temperature and sea level rise binned results.

The main objective of the Framework, and the FrEDI code which implements the approach, is to provide estimates of the physical and economic impacts in the U.S. from 21st century trajectories of temperature and sea level rise. The framework is parameterized using a set of underlying published literature which relates climate change projections to:

1. **Related environmental stressors** (e.g., extreme temperatures, precipitation, floods, air quality) to assess exposure to vulnerable individuals and physical assets;
2. **Physical impacts of climate-driven environmental stressors**, such as property damage, health effects, or damaged infrastructure; and
3. **Economic processes** that are important to understand the relationship between physical impacts and economic outcomes, such as reduced economic welfare.

FrEDI was designed using a flexible approach that allows for the continued expansion of sectoral coverage, as new data from additional studies become available and meet the Framework requirements. For example, FrEDI was originally developed with nine sectors[1] (Sarofim et al., 2021a), derived from the second modeling phase of the U.S. EPA's Climate change Impacts and Risk Analysis (CIRA) project[2] and its associated technical report (EPA, 2017a). The current version of the FrEDI code (v3.4) now also incorporates the results of sectoral impact studies completed after the 2017 CIRA results, as well as peer-reviewed studies from other research groups (see Appendix B more information on the included sectoral impact studies). The Framework's flexibility enables incorporation of additional sectoral results over time and allows the unique capability to use a consistent framework to compare absolute and relative climate-driven impacts across a wide-range of sectors under any custom temperature scenario.

1.2 Intended Use

The EPA developed FrEDI and the FrEDI code to provide a quantitative storyline of physical and economic impacts of climate change in the U.S., by degree of warming or custom temperature trajectory, region, and sector. These applications are intended to support analysis coordinated by EPA; however, the Framework and its underlying damage functions may be of use to others working in the field. Defining the relationship between different levels of warming and the associated impacts is also of interest to audiences outside the modeling community, including decisionmakers, planners, and the public.

Outputs of FrEDI can readily synthesize the results of a broad range of peer-reviewed climate change impacts projections and support analysis of other climate change and socioeconomic scenarios not directly assessed in the supporting literature. This information is intended to supplement and complement more aggregate economic impact estimates derived from integrated assessment models, such as the Social Cost of Greenhouse Gases.

For certain sectors, FrEDI can also analyze the potential for adaptation to reduce the physical and economic impacts of climate change. For sectors with available information, the potential implications of no

[1] The nine sectors in Sarofim et al. (2021a) are Labor, Roads, Extreme Temperature Mortality, Electricity Demand and Supply, Rail, Coastal Properties, Electricity Transmission and Distribution, Southwest Dust, and Winter Recreation.
[2] EPA's CIRA project seeks to quantify and monetize the impacts of climate change across sectors of the U.S., including how risks can be reduced through greenhouse gas mitigation and adaptation actions. CIRA is an ongoing project led by EPA, but with contributions from a large number of sectoral impact modeling teams. More information about the CIRA project, including links to reports and publications, can be found at: www.epa.gov/cira.

additional adaptation, reactive (or reasonably anticipated) adaptation, and proactive (or direct) adaptation response scenarios can be evaluated.

Temperature binning involves the use of GCM output “binned” by degree rather than by scenario or time to drive sectoral impact models. This enables the production of impacts by degree for the included sectors at specific dates (explicitly modeled for 2010 and 2090 for several sectors here, though impacts at other dates can also be estimated through the use of interpolation as well as socioeconomic parameters such as population and GDP). These impacts by degree can be a communications product in and of themselves, but can also be used to estimate the impact of future trajectories of global or national temperatures. More details on the method used are provided in Section 2, and example outputs are provided in Section 3 and Appendix C.

In addition, although most of the economic impact literature on which the approach is based was developed using a consistent set of GCMs, climate scenarios, and socioeconomic inputs, the approach, as demonstrated in this documentation, is well-suited to incorporate results from other studies. This is important as the current version of FrEDI only includes a subset of the potential impacts of climate change in the U.S. FrEDI’s flexibility to incorporate results from external studies drives a long-term objective to populate the Framework with impact estimates and functions from the broader climate literature. This will ensure that FrEDI is informed by the best available data and methods, which can then be revisited and updated over time as scientific and economic capabilities continue to advance.

Finally, FrEDI is designed to quantify the sectoral impacts of climate change in the U.S., which provides insight on how different levels of greenhouse gas (GHG) mitigation can reduce future impacts. As such, this Framework does not address the costs of reducing emissions, which have been well-examined elsewhere in the literature (e.g., Energy Modeling Forum, 2021). Similarly, the health benefits associated with reductions in other co-emitted air pollutants, beyond the two conventional pollutant emission scenarios considered in the Air Quality sector that are not tied to GHG mitigation, are beyond the scope of this Framework. FrEDI also does not capture interactions between sectors (such as the land-energy-water nexus), including the potential for compounding or cascading effects across sectors.

1.3 Comparison to Existing Methods

The modeling of climate change impacts typically begins with running a set of emissions or concentration scenarios (IPCC 2000, Meinshausen et al. 2011, Taylor et al., 2012, IPCC 2013, Hayhoe et al., 2017, Riahi et al., 2017) through complex earth system models, followed by using the temperature and precipitation outputs of those climate models as inputs to sectoral impacts models. Scenario-based analysis has been the “gold-standard” approach to projecting future climate impacts for several decades and has successfully served as the backbone of international and federal climate assessments and special reports (e.g., IPCC 2018, USGCRP 2018), modeling intercomparison efforts (e.g., Knutti and Sedlácek, 2013; Warszawski et al., 2014; Eyring et al., 2016), and individual modeling studies. The Representative Concentration Pathways (RCP) (Moss et al., 2010) and the Shared Socioeconomic Pathways (SSP) (Riahi et al., 2017) provide projections over the 21st century of possible future climates ranging from low to high greenhouse gas concentrations and radiative forcing, allowing for economic modeling to proceed concurrently with, rather than sequential to, physical scientific modeling (van Vuuren et al., 2014). However, there are some important limitations and challenges to relying primarily on the traditional scenario-based approach for driving climate impacts analysis.

One difficulty is that it is challenging for there to be a comprehensive set of scenarios that explore all potential futures. Greenhouse gas emissions or atmospheric concentrations from these scenarios are used as inputs to climate models with the goal of producing comparable results. However, when using climate model output to drive impacts analyses, some analysts have pointed out that differences in climate sensitivity between different models can have a dominant effect, obscuring the role of other structural differences between the models (e.g., different responses of precipitation, cloudiness, stagnation events, or other climatic outcomes) (Schleussner et al., 2016). An additional challenge is one of communication: scenario names can be enigmatic for the public, whether it is “A1B” from the SRES scenarios, “RCP8.5” of the RCP scenarios, or “SSP4-6.0” from the SSP/RCP based scenarios. Characterizing changes in impacts that track with temperature rather than complex scenarios is more intuitive for non-technical audiences, and more easily associated with the global temperature targets discussed in international negotiations (IPCC, 2018) or reported in media stories (World Bank 2013; Plumer and Popovich 2018). Moreover, different research groups and individual assessments highlight different scenarios that may not be directly comparable across assessments, whereas temperature changes are a stable metric.

To address these challenges, the most common technique used is to discuss climatic impacts by degree rather than by scenario. The National Research Council (NRC) “Climate Stabilization Targets” assessment (NRC, 2011) presented most of its finding by degree, noting that “using warming as the frame of reference provides a picture of impacts and their associated uncertainties in a warming world – uncertainties that are distinct from the uncertainties in the relationship of CO_2-equivalent concentrations to warming.” The Intergovernmental Panel on Climate Change (IPCC) 1.5 degrees assessment presented a comparison of impacts at 2 degrees and 1.5 degrees in order to inform global temperature targets (IPCC, 2018). The IPCC and some of its contributors also have a long history of presenting risks by degree in the “burning embers” or “reasons for concern” diagram (Smith et al., 2009; Yohe 2010; O’Neill et al., 2017; IPCC, 2019). These estimates were developed from scenario-based analysis, but post-processed and standardized for communications purposes to an “impacts by degree” framework. Patterns of climate change are often presented normalized by temperature, as those patterns are robust when considering the magnitude of change or the scenario (Tebaldi et al., 2020, IPCC 2021), and Herger et al (2015) suggested using a “time-shift” approach as an alternative to pattern-scaling. Wobus et al. (2018) and Sanderson et al. (2019) presented future risks in the U.S. by degree of warming for the impacts of extreme temperatures and extreme precipitation events respectively. Hsiang et al. (2017) used end-of-century impacts from four RCPs, applied to 2012 economic and population values, to calculate percent GDP damages to the U.S. across eight sectors. Finally, Schleussner et al. (2016) applied a “time-slice” approach to estimate the effects of climate on a half-dozen global sectors at 1.5 and 2°.

As demonstrated in Sarofim et al. (2021a), designing analyses with relational temperature-impact functions for a given sector can improve comparability between analyses, yield results in a framework that is more intuitive for communications purposes, and be used to inform simple computational models that can rapidly and flexibly estimate impacts by sector for any desired scenario. In addition, the temperature binning approach provides a capability to examine alternative socioeconomic impact scenarios, with nuanced non-linear or combinatorial treatment of the effect of socioeconomic drivers on specific sectors, which is not possible using some econometric techniques.

Work by researchers affiliated with the Climate Impact Lab[3] is also focused on estimating economic impacts of climate change for the U.S. (e.g., Hsiang et al., 2017; Houser et al., 2015). Similar to some econometric sectoral analyses included in the FrEDI Framework, the Climate Impact Lab sectoral analyses rely on interpretation of historical data to identify relationships between climate metrics or events and the economic impacts that result, which are then applied to project economic impacts for future climate and event forecasts. Other work in the FrEDI Framework relies on process-based simulation models constructed to reflect physical and economic responses to climate stressors. Both types of approaches yield important insights about impacts, which often complements understanding of complex feedbacks, the influence of adaptation responses, and the influence of socioeconomic drivers.[4] A key advantage of FrEDI is that it can readily accommodate both types of studies, which provides an opportunity for significant expansion of sectoral coverage beyond those in the CIRA project and specifically made ready for incorporation in the Framework. Three sectoral impacts from the Climate Impact Lab's work are included in the FrEDI Framework (i.e., Extreme Temperature Mortality, Agriculture, and Crime) and FrEDI's flexibility allows for the possibility of accommodating different types of study methodologies and also enables comparisons of structural uncertainties across impacts models estimating impacts for the same sector.

A large number of studies beyond the CIRA project and the Climate Impact Lab have simulated the impacts of climate change on various socio-economic outcomes within the U.S. but many use distinct climate or socio-economic scenarios that are incompatible with each other, or report outcomes in units that require further processing to be comparable across sectors. Underlying impact models often require specialized, sector-specific knowledge to run or, in some cases, may require substantial computational resources, making them inaccessible for a typical user. This framework and R code bridge this gap: by processing climate impact modeling results, users can explore impacts across multiple sectors in a standardized way as well as exploring the effects of temperature, socioeconomic, and adaptation scenarios of interest.

[3] The Climate Impact Lab is collaboration of more than 30 climate scientists, economists, computational experts, researchers, and students from a number of research institutions. The Lab works to build a body of research quantifying the impacts of climate change, sector-by-sector and community-by-community around the world. More information about the Lab's research and publications can be found at: https://impactlab.org/

[4] It is important to note that different kinds of impact models represent different processes, and that process-based simulation models may not be fully commensurate with econometric models (Piontek et al. 2021 – we are grateful to a reviewer for sharing this point). In particular, process-based models may not capture the reactive effect that humans and the environment have on impacts, and econometric approaches may not capture the impact of adaptation actions which might be reasonably anticipated or expected to be cost-effective but are limited in their deployment in the historical period.

Another class of economic impact estimation tools that include components that are in some ways similar to FrEDI are integrated assessment models designed for damage estimation (IAMs - e.g., PAGE, RICE and DICE, FUND, IMAGE). These IAMs contain relationships between temperature and damages, with a range of geographic and sectoral resolutions – Nordhaus and Moffat (2017) and Diaz and Moore (2017) recently assessed the damage function representation in these models in the context of the broader literature. Some IAMs are used to identify an economically optimal GHG mitigation pathway which balances marginal costs of GHG abatement with marginal costs of GHG damage. To do so, marginal abatement cost functions (and GHG offset pools and their costs) are needed, and a means for translating GHG emissions into temperature pathways. IAMs are generally global in scope, although some estimate impacts at finer spatial levels. FrEDI, by contrast, addresses only the impacts associated with a defined temperature and socioeconomic pathway, and, in this application, only for CONUS. Overall, FrEDI provides an efficient and transparent damage estimation approach that operates independently of IAMs and adds the flexibility to use other means of determining temperature trajectories. The Framework also relies on a relatively rich, recent, and peer-reviewed set of economic damage functions for a large number of U.S. sectors. For that reason, the Framework can help in responding to relevant policy questions by estimating the effects of an incremental policy to reduce GHGs, and thereby complement the types of analysis and outputs provided by IAMs.

TWO | TEMPERATURE BINNING METHODOLOGY

This section provides an overview of the methodology underpinning FrEDI, including a discussion of the sectors currently processed for inclusion in the Framework, a summary of how sectoral impact model outputs are pre-processed for FrEDI, an outline of how economic impacts are calculated, an introduction to the FrEDI R code, and finally, a discussion of key limitations and uncertainties of the method.

2.1 Methods Overview

FrEDI produces economic impacts by degree of warming, which can be useful for communicating the risks of climate change.[5] In addition, the temperature binned impacts can be mapped to any temperature pathway and, using year-specific adjustment factors for the 21st century derived from the underlying studies, the series of annual impacts associated with the defined temperature pathway are adjusted (for example, to account for larger populations affected by health impacts or increasing value of coastal property) resulting in a time series of annual impacts that accounts for changing socioeconomic conditions. Additionally, the year-specific adjustment factors for some sectors scale to custom socioeconomic scenarios.

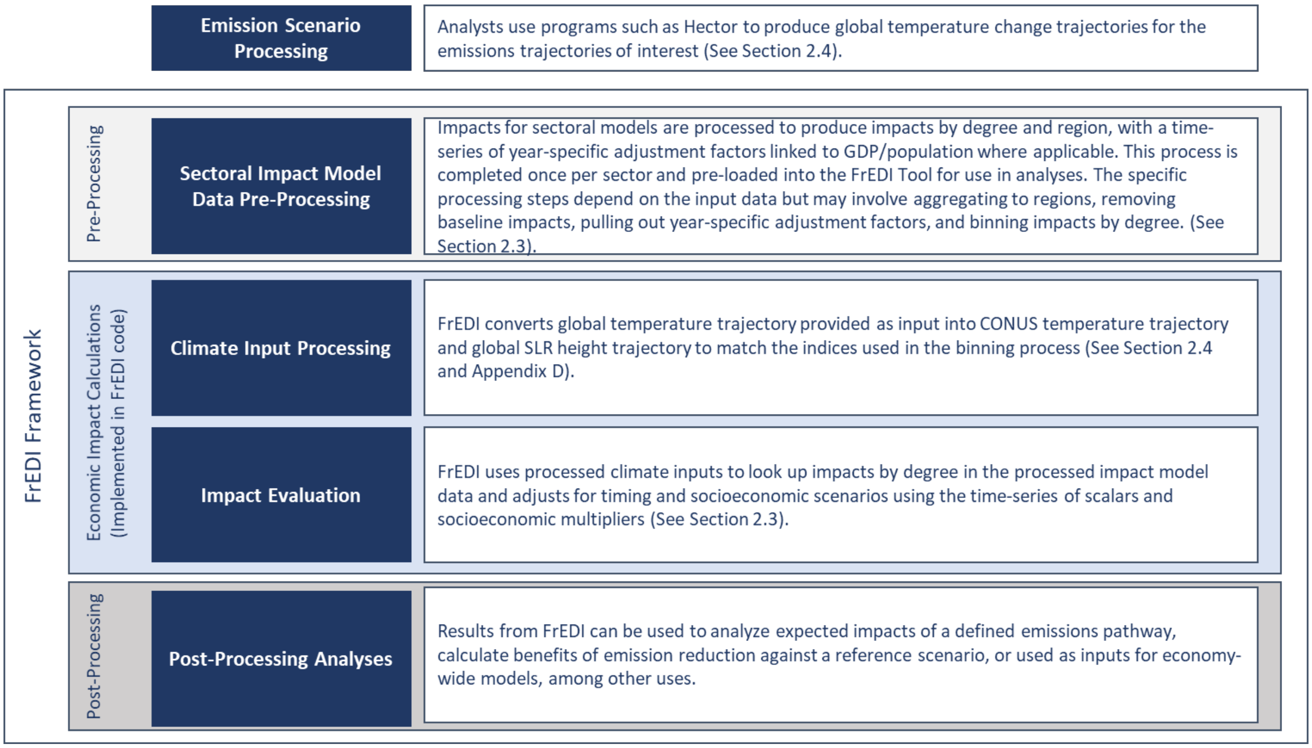
FrEDI provides a framework for evaluating economic impacts of climate change based on a defined emissions scenario. As shown in **Figure 1**, emissions scenario development and processing are completed outside of the FrEDI Framework. Global temperature trajectories based on those emission scenarios are generated using simple climate models, such as Hector (Hartin et al. 2015). In the pre-processing stage, temperature binned impacts are developed from the underlying sectoral impact literature. For temperature-driven sectors (sectors in FrEDI that are indexed to changes in temperature), this process results in impacts by region and degree of warming, with results by GCM, adaptation scenario, and socioeconomic scenario, as available. For GMSL-based sectors (sectors where impacts are a result of GMSL rise, and that are indexed to GMSL in FrEDI), this process is done once for each sector and is pre-loaded into the FrEDI Framework for rapid implementation of the framework.

During the economic impact calculation stage (the portion of the process implemented in the FrEDI R code), the user defined temperature trajectory and socioeconomic conditions, along with the pre-processed sectoral impact data are used to evaluate annual impacts for the defined scenario for all pre-processed sectors. This is implemented in the FrEDI Framework by first transforming the climate scenario into the necessary inputs (i.e., CONUS degrees of warming and GMSL rise, see Appendix D) and using those inputs to look up impacts by degree or GMSL rise. Finally, results are adjusted using the year-specific adjustment factors to produce a time series of impacts.

[5] The term ‘impacts by degree’ should be interpreted to include ‘impacts by sea level rise increment’ for the select sectors where impacts are driven by sea level rise (i.e., Coastal Property and High Tide Flooding).

The results from the FrEDI Framework can be used in a number of applications including as inputs to economy-wide models and to calculate benefits or damages associated with policies that result in new emissions scenarios.

FIGURE 1. FrEDI FRAMEWORK SUMMARY



Summary of the components of FrEDI, including pre-processing sectoral data and emission scenarios, economic impact calculations, and post-processing and analysis. References in each component identify the relevant sections in this report for more information.

Scope of Temperature Binning Methodology

FrEDI evaluates climate impacts for seven regions of the contiguous U.S. (CONUS) at annual timesteps across the 21st century (2010-2090).[6] The regional delineations are based on those used in the 4th National Climate Assessment (NCA) of the U.S. Global Change Research Program. The underlying climate and impacts data are typically sourced for years 2006 to 2100 for sectors influenced by temperature and precipitation stressors[7] and 2000 to 2100 for sectors vulnerable to sea level rise. The 2006 start year is the earliest year included in a one-degree temperature bin for the six core GCMs (i.e., the GCMs used by CIRA sectors[8]) and the sea level rise (SLR) sector models run from the base year 2000. The underlying impact

[6] The current base Framework produces results through 2090 due to the definition of era runs used to define early and late century estimates. Future versions could extend to 2100.

[7] While not used in this Framework, the underlying downscaled dataset also contains hindcast results ('model historical') for the years 1950-2006. Since the purpose of the Framework, and its underlying studies, is projecting future damages, this hindcast dataset is less relevant.

[8] The Framework uses climate modeling outputs from the fifth phase of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012). A 2016 dataset of downscaled CMIP5 climate projections was commissioned by the U.S. Bureau of Reclamation and Army Corps of

data in the Framework covers a range of warming from zero to six degrees, however higher degrees of warming can be extrapolated. FrEDI is not designed for estimating effects of cooling, or negative changes in temperature, relative to the baseline period, although it does not require temperatures to monotonically increase over the analysis period. GMSL inputs are restricted to positive values and the upper bound is defined by the 250cm scenario sea level rise from Sweet et al. (2017) in each year. The damage functions within FrEDI are not required to increase with temperature or sea level rise and thus FrEDI has the capability to assess both positive and negative effects of future climate change.

Although the base Framework is designed to project damages through 2090, by utilizing underlying impact studies that cover the same timeframe, the Framework also contains an extension module that projects impacts through 2300. This extension linearly extrapolates temperature-binned damage functions above six degrees and extrapolates time-dependent trends 2010 through 2090 out to 2300. Sea level rise based damages are also extrapolated using the variation in sea level across scenarios in 2090, along with an adjusted for property values tied to GDP per capita. Further details on the extension methods are provided in Appendix D.3.

Currently (version 3.4), the Framework includes 25 sectors, however the method is designed to be flexible in accommodating additional sector studies as they become available. Sectoral coverage of the Framework is described further in Section 2.2. EPA will update relevant components of this technical documentation as additional sectoral studies and impacts are added to the Framework.

Defining Binning Windows

The first step in the temperature binning method is to process the underlying sectoral impact model results. Temperature binned damages are most often calculated from a time series of impacts with a known associated time series of temperature changes, often defined by a particular GCM and forcing scenario (e.g., RCP). A smoothed temperature pathway is first developed from the known temperature pathway using 11-year averages over the period of analysis compared to the baseline climate era (1986-2005). Temperatures in this report are therefore temperature anomalies from the baseline era, referred to in this report as temperature change (ΔT) or degrees of warming. The size of the binning window is a balance between smoothing out interannual variability and the inclusion of years at the beginning and end of the window that would not be representative of the window's average temperature: the smooth behavior of the damage curves for most sectors and GCMs indicates that 11 years is likely sufficient (see Appendix E for further discussion). From the smoothed pathway, 11-year windows are identified around

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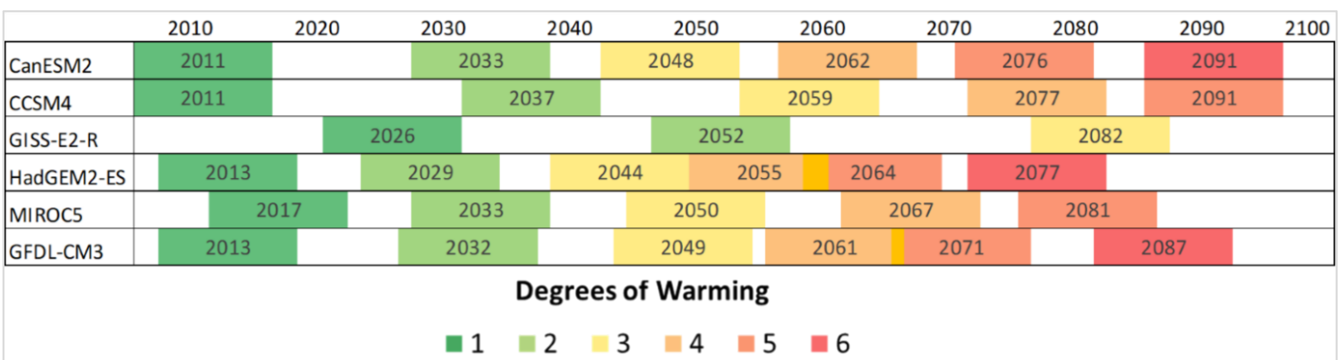
Engineers and developed by the Scripps Institution of Oceanography with a number of collaborators. This dataset, called LOCA (which stands for Localized Constructed Analogs), was the primary dataset underlying the 2018 Fourth National Climate Assessment. While more than 20 GCMs are available in the LOCA dataset, the selection of a subset of GCMs is necessary due to computational, time, and resource constraints. These six GCMs used in the CIRA2.0 project (EPA, 2017a) were chosen based on their ability to capture variability in temperature and precipitation outcomes, and a consideration of demonstrated independence and quality. A detailed description of the criteria used to select GCMs can be found in EPA (2017a). The supplemental material for Sarofim et al. (2021a) contains information and figures showing the distribution of annual and seasonal temperature and precipitation outcomes across the entire CMIP5-LOCA ensemble, including where the six GCMs lie.

the first arrival year of each integer one to six degrees Celsius above baseline, and impacts are averaged within each window to represent the corresponding integer degree of warming.

Figure 2 shows the temperature binning windows for six GCMs, under RCP8.5, used in sectoral models currently processed for the Framework from the CIRA project.[9] Although most CIRA sectoral models produced results for RCP8.5 and RCP4.5, only RCP8.5 impacts are processed for the Framework. RCP8.5 is a pathway with relatively high greenhouse gas concentrations, leading to substantial warming by 2100. RCP8.5 was chosen to assess a wide range of future temperatures, and the selection of a higher emissions scenario ensures that this temperature binning approach evaluates the broadest range of sectoral impacts at higher levels of warming (e.g., 4 or 5 degrees C) in addition to smaller levels (i.e., an RCP with considerably lower forcing may not reach higher degree bins, therefore leading to data gaps on the sectoral impact response to higher levels of warming). It is important to note that the selection of RCP8.5 does not imply a judgment regarding the likelihood of that scenario. Recent research, such as Christensen et al. (2018) suggests that even in the absence of any global climate policy, RCP8.5 has a higher forcing than the most likely future concentration pathway. See Appendix E for a discussion of how the choice of RCP8.5 versus a more modest pathway (RCP4.5) may impact the results.

Sector impact models driven by other GCMs and/or emission scenarios function in the same way: 11-year windows are defined for each integer degree based on the CONUS temperature trajectory defined by the climate model employed, compared to the 1986-2005 baseline era or a custom baseline used in the relevant work.

FIGURE 2. TEMPERATURE BINNING WINDOWS FOR SIX GCMS



This graphic shows the 11-year windows centered around the arrival year of each integer CONUS temperature change by CIRA GCM for RCP8.5. Arrival years, or the year at which the 11-year moving average reaches the given integer, are listed in each bin. The six GCMs are the suite used in the CIRA project, which represents the majority of the sectoral impact studies

Results are averaged for each degree of warming across all available climate models. Note that some GCMs do not reach six (or 10) degrees of warming by the end of the century. Impacts associated with higher degrees of warming are therefore defined only by those GCMs that reach those levels of warming.

[9] Figure 2 only includes the GCM's used in the CIRA studies, however the method illustrated is used for the non-CIRA study GCMs currently processed for FrEDI and can be used for any additional sector studies with non-CIRA GCMs.

For example, as shown in **Figure 2**, impacts at six degrees are only available for three of the six CIRA GCMs (CanESM2, HadGEM2-ES, and GFDL-CM3).[10]

Indexing impacts to CONUS degrees of warming streamlines the required climate data to run the Framework compared to detailed impact models that might require more spatially or temporally refined climate inputs. In doing so, however, representation of regional or temporal variation of climate variables in the Framework is fixed and limited to the variation in the underlying climate scenarios used to produce the binned results. For example, **Table 1** shows degrees of warming by NCA region averaged over the six CIRA framework GCMs (RCP8.5) by integer of CONUS warming. The bins are defined by average annual temperatures across CONUS and an infinite combination of daily or even hourly temperatures across CONUS can reach the same average annual temperature; FrEDI will not precisely capture that nuance as it relates to a GCM not included in the underlying model runs. For example, a GCM not included in the calibration of FrEDI may have a different distribution of extreme high and low temperature days than any of the GCMs that were considered, which could have implications for the resulting extreme temperature mortality. That is not to say extreme temperatures are not represented in the Framework; they are present as defined by the underlying climate models. **Table 1** also provides the global mean temperature change from the 1986-2005 baseline, for comparison (see Section 2.4 for more details on this conversion). Although in this application the Framework utilizes CONUS temperatures, some audiences may be more accustomed to global temperature changes. Using CONUS temperatures allows for a closer match between the climate variable and impacts but simplified conversion factors can be used to translate between CONUS and global temperature changes for the purpose of communication.

TABLE 1. AVERAGE REGIONAL TEMPERATURES BY DEGREE OF WARMING

Temperature change by National Climate Assessment region and integer degrees of national (CONUS) warming (Celsius) from 1986-2005 average baseline, six GCM average for RCP8.5, with corresponding global mean surface temperature (GMST) change. The six GCMs are the suite used in the CIRA project, which represents the majority of the sectoral impact studies.

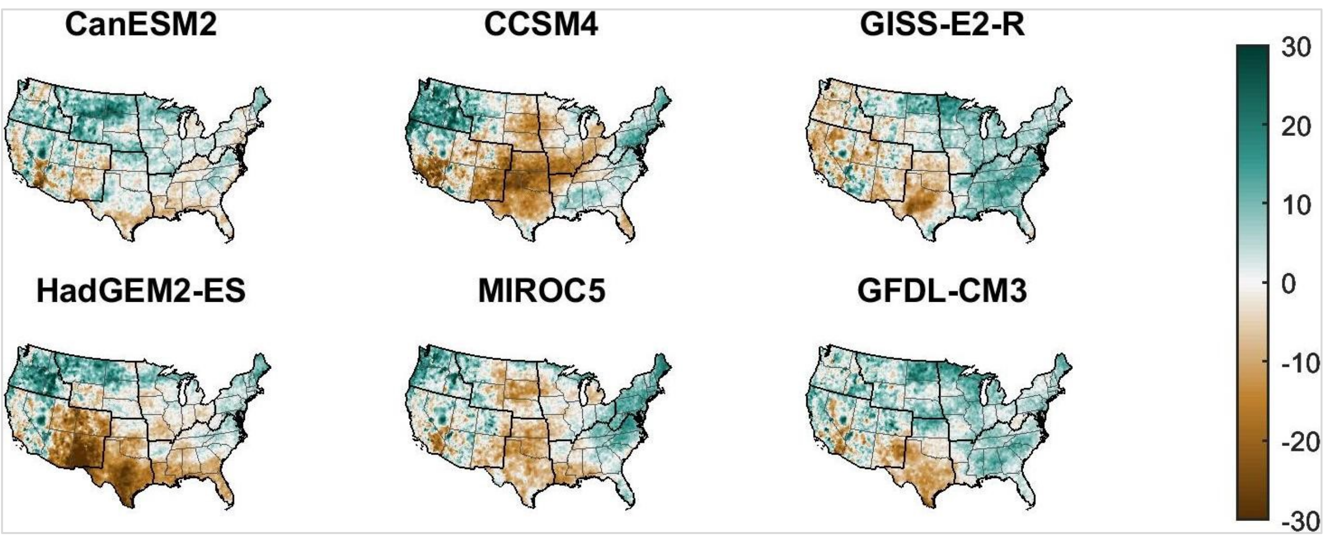
	CONUS Δ T (C) from 1986-2005 baseline					
	1	**2**	**3**	**4**	**5**	**6**
Midwest	1.4	2.3	3.4	4.5	5.6	6.6
Northeast	1.2	2.3	3.4	4.5	5.5	6.8
Northern Plains	1.1	2.1	3.1	4.2	5.4	6.3
Northwest	0.9	1.8	2.6	3.8	4.7	5.8
Southeast	1.1	1.9	2.9	3.8	4.6	5.5
Southern Plains	1.1	2.2	3.1	3.9	4.9	5.6

[10] The lack of GCM coverage at higher temperatures may in some cases present inconsistencies in the impacts by degree approach. Changes in in daily or seasonal temperature, precipitation, and other climatic factors implicitly incorporated in the underlying sectoral models where it is potentially important (e.g., Southwest Dust), but these patterns of climate hazards may be distinct to individual GCMs. As a result, temperature bins that are based on different groups of GCMs are likely to display some differences when non-temperature stressors are influential, such as for sectors that are driven by extreme events. Further research could be needed to assess the potential importance of this factor, but it is also clear that the potential bias is likely to be smaller for more moderate warming scenarios, where more GCMs are available. More detail on this point can be found in Sarofim et al. (2021a).

	CONUS Δ T (C) from 1986-2005 baseline					
	1	2	3	4	5	6
Southwest	0.9	2.0	2.9	3.8	4.7	5.7
Global Δ T	**0.4**	**1.2**	**2.0**	**2.7**	**3.5**	**4.2**
Note: Global temperatures increases from a pre-industrial baseline are 0.454 degrees C higher than the 1986-2005 baseline values presented above.						

Precipitation patterns, and therefore precipitation driven impacts, are also represented by degrees of CONUS temperature change. For precipitation-driven impact sectors, this can result in larger variations between GCM-specific impacts by degree compared to temperature-driven sectors. **Figure 3** shows the percent change in precipitation compared to baseline for the six CIRA GCMs at two degrees of warming. The suggested method in this Framework is to calculate impacts using several GCMs and use the average for interpretation. An alternative method could be to rely upon results from a subset of GCMs that are known to have similar climate patterns to the scenario of interest. For example, if there is interest in the implications of a relatively wet future, an analysis using the CMIP5 CanESM2 GCM, the wettest of the CIRA ensemble, could provide insights.

FIGURE 3. PERCENTAGE DIFFERENCE IN PRECIPITATION FOR THE 2-DEGREE TEMPERATURE BIN



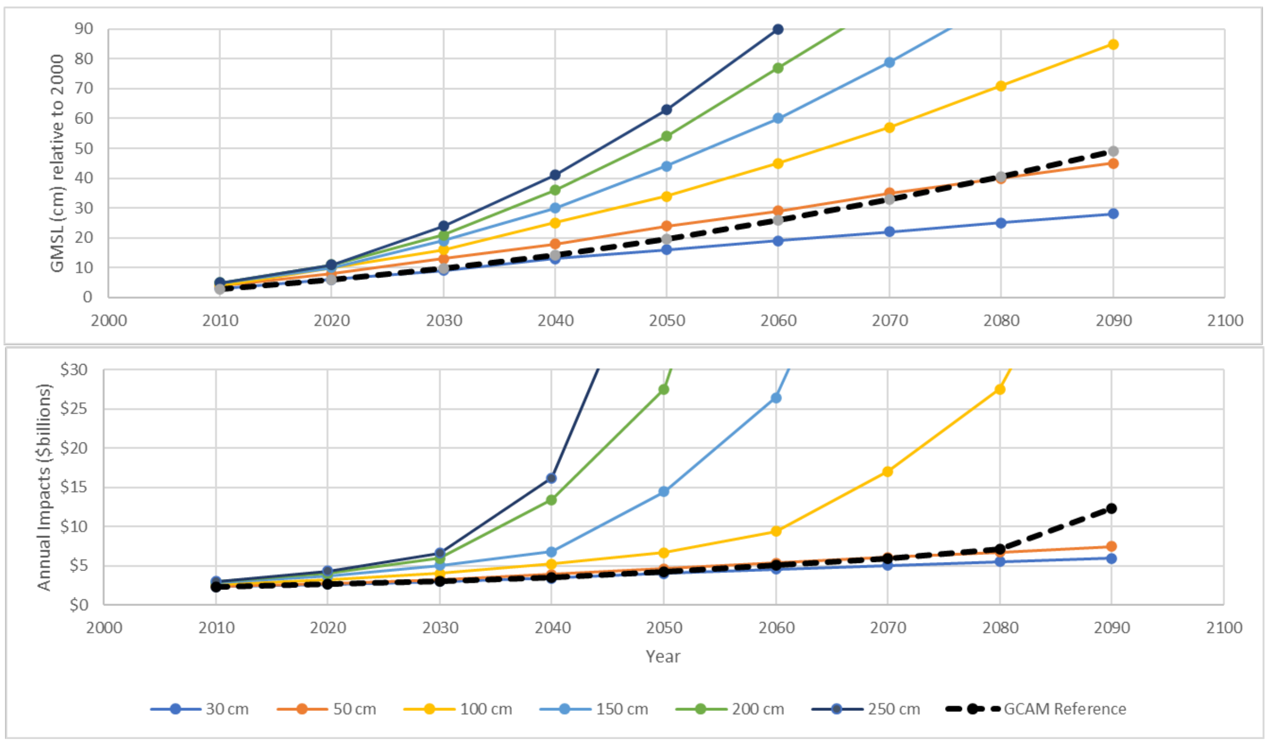
Maps of the differences in annual mean precipitation (%) from 1986-2005 average baseline annual mean precipitation at 1/16th degree.

For sectors vulnerable to sea level rise, binning by degree of warming presents challenges for precisely capturing the links between climate stressors and economic impacts. Degrees of warming are correlated with sea level rise but non-linearities and time dependencies in the relationship make tying sea level rise driven impacts to temperatures a suboptimal option. The underlying CIRA sea level rise sector studies (Coastal Properties and High Tide Flooding) estimate economic impacts for six probabilistic GMSL projections first established by Kopp et al. (2014) and more recent localized scenarios developed by Sweet et al. (2017), ranging from 30cm to 250cm of GMSL rise by the end of the century. The method makes use of these results in a two-step process that includes a reduced complexity model of the relationship between temperature and GMSL (Appendix D), and a mapping of results using time-specific damage trajectories established by the underlying studies.

The approach for relating global mean sea level rise to damages relies on the 11-year rolling average damages for each of the six sea level rise scenario from Sweet et al., direct from the underlying studies (shown in the bottom panel of **Figure 4**), which gives six pairs (from the six underlying scenarios) of GMSL and impact trajectories. We then compare the GMSL from the defined input SLR scenario (in the example here, that is the GCAM reference scenario as estimated semi-empirically using the method described in Appendix D) to the six GMSL trajectories and find the two scenarios from Sweet et al. that bracket the custom scenario in each year, in terms of sea level rise heights (see the top panel of **Figure 4**). Using that information, and where exactly the custom scenario falls in between the two bracketing Sweet et al. scenarios to then interpolate damages for the custom scenario. For example, in 2090 the custom sea level rise scenario falls between the 50cm and 100cm scenarios. Therefore, we interpolate between the damages of these scenarios to calculate the resulting damages in 2090, using the following equation:

$$Impact_{custom} = Impact_{lowScen} + (Impact_{highScen} - Impact_{lowScen}) \times (1- (GMSL_{highScen} - GMSL_{custom}) / (GMSL_{highScen} - GMSL_{lowScen}))$$

FIGURE 4. GMSL AND ANNUAL IMPACTS: INTERPOLATION ILLUSTRATION



Example conversion of a custom sea level rise scenario (the GCAM reference scenario, shown as the dotted line) to a damage trajectory by interpolating between the associated damages with the two scenarios from Sweet et al. 2017 that bracket the custom sea level rise in each year.

As with the temperature bin indexing, regional and local sea levels are mapped to GMSL based on the localized sea level rise projections from Sweet et al. (2017), which include effects such as land uplift or subsidence, oceanographic effects, and responses of the geoid and the lithosphere to shrinking land ice. When custom sea level rise scenarios are used in the Framework, the relationship between GMSL and regional sea levels, and ultimately regional impacts, are mapped implicitly based on the underlying models.[11]

2.2 Available Sectoral Impacts

The FrEDI Framework is a secondary data synthesis application that relies on existing primary research quantifying sectoral impacts and is designed to accommodate a variety of impact estimates, including those run with unique climate trajectories, socioeconomic assumptions, and temporal scopes.

Many of the sectoral studies currently processed for this Framework are part of the CIRA framework, and therefore rely on a consistent set of climate models and socioeconomic scenarios (see Martinich and Crimmins, 2019; EPA 2017a; Neumann et al., 2020; and Sarofim et al., 2021a for more details on sector studies and the CIRA framework). However, other studies with different climate or socioeconomic projections can also be integrated into the Framework if the necessary information is available. Necessary data and specifications include that the underlying study provides regional impacts by degree of warming (or cm of SLR) that can be scaled for socioeconomic changes and adjusted for other time dependencies unique to the sectoral impact function. Although ideally the introduced sectors meet all of these qualifications, there may be instances where methods are adapted to allow for the inclusion of certain studies and their results. For example, if a study only provides national estimates, impacts could be distributed to the regions based on population or another relevant proxy. In addition to CIRA framework studies, the FrEDI framework currently incorporates multiple sectoral results from the Climate Impact Laboratory (CIL), and single sectoral studies from several other researchers, including a panel organized through the American Thoracic Society (ATS). See Section 2.3 for more discussion of necessary information.

FrEDI currently includes 25 sectoral impacts, many with multiple adaptation scenarios and sub-impacts, as seen in **Table 2**. This list will continue to evolve as new sector studies are published and processed for temperature binning (see Section 2.7 for a description of limitations regarding omitted impacts and sectors). EPA intends to carefully monitor the literature to identify appropriate sectoral studies for inclusion in the Framework. In order to advance the utility of the Framework, EPA encourages researchers and practitioners to develop additional sectoral impact studies that can be considered for use in FrEDI. Moving forward, EPA intends to prioritize adding sectoral studies that fill gaps in the existing coverage and/or provide alternative estimates for the sectors with the largest impacts. See Appendix B for more details on the sectors currently processed for the Framework, including citations for the underlying studies.

To account for potential overlap between sectors (e.g., All Roads and Asphalt Road Maintenance) a priority flag is assigned to each and one adaptation scenario per sector, as well as a flag for which sectors to

[11] Analyses conducted to support Neumann et al. (2020), Yohe et al. (2020), and Lorie et al. (2020) showed that economic impact results for the Coastal Property sector were consistent for like increments of SLR across SLR trajectories within about 10 percent tolerance, if socioeconomic trends are controlled (socioeconomics drives a function for real property value appreciation in the National Coastal Property Model).

include in any aggregated results. As additional sectoral impact studies are added to FrEDI, this will allow analysts to remove overlapping sectors from aggregations to avoid double counting. Note also that three of the sectoral analyses listed in Table 2 (Air Quality, Wildfires, and Southwest Dust) estimate the health impact of exposure to fine particulate matter ($PM_{2.5}$). Each of these studies uses epidemiological functions which depend on a baseline $PM_{2.5}$ estimate, presenting the possibility of inconsistency and/or double counting. All three studies employ the same $PM_{2.5}$ baseline data, however, avoiding issues of inconsistency. The non-linear nature of the epidemiological function could imply some double-counting of benefits, but any issue with double-counting should be small as the relevant concentration-response function is nearly linear at $PM_{2.5}$ concentrations typically encountered in CONUS.

TABLE 2. SUMMARY OF SECTORAL IMPACTS IN FREDI

Impacts types refer to the sub-impacts processed for FrEDI and available as outputs in the Framework. Key socioeconomic drivers represent the key model drivers in the underlying studies. References for the underlying studies listed in the first column. More details on the underlying studies can be found in Appendix B.

<table>
<tr><th colspan="2">Sector</th><th>Impact Types[a]</th><th>Key Socioeconomic Drivers in Underlying Study</th><th>Adaptation or Variant Scenarios[b,c]</th></tr>
<tr><td colspan="2">Air Quality
Fann et al. (2021)</td><td>• Ozone Mortality
• Particulate Matter (PM) 2.5 Mortality</td><td>• Population
• GDP/capita (for calculating the Value of Statistical Life, or VSL)</td><td>• 2011 Air Pollutant Emissions Level[a]
• 2040 Air Pollutant Emissions Level[a]</td></tr>
<tr><td rowspan="3">Extreme Temper-ature</td><td>Extreme Temperature
Mills et al. (2014)</td><td>• Heat-related mortality (VSL)
• Cold-related mortality (VSL)</td><td>• Age-stratified city population
• GDP/capita (VSL)</td><td>• No Additional Adaptation
• Adaptation, using the bounding assumption that all cities exhibit an extreme heat response function consistent with the historical response of the city of Dallas</td></tr>
<tr><td>CIL Extreme Temperature*
Hsiang et al. (2017); Deschênes & Greenstone (2011); & Barreca et al. (2016)</td><td>• Net heat- and cold-related mortality (VSL)</td><td>• Population</td><td>• No Additional Adaptation</td></tr>
<tr><td>ATS Extreme Temperature*
Cromar et al. (2022)</td><td>Net heat- and cold-related mortality (VSL)</td><td>• Age-stratified city population
• GDP/capita (VSL)</td><td>• No Additional Adaptation Mean
• No Additional Adaptation Low (approximate 5th percentile)
• No Additional Adaptation High (approximate 95th percentile)</td></tr>
<tr><td colspan="2">Labor
Neidell et al. (2021)</td><td>• Lost Wages</td><td>• Population (limited to high-risk workers)
• GDP/capita (wages)</td><td>• No Additional Adaptation</td></tr>
<tr><td colspan="2">Hurricane Wind Damage*
Dinan (2017); CBO (2016); & Marsooli et al. (2019)</td><td>• Property damage</td><td>• None</td><td>• No Additional Adaptation beyond currently implemented wind risk mitigation at property level</td></tr>
<tr><td colspan="2">Rail
Neumann, Chinowsky, et al. (2021a) & Chinowsky et al. (2019)</td><td>• Repair (including equipment and labor) and delay costs</td><td>• Population (passenger traffic)
• GDP (freight traffic)</td><td>• No Additional Adaptation
• Reactive Adaptation
• Proactive Adaptation</td></tr>
</table>

Sector	Impact Types[a]	Key Socioeconomic Drivers in Underlying Study	Adaptation or Variant Scenarios[b,c]
Wildfires *Neumann, et al. (2021b)*	• Morbidity from air quality (hospitalization costs and lost productivity) • Mortality from air quality • Response Costs	• Population • GDP/capita (VSL)	• **No Additional Adaptation**
Roads – **All Roads** *Neumann, Chinowsky, et al. (2021a) & Neumann et al. (2015)*	• Road repair, user cost (vehicle damage), and delay costs	• Population (traffic)	• No Additional Adaptation • **Reactive Adaptation** • Proactive Adaptation
Roads – **Asphalt Road Maintenance*** *Underwood et al. (2017)*	• Asphalt road surface repairs, temperature stress only	• None	• ***No Additional Adaptation***
CIL Agriculture *Hsiang et al. (2017); Hsiang et al. (2013); McGrath & Lobell (2013); & Schlenker & Roberts (2009)*	• Lost wheat production value • Lost maize production value • Lost soybeans production value • Lost cotton production value	• None	• **With CO_2 fertilization[b]** • Without CO_2 fertilization[b]
Electricity Demand and Supply *McFarland et al. (2015)*	• Power sector costs	• Electricity demand forecast	• **No Additional Adaptation**
Electricity Transmission and Distribution Infrastructure *Fant et al. (2020)*	• Repair or replacement of transmission and distribution lines, poles/towers, and transformers	• Electricity demand forecast	• No Additional Adaptation • **Reactive Adaptation** • Proactive Adaptation
Southwest Dust *Achakulwisut et al. (2019)*	• All Mortality • All Respiratory Morbidity • All Cardiovascular Morbidity • Asthma ER • Acute Myocardial Infarction Morbidity	• Age-stratified population • GDP/capita (VSL)	• **No Additional Adaptation**
Valley Fever *Gorris et al. (2020)*	• Morbidity - Hospitalization Costs • Morbidity – Lost Productivity • Mortality	• Population • GDP/capita (VSL)	• **No Additional Adaptation**
Urban Drainage *Price et al. (2016)*	• Upgrading urban stormwater infrastructure	• None	• **Proactive Adaptation**
Winter Recreation *Wobus et al. (2017)*	• Lost snowmobiling revenues • Lost alpine skiing revenues • Lost cross country skiing revenues	• Population (potential recreators)	• **No Additional Adaptation** (defined by snowmaking for alpine skiing)
Water Quality *Fant et al. (2017); Boehlert et al. (2015); & Yen et al. (2016)*	• Lost recreational value	• Population	• **No Additional Adaptation**
Inland Flooding *Wobus et al. (2021) & Wobus et al. (2019)*	• Property damage	• None	• **No Additional Adaptation** beyond currently implemented flood protection measures at property and collective level
CIL Crime *Hsiang et al. (2017), Ranson (2014); Heaton (2010); & Jacob et al. (2007)*	• Violent crime value • Property crime value	• None	• **No Additional Adaptation**
Marine Fisheries *Moore et al. (2020) & Morley et al. (2018)*	• Lost value of marine fisheries landings	• None	• **No Additional Adaptation**
Suicide *Belova et al. (2022)*	• Mortality from suicide	• Population • GDP/capita (VSL)	• **No Additional Adaptation**

Sector	Impact Types[a]	Key Socioeconomic Drivers in Underlying Study	Adaptation or Variant Scenarios[b,c]
Vibriosis *Sheahan et al. (2022)*	• Morbidity - Hospitalization Costs • Morbidity – Lost Productivity • Mortality	• Population • GDP/capita (VSL and wages)	• **No Additional Adaptation**
Traffic and High Tide Flooding *Fant et al. (2021)*	• Traffic delays, road elevation costs	• Population (traffic)	• No Additional Adaptation • **Reasonably Anticipated Adaptation** • Direct Adaptation
Coastal Properties *Neumann, Chinowsky, et al. (2021a) & Lorie et al. (2020)*	• Costs related to armoring, elevation, nourishment, and abandonment (including storm surge impacts)	• GDP/capita (property values)	• No Additional Adaptation • **Reactive Adaptation** • Proactive Adaptation

*Non-CIRA study. Non-CIRA studies are from the peer-reviewed literature and are processed in the same manner as CIRA-studies, however they may not follow the same consistent framework assumptions as the CIRA-studies (GCM ensemble modeled, population assumptions, etc.).
Blue rows are SLR- sectors
Notes:

a. Impacts types refer to the sub-impacts processed for the Framework and available as outputs in the Framework.
b. The two emissions levels in the underlying Air Quality study are not strictly adaptation scenarios however they are entered into the Framework using the same structure. Emissions scenarios for $PM_{2.5}$ and ozone precursor pollutants are independent of GHG mitigation and temperature trajectory scenarios, although it is true that GHG mitigation would likely lead to changes in co-emitted $PM_{2.5}$ and ozone precursors. CIL Agriculture also has two variants represented in the Adaptation/Variants column.
c. Adaptation scenarios bolded represent the "priority" runs per sector. In cases where the Framework includes multiple sectoral models (i.e., roads and extreme temperature) the italicized priority run is excluded from summaries in the default settings to avoid double counting.

The majority of the sectors currently processed for FrEDI are temperature-driven, meaning that within FrEDI, impacts in these sectors are indexed to CONUS temperatures. The relationship between climate and impacts in the underlying models often includes other factors, such as precipitation. The remaining sectors (highlighted in blue in **Table 2**) are SLR-driven. Impacts in these sectors are indexed to centimeters of GMSL in FrEDI.

Adaptation Scenarios

The Framework accounts for adaptation by reflecting treatment of adaptation in the underlying sectoral studies and enabling the comparison of results from the underlying sectoral studies, grouped by an adaptation nomenclature adopted in the Fourth National Climate Assessment (reactive and proactive adaptation responses – see Lempert et al. 2018 for example). The last column in **Table 2** identifies the available adaptation scenarios for each sector currently in the Framework. The available adaptation options generally fall in three categories, one reflecting current adaptation actions and two reflecting the impact of additional actions and investments in response to emerging climate hazards:

- **No additional adaptation.** The no additional adaptation scenario represents a "business as usual" scenario, but incorporates adaptive measures and strategies reflected in historical actions to respond to climate hazards. For econometrically based sectors (e.g., Labor), adaptation is included to the extent that adaptation is currently occurring. For infrastructure sectors (i.e., Rail, Roads, Electricity Transmission and Distribution Infrastructure, Coastal Properties, and High Tide Flooding), a no additional adaptation approach to infrastructure management does not incorporate climate change risks into the maintenance and repair decision-making process beyond baseline expectations and practice.

- **Adaptation.** The adaptation scenario explicitly accounts for some climate change-induced behavioral change in response to changing climate. Currently, the infrastructure sectors include two adaptation scenarios, following Melvin et al. (2016):
    - **Reactive adaptation**, where decision makers respond to climate change impacts by repairing damaged infrastructure, but do not take actions to prevent or mitigate future climate change impacts (a variant on this scenario is the "Reasonably anticipated adaptation" option for the High-Tide Flooding and Traffic sector, which is defined similarly to the Reactive scenario); and
    - **Proactive adaptation**, where decision makers take adaptive action with the goal of preventing infrastructure repair costs associated with future climate change impacts. This Proactive Adaptation scenario assumes well-timed infrastructure investments, which may be overly optimistic given that such investments have oftentimes been delayed and underfunded in the past, and because decisionmakers and the public are typically not fully aware of potential climate risks (these barriers to realizing full deployment of cost-effective adaptation are described in Chambwera et al., 2014).

The adaptation options in FrEDI are based on scenarios and information included in the underlying sector impact studies. An absence of adaptation variants for certain sectors means that the underlying literature does not separately identify impact estimates that vary by projected adaptation effort, although in virtually all cases some default specification of adaptation to climate hazards is included in the underlying study. To the extent that new and emerging literature addresses the dimension of multiple levels of human and natural system acclimation to future climate, as well as adaptation effort and investment uncertainty, future additions to the Framework can reflect this additional information.

The general adaptation scenarios considered in the Framework will not capture the complex issues that drive adaptation decision-making at regional and local scales. As such, the adaptation scenarios and estimates should not be construed as recommending any specific policy or adaptive action.

Note that in some cases, the "Variant" scenario field in the FrEDI R code output is used to describe a sector variant rather than a true adaptation scenario. For example, the CIL Agriculture sector includes results with and without a CO_2 fertilization treatment, which is not an adaptation scenario. In another example, the ATS Extreme Temperature sector includes results from the mean, high confidence interval and low confidence interval, which are also not adaptation scenarios. The same field is used for both adaptation scenarios and other types of variants to streamline the FrEDI coding.

Climate Scenarios in Underlying Models

The CIRA sectors in FrEDI are parameterized based on a set of results from underlying sectoral models that use one RCP that spans the largest range of future temperature projections for the 21st century U.S.[12] RCPs are identified by their approximate total radiative forcing (not emissions) in the year 2100, relative to the year 1750. RCPs developed for the IPCC's Fifth Assessment Report released in 2014 include 2.6 W/m^2 (RCP2.6), 4.5 W/m^2 (RCP4.5), 6.0 W/m^2 (RCP6.0), and 8.5 W/m^2 (RCP8.5). The baseline climatic data within FrEDI was created using RCP8.5 to ensure the broadest possible range of application to both low and high temperature bins. RCP8.5 is a pathway with relatively high greenhouse gas concentrations, leading to substantial warming by 2100. Note that RCP8.5 does not represent any particular national or global policy and is used in the Framework because it covers a wide range of warming levels (low to high). Results for RCP4.5 would likely be comparable, once binned into comparable integer temperature bins, but RCP8.5 results are employed.[13] Although RCP8.5 is preferred for scenario-based result inputs to the Framework, potential new sectoral studies that are run at different RCPs or other scenarios are not excluded from the Framework.

The CIRA sectors rely on six GCMs from the fifth phase of CMIP (CMIP5) shown in **Table 3**: CCSM4, GFDL-CM3, GISS-E2-R, HadGEM2-ES, MIRO5, and CanESM2.[14,15]

[12] See the Third National Climate Assessment (2014) and Climate Impacts Group (2013) for useful descriptions of how the RCPs compare to other common scenarios. References: Walsh, J., D. Wuebbles, K. Hayhoe, J. Kossinet al., 2014: Ch. 2: Our Changing Climate. Climate Change Impacts in the United States: The Third National Climate Assessment, J. M. Melillo, Terese (T.C.) Richmond, and G. W. Yohe, Eds., U.S. Global Change Research Program, 19-67. doi:10.7930/J0KW5CXT; Climate Impacts Group, 2013. Making sense of the new climate change scenarios. University of Washington, available at: http://cses.washington.edu/db/pdf/snoveretalsok2013sec3.pdf.

[13] In general, studies have found that the sensitivity of impacts for a given temperature level to the specific scenario is low compared to other sources of uncertainty. Appendix E includes a sensitivity analysis comparing results for the Roads sector using RCP4.5 and RCP8.5 runs and concludes that while there are differences for individual GCMs, the differences for the ensemble of GCMs employed here is small.

[14] Sectors developed for EPA 2017a used only five GCMs (they did not include GFDL-CM3). Several sectoral models (e.g., Water Quality, Urban Drainage, etc.) were not updated since 2017 and therefore do not include results for GFDL. These sectors were generally ones with smaller overall economic impacts.

[15] The Framework uses climate modeling outputs from the fifth phase of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012). A 2016 dataset of downscaled CMIP5 climate projections was commissioned by the U.S. Bureau of Reclamation and Army Corps of Engineers and developed by the Scripps Institution of Oceanography with a number of collaborators. This dataset, called LOCA (which stands for Localized Constructed Analogs), was the primary dataset underlying the 2018 Fourth National Climate Assessment. While more than 20 GCMs are available in the LOCA dataset, the selection of a subset of GCMs is necessary due to computational, time, and resource constraints. These six GCMs used in the CIRA2.0 project (EPA, 2017a) were chosen based on their ability to capture variability in temperature and precipitation outcomes, and a consideration of demonstrated independence and quality. A detailed description of the criteria used to select GCMs can be found in EPA (2017a). The supplemental material for Sarofim et al. (2012) contains information and figures showing the distribution of annual and seasonal temperature and precipitation outcomes across the entire CMIP5-LOCA ensemble, including where the six GCMs lie.

TABLE 3. GCMS USED BY CIRA SECTORS IN FREDI

Names and citations for the six GCMs used in the underlying sectoral impact models for the CIRA sectors, which make up the majority of damage categories.

Center (Modeling Group)	Model Acronym	References
Canadian Centre for Climate Modeling and Analysis	CanESM2	Von Salzen et al. (2013)
National Center for Atmospheric Research	CCSM4	Gent et al. (2011) Neale et al. (2013)
NASA Goddard Institute for Space Studies	GISS-E2-R	Schmidt et al. (2006)
Met Office Hadley Centre	HadGEM2-ES	Collins et al. (2011) Davies et al. (2005)
Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC5	Watanabe et al. (2010)
Geophysical Fluid Dynamics Laboratory	GFDL-CM3	Donner et al. (2011)

2.3 Sectoral Impact Data Pre-Processing: Developing Impact Function Parameters

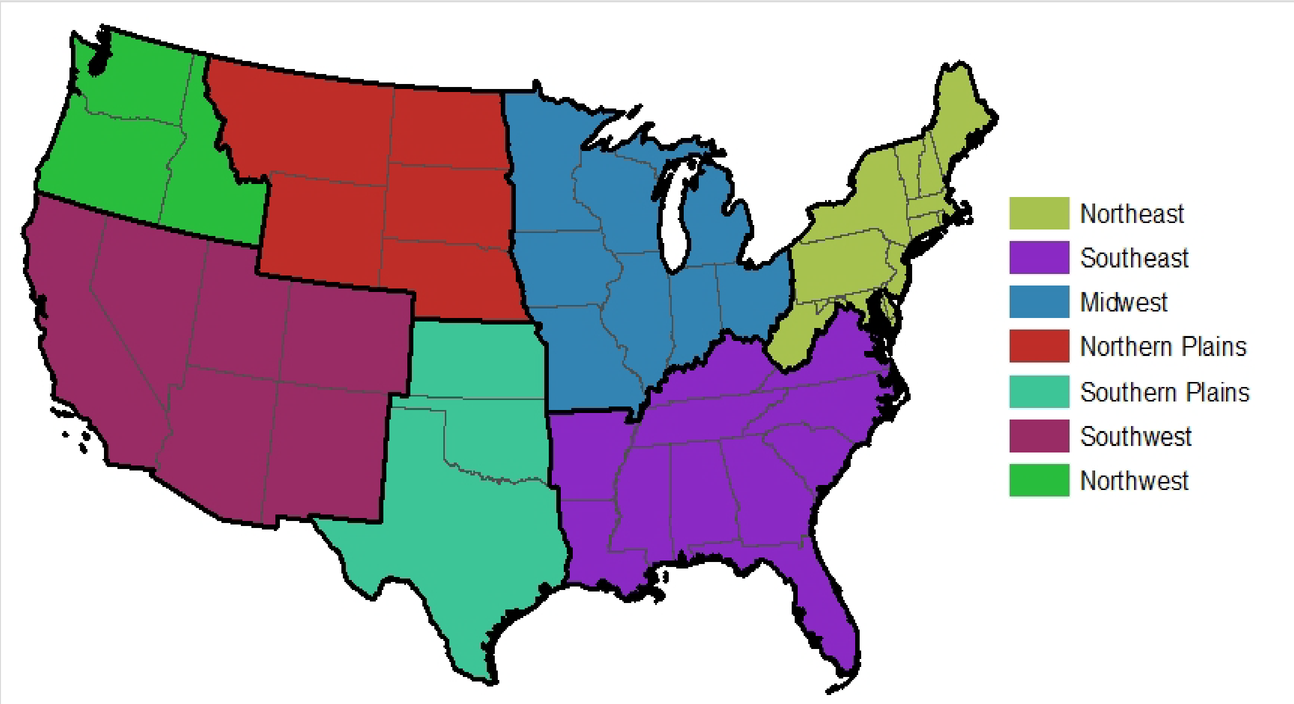
Impact function parameters are sector-specific functions that define impacts by degree, which can then be applied to any temperature and socioeconomic trajectories. Parameters must be 1) regional (NCA region), 2) scaled by sector-specific, tailored socioeconomic scalars (to allow for custom scenario inputs, where possible), 3) adjusted for other time-dependent factors, where applicable, and 4) available by degree of warming.

The objective of this pre-processing step is to define regional impacts that can be scaled (e.g., impacts per capita, impacts per road mile using the inverse of the scalars), are tied to degrees of warming (or cm of SLR), and can be adjusted for additional time-dependent aspects of the impact function (e.g., demographic shifts and energy demand shifts).

Regional Impacts

FrEDI is run at a subnational scale. Results are currently processed and presented at the regional levels used in the 4th NCA, of which there are seven across the CONUS (see **Figure 5**). The NCA regions are aggregations of states, therefore most impacts estimated by administrative boundaries (e.g., county, state, zip code) sum cleanly to regions and do not require any weighting. Physical boundaries, such as Hydrological Unit Codes (HUCs)—common in water resource models, can also be attributed to regions using spatial weighting to account for areas that span regions. It is not necessary for a sector study to include all regions to work in FrEDI. Southwest Dust and Winter Recreation, for example, are two studies that are limited to specific regions of the CONUS. Aggregate national impacts are calculated by summing over the seven regions.

FIGURE 5. NATIONAL CLIMATE ASSESSMENT (NCA) REGIONS



Map of seven NCA regions of the U.S. Global Change Research Program at which impacts are reported in FrEDI.

To scale results, population is input at the regional level, and GDP at the national level. Additional scalars, such as road or rail miles or property values, are also input at the regional level (see Section 2.4).

FrEDI uses NCA regions for consistency, however there is no methodological reason why another spatial scale could not be used, for example counties. Sectoral impact studies that only produce national estimates can also be used in the Framework, either to produce national results or with impacts allocated across regions using a proxy scalar such as population.

Accounting for Socioeconomic Conditions

Total impacts per sector for a given period are a function of climate and socioeconomic drivers. One of the key characteristics of FrEDI is the ability to analyze changes in temperature at different points throughout the century that account for socioeconomic trends. Previous methods have allowed for scaling by presenting impacts as proportional to GDP (see Hsiang et al., 2017 for example). This method, however, does not account for non-linearities in the relationship between GDP, population, and impacts (e.g., the value of a statistical life, which is valued using a non-linear elasticity of GDP per capita) and it does not capture how variations in population demographics (particularly geographic distribution and age) affect impact estimates.[16]

[16] The current default EPA policy for use of an income elasticity adjustment to VSL, based on the most recent Science Advisory Board review of this parameter, uses the 0.4 value, as described in the referenced documentation for the BenMAP-CE model in Appendix B.

The Framework improves on the traditional scalar approach by explicitly accounting for two components of time dependencies that can broadly be thought of in terms of quantity and composition, where quantity is the traditional scalar (e.g., damages per capita or as a percent of GDP) and composition refers to the changes in vulnerability or exposure within a given population. For example, at a given temperature, health and recreation impacts in 2010 will differ from those in 2090 based on both the *total* population and the *demographic composition* of the population. FrEDI evaluates impacts for a given scenario defined by a trajectory of climate change, a given trajectory of "quantity" measures (i.e., GDP and regional population), and a time series of year-specific adjustment factors for each sector and impact type developed during sectoral data pre-processing. [17]

Scaling per Capita Impacts and GDP/Capita Valuation

In some but not all sectors, the input GDP and regional population values are used to scale results (see **Table 4** for a list of the sectors with this capability). The ability of FrEDI to include a linkage between input population and GDP and sectoral impacts is dependent on the modeling assumptions and data outputs of the underlying sector studies. Many of the underlying health impact studies generate mortality per capita estimates, which are scaled by population for total impacts. Valuation of impacts can scale linearly (e.g., wage rates for Labor and Valley Fever sectors, where impacts are multiplied by the ratio of the future year GDP per capita to 2010 GDP per capita) or via non-linear elasticities (e.g., VSL for Air Quality, Extreme Temperature, Southwest Dust, Wildfire, and Valley Fever sectors).

TABLE 4. SECTORAL IMPACTS LINKED TO CUSTOM SOCIOECONOMIC SCENARIOS

Identification of sectors for which impacts scale with population and GDP per capita inputs. Sectors that scale with population at aggregations other than the regional level are noted. These instances are driven by the populations studied in the underlying sectoral models.

Sector	Link with Regional Population Input	Link with GDP per Capita Input
Air Quality	X	X
Extreme Temperature	X[a]	X
CIL Extreme Temperature	X	X
ATS Extreme Temperature	X	X
Labor[b]		X
Suicide	X[c]	X
Southwest Dust	X[d]	X[e]
Water Quality	X	
Wildfire[f]	X	X[e]
Winter Recreation	X	
Valley Fever	X	X[g]
Vibriosis[h]		X

Many of the underlying studies that rely on VSL test the sensitivity of impact results to this assumption and include consideration of an elasticity of 1.0 that is more consistent with current literature. The latest version of FrEDI allows the user to choose a custom income elasticity, with a default value of 0.4.

[17] FrEDI does not model feedbacks between climate and socioeconomic scenarios. It also does not account for the relationship between socioeconomics and adaptation capacity. See Sections 2.6 and 2.7 for more details.

Notes:

a. Scaled to city populations to reflect the coverage of the underlying study.
b. The underlying labor study finds that the number of high-risk workers is projected to remain constant in absolute terms throughout the century; therefore, labor impacts do not scale with population.
c. Scaled to population over 5 years of age to reflect the coverage of the underlying study.
d. Scaled to Arizona, Colorado, New Mexico, and Utah populations to reflect the coverage of the underlying study.
e. Mortality impacts scale with GDP per capita; morbidity impacts do not.
f. Wildfire mortality and morbidity impacts. Wildfire response costs do not scale with population or GDP per capita.
g. Mortality impacts and lost productivity scale with GDP per capita; morbidity impacts do not.
h. The underlying vibriosis study does not tie impacts to population because cases are not tied to where people live and, given limits on shellfish harvesting, cases are unlikely to scale linearly with population.

Year-Specific Adjustment Factors

Another set of sectors, typically process-based sectors where population and GDP per capita enter the impact function in complex ways, adjusting impact results in FrEDI based on custom GDP and population scenarios is not possible at this time. For example, in the Coastal Property sector, property values are projected to change over time, and therefore an efficient adaptation option late in the century may not be efficient early in the century when property values are different. At the same time, threats early in the century trigger adaptation actions, and therefore the property is no longer vulnerable later in the century, which could cause damages to decrease over time. The Roads sector provides another example. Under no additional adaptation, increases in population lead to increased road traffic which, in combination with freeze/thaw patterns, drive road surface degradation. In some sectors that are sensitive to changes in population (such as the health impact sectors), the underlying studies calculate impacts at a finer resolution than regional totals, and while impacts primarily scale linearly with the total population exposed, the vulnerability of that population changes over time. For example, the Extreme Temperature and Southwest Dust studies have age-stratified impact functions and Winter Recreation impacts vary by state. This type of dynamic decision-making, feedback loops, and demographic distributions cannot be calculated dynamically for custom GDP and population scenarios in FrEDI using the pre-processed results. For these sectors, FrEDI adjusts for the modeled differences in the relationship between temperature and impacts over time by using a series of year-specific adjustment factors for each region defined empirically from the underlying studies, shown in **Table 5**.

Because the year-specific adjustment factors are not linked to the custom population and GDP inputs to the Framework, it is possible that results for these sectors become out of sync with the custom inputs. This is a limitation of the method. The adjustment factors are designed to reasonably approximate changes in the relationship between temperature and impacts for most commonly evaluated and direct effect of population and GDP scenarios. They also minimize the required spatial resolution of custom inputs by working off regional population and GDP inputs to estimate more detailed changes over time. In Appendix E, a sensitivity test is conducted for the Extreme Temperature category which shows that the direct influence of adjustments for population and GDP (accounting for 50 to 75% or larger adjustments) is much larger than that of the year-specific factors (accounting for 5 to 10% or smaller adjustments, of varying sign), showing that the likely impact of any non-synchronous effect is small.

TABLE 5. SECTORAL IMPACTS AND YEAR-SPECIFIC ADJUSTMENT FACTORS

Year-specific adjustment factors are used to transform general estimates of impacts by degree to estimates tied to a particular year based on socioeconomic trends that are too complex to model in FrEDI but are observed in the underlying sector models.

Sector	Adjustment Factor	Adjustment Factor Construction
Electricity Demand and Supply	Electricity demand and supply growth factor	Ratio of impacts with conditions held constant at 2010 levels and impacts with dynamic conditions[a]
Electricity Transmission and Distribution Infrastructure	Electricity demand growth factor	
Suicide	Demographic composition factor	
Rail	Rail traffic growth factor	
Roads	Road traffic growth factor	
Coastal Properties	Property values and adaptation decision making	Interpolation between impacts with conditions held constant at 2010 levels and impacts with conditions held constant at 2090[b]
High Tide Flooding	Road traffic and adaptation decision making	
Extreme Temperature	Demographic composition factor	
Southwest Dust	Demographic composition factor	

Notes:

a. Annual series of impacts with socioeconomic change are compared to a constant 2010 socioeconomic scenario run.
b. Impacts are estimated using constant 2010 socioeconomic conditions and 2090 socioeconomic conditions, then a ratio is taken between the two and interpolated for the intervening years.

There are multiple methods for constructing years-specific adjustment factors from the underlying sectoral study results. For the first four sectors listed in **Table 5,** adjustment factors are calculated as the ratio of future annual impact projections (i.e., changing climate and changing socioeconomics) versus impacts with a constant 2010 socioeconomic scenario (i.e., changing climate and constant socioeconomics). Comparing the two runs yields an adjustment factor for each year that represents the difference in the relationship between temperature and impacts relative to 2010 socioeconomic conditions.[18] This type of information is most often provided for processed-based sectoral modeling, where socioeconomic growth can be switched on and off. The last five sectors in **Table 5** use year-specific adjustment factors based on two runs with constant socioeconomic conditions, defined by 2010 and 2090. The 2090 scalar is then calculated as the ratio of estimated impacts using 2090 population versus 2010 population. Scalars for years between 2010 and 2090 are interpolated between the two end points. This option is less data intensive but does not provide the same level of detail as the trajectory-based scalars.[19]

Impacts for Urban Drainage, Asphalt Roads, Inland Flooding, Wind Damage, Marine Fisheries, CIL Agriculture, CIL Crime, and the response (suppression) cost portion of Wildfire impacts do not have year-specific adjustment factors, nor do they scale directly with population and GDP. While impacts in many of

[18] Note that the FrEDI Framework calculates trajectory-based scalars for every five years (not annually), but the method and Framework would support annual scalars as well.

[19] A possible extension could be to add more intermediate runs, such as 2050 scenario run to add detail to the interpolated scalars. Linear interpolation between the two time periods does not perfectly capture non-linear trends in the year-specific factors, however this is likely to be a small uncertainty relative to the scaling for population and GDP, which does capture non-linear trends. See Appendix E for further discussion.

these sectors likely are driven by socioeconomic conditions (for example, Urban Drainage impacts increase with expanding urban areas driven by population growth), FrEDI is constrained by the assumptions made in the underlying studies, and the underlying studies in these cases did not model impacts under changing socioeconomic conditions.[20]

Socioeconomic Condition Factors Extension through 2300

The Framework was calibrated to estimate impacts for detailed 21st century scenarios. To estimate impacts beyond 2090 in the extension module, the Framework defines extensions of the socioeconomic condition adjustments described above, through 2300. More details are provided in Appendix D.3.

- **Impacts scale with population and/or GDP per capita (Table 4)**: Custom population and GDP trajectories continue to scale damage estimates through 2300.
- **Year-specific Adjustment Factors (Table 5).** For adjustment factors derived by comparing per capita damage rates from a constant population run to a run that incorporates population growth, the time series of adjustment factors is either linearly extrapolated through 2300 or held constant at 2090 levels based on the observed trends 2010 through 2090 and the interpretation of the factor. For adjustment factors derived by comparing per capita damage rates for two constant population scenarios (i.e., 2010 and 2090) and interpolating for between years, per capita damage rate adjustments are held at 2090 levels through 2300. These adjustment factors tend to change only modestly over the 2010 to 2090 period and holding them constant at 2090 levels avoids extreme adjustments due to extrapolation.
- **No time-dependent adjustments.** Some sectors – which, in general, make up a small portion of overall damages– are not adjusted for socioeconomic projections but vary based only on sensitivity to projected temperature. No additional adjustment is necessary for these sectoral impacts through 2300.

Economic Valuation Measures

The underlying sectoral models define economic impacts using a variety of valuation measures suited to the sector and underlying methods. For some sectors and sub-impacts, valuation represents direct costs, e.g., the medical cost to treat an illness, or the expense to repair a road or other physical structure damaged by a climatic hazard. In other cases where no market transactions take place, such as when an individual dies prematurely from a climatic hazard or when water quality is impaired, the economic valuation involves the use of welfare economic techniques. These methodologies are often used to estimate what individuals would be willing to pay to avoid the risk of an undesirable outcome. The VSL is one such measure used to value mortality outcomes in many of the health sectors. **Table 6** presents the valuation measures used for each of the sectors and impacts currently in the Framework. The table also

[20] This may cause an underestimate of damages in the Crime sector where it is likely that the number of crimes scales with population, however the underlying sources (Hsiang et al. 2017 and Ranson 2014, the source of the damage function) do not grow population in their forecasts and therefore there is no clear approach for scaling these impacts. Similarly, the crime values include a VSL component that we do not scale with GDP per capita due to limitations in the available data regarding the share of forecasted violent crimes that result in death.

indicates in which underlying sectoral models valuation occurs as a multiplier on a physical impact, and which underlying sectoral models directly provide economic impacts. For example, the welfare economic measure Value of Statistical Life (VSL) is applied to a modeled risk of premature mortality, while many of the process-based sectors (e.g., Roads, Rail, and Coastal Property) directly estimate economic impacts. Sectoral models that provide physical and economic impacts are preferred, where possible, as they provide an alternative method for communicating climate impacts and comparing the effectiveness of adaptation options (e.g., using number of deaths avoided).

TABLE 6. ECONOMIC VALUATION MEASURES BY SECTORAL IMPACT

For each sector and impact, this table provides the valuation measure and a short description of how the valuation is calculated, either directly from the underlying model (as is more common in process-based models) or as a multiplier on a physical impact measurement (as is more common in econometric models).

<table>
<tr><th colspan="2">Sector</th><th>Impact</th><th>Valuation Measure</th><th>Valuation Application</th></tr>
<tr><td colspan="2" rowspan="2">Air Quality</td><td>Ozone mortality</td><td>VSL</td><td rowspan="2">Multiplier on premature mortality</td></tr>
<tr><td>$PM_{2.5}$ mortality</td><td>VSL</td></tr>
<tr><td colspan="2">Coastal Properties</td><td>Coastal property damage</td><td>Property damage/adaptation costs</td><td>Direct cost, as output from underlying model</td></tr>
<tr><td colspan="2">Electricity Demand and Supply</td><td>Change in power sector costs from reference scenario</td><td>Capital, operations/maintenance, and fuel costs</td><td>Direct cost, as output from underlying model</td></tr>
<tr><td colspan="2" rowspan="2">Extreme Temperature</td><td>Extreme cold mortality</td><td>VSL</td><td rowspan="2">Multiplier on premature mortality</td></tr>
<tr><td>Extreme heat mortality</td><td>VSL</td></tr>
<tr><td colspan="2">CIL Extreme Temperature</td><td>Extreme heat mortality</td><td>VSL</td><td>Multiplier on premature mortality</td></tr>
<tr><td colspan="2" rowspan="2">ATS Extreme Temperature</td><td>Extreme cold mortality</td><td>VSL</td><td rowspan="2">Multiplier on premature mortality</td></tr>
<tr><td>Extreme heat mortality</td><td>VSL</td></tr>
<tr><td colspan="2">Electricity Transmission and Distribution Infrastructure</td><td>Stress to transmission and distribution infrastructure</td><td>Repair and replacement costs</td><td>Direct cost, as output from underlying model</td></tr>
<tr><td colspan="2">High Tide Flooding</td><td>Traffic delays and adaptation costs due to high tide flooding</td><td>Delay costs</td><td>Direct cost, as output from underlying model</td></tr>
<tr><td colspan="2">Inland Flooding</td><td>Inland property damage</td><td>Property damage</td><td>Direct cost, as output from underlying model</td></tr>
<tr><td colspan="2">Labor</td><td>Lost wages for high-risk occupations</td><td>Wages: annual, high risk workers</td><td>Multiplier on hours lost</td></tr>
<tr><td colspan="2">Rail</td><td>Rail impacts, risk of track buckling</td><td>Repair and delay costs</td><td>Direct cost, as output from underlying model</td></tr>
<tr><td rowspan="2">Roads</td><td>All Roads</td><td>Damage to paved and unpaved road surfaces</td><td>Repair and delay cost</td><td>Direct cost, as output from underlying model</td></tr>
<tr><td>Asphalt Roads Maintenance</td><td>Road impacts</td><td>Repair costs</td><td>Direct cost, as output from underlying model</td></tr>
<tr><td colspan="2" rowspan="4">CIL Agriculture</td><td>Lost maize production value</td><td>Production values: maize</td><td rowspan="4">Direct cost, as output from underlying model</td></tr>
<tr><td>Lost wheat production value</td><td>Production values: wheat</td></tr>
<tr><td>Lost soybean production value</td><td>Production values: soybean</td></tr>
<tr><td>Lost cotton production value</td><td>Production values: cotton</td></tr>
</table>

Sector	Impact	Valuation Measure	Valuation Application
Southwest Dust	Hospitalization (acute myocardial infarction)	Hospitalization costs: cardiovascular	Multiplier on incidences
	Hospitalization (cardiovascular)	Hospitalization costs: cardiovascular	
	All mortality	VSL	
	Hospitalization (respiratory)	Hospitalization costs: respiratory	
	Asthma ED visits	Hospitalization Costs: Asthma	
Urban Drainage	Proactive costs of improving urban drainage infrastructure	Repair costs	Direct cost, as output from underlying model
Water Quality	Water quality impacts	Lost welfare	Willingness to pay for improvements in water quality, direct from underlying model
Wildfire	Morbidity	Hospitalization costs	Direct cost, as output from underlying model
	Mortality	VSL	Multiplier on premature mortality
	Response or suppression costs	Wildfire response costs	Multiplier on acres burned
Hurricane Wind Damage	Property damage from hurricane winds	Lost property value	Direct cost, as output from underlying model
Winter Recreation	Lost ticket sales from alpine skiing	Lost ticket revenues	Direct cost, as output from underlying model
	Lost ticket sales from cross-country skiing	Lost ticket revenues	
	Lost ticket sales from snowmobiling	Lost ticket revenues	
Valley Fever	Mortality	VSL	Multiplier on incidences
	Morbidity	Cost of illness: Valley Fever	
	Lost wages	Wages: daily, all workers	
CIL Crime	Violent crime	Injury/loss of life, enforcement, and other indirect costs	Multiplier on incidences
	Property crime	Property damage, enforcement costs, and other indirect costs	
Marine Fisheries	Change in weight of marine fisheries landings	Lost or increased *ex vessel* revenue	Direct cost, as output from underlying model
Suicide	Mortality	VSL	Multiplier on premature mortality
Vibriosis	Direct medical costs	Medical cost of illness for doctor visit or hospitalization	Direct cost, as output from underlying model
	Lost wages	Wages: daily, all workers	Multiplier on lost days of work
	Mortality	VSL	Multiplier on premature mortality

The reader should note that the underlying sector studies measure economic impacts through widely varying methods, including welfare economic measures, expenditure/direct cost measures, or a mix of these methods. Details are provided in the Appendix B for each of the underlying sectoral studies. Summing across these measures may result in some confusion about what is represented by the total and is not strictly supported by economic theory. In applied economic analyses such as EPA Regulatory Impact Analyses, however, these sums are commonly encountered, and no specific advice is yet provided in EPA's Guidelines for Preparing Economic Analyses (2014).[21] As a result, values are summed in this report, but advise that subsequent use of the sums include an appropriate caveat such as those included in the tables and figures in this section.

Impacts by Degree

After adjusting for socioeconomic and other time-dependent trends, impacts are mapped to degrees of warming through the binning process. Section 2.1 describes the binning process, whereby binning windows for each integer degree of warming zero to six degrees are defined across a timeseries of impacts, specific to the GCM(s) used in the underlying sectoral impact model. This process is used to estimate regional impacts by degree when sectoral impact results are available annually.[22]

Not all sectoral impact studies produce annual results, either due to computational constraints or the structure of the underlying model. For example, Urban Drainage and Water Quality, two sectors part of the CIRA project that were not specifically simulated using the temperature binning arrival times, produce results only at a set number of eras. Similarly, asphalt roads, a non-CIRA sector, also provide era-level results. The Framework is flexible to these inputs provided the underlying climate projections are well-documented and available. For these sectors, bins are defined by first constructing a time series of impacts using the era-impact pairings, with an added pair for zero damages for the baseline period (1986-2005). Years within known pairings are linearly interpolated and end of century results are extrapolated linearly based on the latest two available pairings. Binning windows are defined for the synthetic time series of impacts using the underlying climate data. This process adds uncertainty through imposing linear interpolations between known points, and the level of uncertainty is higher when fewer eras of results are available (for example, Water Quality impacts rely on 2050 and 2090-era results only, while projections for Urban Drainage impacts are available for 2030, 2050, 2070, and 2090 eras). Building a synthetic time series potentially overstates confidence in the shape of the time series, but it allows for the inclusion of a wider set of potential impact studies, particularly those developed outside of the CIRA framework.

[21] See in particular Chapter 11 of EPA (2014), on Presentation of Analysis and Results, which implies an inclusive approach to estimates of total monetized benefits rather than a disaggregation by method by which they are monetized or special considerations in developing the sums (such as use of compensating variation equivalents for welfare estimates or use of a general equilibrium approach for aggregating expenditure/direct cost estimates). As recommended in the Guidelines, in this report we provide detailed information on how each of the monetized estimates were developed. In addition to the summary provided in Table 6, detailed information is provided in Appendix B for each of the underlying sector studies.

[22] The bins shown in Section 2.1 are specific to the six GCMs used in the CIRA framework, downscaled and bias corrected for the LOCA dataset. When using non-CIRA sectors in the Framework, bins are defined following the same process, which requires access to the climate data used in the underlying impact analysis. Note that new bins based on integer degree arrival times should be defined for all outside climate models, even those using the same GCMs, unless they rely on the same LOCA downscaling and bias correction methods.

A final consideration in defining impacts by degree is the assignment of baseline periods. The majority of CIRA sectors use the default climate baseline (1986-2005), but outside studies and select CIRA sectors define future climate change against different baseline periods. Where possible (i.e., where consistent baseline data is available), the baseline is shifted to match the Framework default. This is not possible in all cases, and in those instances, temperature binning windows are developed based on the available baseline. A requirement for a study to be included in FrEDI is, at minimum, a clearly defined and transparent baseline scenario – including potentially important information beyond the climate baseline, such as any projection of baseline mortality rates, or assumptions about baseline infrastructure repair or replacement cycles, with information provided in the study that is sufficient to facilitate an adjustment if necessary. See Appendix B for details.

2.4 Economic Impacts Calculation

The pre-processing described above results in a database of information that can be used to evaluate impacts of climate change in a relatively quick process. FrEDI can be used to estimate climate impacts in several ways, including impacts by degree, impacts for a specified scenario, and the difference in impacts for two emission scenarios. Using the processed results data from the underlying sectoral studies and defined socioeconomic scenarios, the Framework calculates regional damages per time step. Results are then aggregated to the national scale, and when two or more scenarios are analyzed, physical and economic impact projections under a mitigation scenario are compared to estimated impacts under a reference case. The results can also be used as inputs to other post-processing analyses, such as economy wide models. This section describes the process for estimating impacts for one or more climate scenarios

Defining Climate Scenarios

FrEDI aims to provide reliable climate impact estimates with limited input requirements to support rapid assessment. To that end, the Framework is flexible in terms of the necessary climate inputs. Impacts in the Framework are keyed to CONUS temperature change and global sea level rise, however the minimum required input is global mean temperature change, which can then be translated to the necessary climate variables within the Framework.[23] The FrEDI approach accepts global mean temperatures and translates them to CONUS temperatures using a reduced form function.[24] FrEDI also generates global mean sea level from global mean temperature using the semi-empirical model from Kopp et al., 2016. The Framework runs on an annual scale; however, it can work with any timestep of input data by interpolating between known points.

[23] If analysts begin with an emissions scenario, rather than a global mean temperature trajectory, emissions trajectories can be converted to global mean temperatures using a reduced complexity climate model, such as Hector or FaIR (Hartin et al., 2015; Smith et al., 2018). Reduced complexity climate models (Nicholls et al., 2020; Sarofim et al., 2021b) work well in this setting as they can emulate some of the aggregate response characteristics of GCMs within seconds, allowing for exploration into a range of scenarios, uncertainties, and small perturbations to the climate system. Reduced complexity climate models are defined by a series of parameters that can be optimized to emulate more complex GCMs, retaining the computationally efficiency and ease of use while replicating the global mean outputs of these models. An example (used in the case studies presented in Appendix C) uses Hector, a reduced-form global climate carbon-cycle model, to develop temperature inputs from a custom emission scenarios. For more information on Hector, see: https://jgcri.github.io/hector/.

[24] See Appendix D for more details.

- **Temperature Inputs: CONUS or Global temperature change, relative to a 1986-2005 baseline.** Temperature-driven sectors are indexed to CONUS degrees of warming, relative to the 1986-2005 baseline. An annual timeseries of temperatures is preferred, although interpolation (and extrapolation) can be used to fill in a timeseries from a minimum of two points. CONUS degrees of warming are used in FrEDI because, relative to global temperatures, they provide a closer link to the local climate stressors influencing the underlying models (Sarofim et al., 2021a). For some climate models and other sources of temperature trajectories, CONUS degrees of warming might not be a readily available, and instead the climate scenarios are defined by global temperature change. FrEDI includes a translation function to convert global changes in temperature (from the 1986-2005 baseline) to CONUS changes in temperature, based on a statistical relationship derived from the LOCA dataset.[25,26]
- **Sea Level Rise Inputs: Global mean sea level, relative to a 2000 baseline or no custom input.** Sea level-driven damages are indexed to global mean sea levels, relative to a 2000 baseline. Although considered a separate input from the temperature pathway, the sea level rise inputs should be consistent with the temperature pathway to maintain consistency across all sectoral results. In some cases, the same models used to develop temperature trajectories might also produce sea level rise pathways. In other cases, sea level rise pathway could be developed in a separate model from the same emissions trajectory used to develop the temperature trajectory. Finally, if the input climate scenario does not include a defined sea level pathway, the Framework includes a translation function, modeled after Kopp et al. (2016), to estimate global mean sea level from global temperatures.[27]

Defining Socioeconomic Trajectories

The Framework allows custom regional population and national GDP inputs, which drive impact projections through the adjustments for socioeconomic conditions described in Section 2.3. In the absence of custom scenarios, FrEDI applies default population and GDP projections that are consistent with the CIRA project's scenarios (see EPA 2017 for more details), and therefore align with the scenarios used in many of the underlying sectoral impact studies. The default population scenario is based on the national-level UN Median Population projection (United Nations 2015), disaggregated to the county-level using EPA's ICLUSv2 model (Bierwagen et al., 2010; EPA 2017b) and reaggregated to NCA regions for this analysis. GDP projection is defined by the EPPA, version 6 model (Chen et al., 2015), using the aforementioned UN

[25] U.S. Bureau of Reclamation, Climate Analytics Group, Climate Central, Lawrence Livermore National Laboratory, Santa Clara University, Scripps Institution of Oceanography, U.S. Army Corps of Engineers, and U.S. Geological Survey, 2016: Downscaled CMIP3 and CMIP5 Climate Projections: Release of Downscaled CMIP5 Climate Projections, Comparison with Preceding Information, and Summary of User Needs. Available online at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/techmemo/downscaled_climate.pdf. Data available at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/.
[26] Global to CONUS mean temperature change estimated as CONUS Temp =1.42*Global Temp. See Appendix D for more information.
[27] Global mean sea level is calculated from global mean temperature using a semi-empirical method that estimates global sea level change based up a statistical synthesis of a global database of regional sea-level reconstructions from Kopp et al., 2016. The function used in the temperature input stage to translate global temperatures to CONUS temperatures is inverted to produce global temperature from CONUS inputs when necessary. See Appendix D for more information.

Median population projection for the U.S. (United Nations 2015) and the 2016 Annual Energy Outlook reference case (USEIA 2016) for the U.S. through 2040.[28]

Defining Output Sets

The Framework calculates impacts across multiple dimensions: year, region, sector, sub-impact, and adaptation scenario. Results can be aggregated across these dimensions to meet the needs of analysis, with the exception of the adaptation scenarios, which represent different options for future societal responses to climate change and should not be summed.

The results can feed into a number of post-processing analyses, including comparisons across emission policies or climate sensitivities, or feed into economy-wide models.

Assessing Social Vulnerability Metrics

A custom capability of the Framework is the additional assessment of social vulnerability implications of the impacts of climate change from select sectors on specific demographic groups. This capability is provided through a linked module that is provided with the FrEDI code and is described in more detail in Appendix G. Example calculations are also presented in Section 3.6 below.

The basic structure, specific methodology, and data for the module are derived from EPA's independently peer-reviewed September 2021 report, *Climate Change and Social Vulnerability in the United States: A Focus on Six Impacts*.[29] The code in the linked FrEDI Social Vulnerability (or FrEDI-SV) module provides access to data, results, and calculations reported at the Census tract level in EPA's Climate Change and Social Vulnerability report, but provides the user an enhanced ability to aggregate results by region and nationally, and examine aggregated incidence of impacts, rates of incidence, and metrics of disproportionate exposure to impacts. Appendix G also includes reports of several validation tests which demonstrate consistency between results from the FrEDI-SV module and those presented in EPA's Climate Change and Social Vulnerability report.

Assessment of social vulnerability implications and distributional analyses is based on the spatial intersection of climate impacts in select underlying impact literature, at minimum at the county level and often approaching Census tract level, and data on the current location of demographic groups as characterized by the Census American Community Survey (ACS) data. The module's current scope includes a subset of FrEDI's sectors (Air quality (mortality (ages 65+) and childhood asthma cases); Extreme Temperature; Labor; Roads; High Tide Flooding; and Coastal Properties) and four dimensions of overburdened populations (Low Income; Black, Indigenous, and People of Color (BIPOC);[30] No High School

[28] The extended FrEDI module through 2300 does not include default GDP or population projections from 2091 to 2300. The default inputs are zero.

[29] See EPA. 2021. Climate Change and Social Vulnerability in the United States: A Focus on Six Impacts. U.S. Environmental Protection Agency, EPA 430-R-21-003. www.epa.gov/cira/social-vulnerability-report

[30] Consistent with other EPA reports, FrEDI-SV uses the abbreviation "BIPOC" (for Black, Indigenous, and people of color) to refer to individuals identifying as Black or African American; American Indian or Alaska Native; Asian; Native Hawaiian or Other Pacific Islander;

Diploma; and 65 and Older) and also includes the ability to assess multiple specific racial and ethnic subdivisions of the BIPOC category.

2.5 FrEDI R Package

FrEDI is implemented through the use of a process tool developed in R, a popular free software environment for statistical computing and graphics. The code consists of an R Package available for download and installation at https://github.com/USEPA/FrEDI. The R Package allows users to import custom temperature, sea level rise, national GDP, and regional population scenarios into R from Excel and CSV files, and to use these scenarios to project annual average damages throughout the 21st century due to climate change for any and all sectors available in FrEDI.[31] The output is a dataset of average annual economic damage estimates at single year intervals from 2010 through 2100 for each sector, variant (or adaptation), impact type, model (GCM or SLR scenario), and region.[32] The code also provides options for aggregation of outputs (i.e., summing all impact types for each sector), calculating discounted damages (annual and cumulative), plotting damages over time, and saving output tables. Additional information in the R Package is provided in Appendix F.

2.6 Sources and Treatment of Uncertainty

The FrEDI framework is designed to estimate climate change economic impacts in a deterministic framework, but with the capacity to employ a range of inputs and as needed to operate in batch mode to efficient process a range of results. With respect to uncertainty analysis, the framework is fundamentally an aggregation tool to synthesize and standardize a broad set of U.S. sectoral studies for use with common climate inputs and, to the extent possible, common socioeconomic and impact valuation driver data. The framework is therefore limited in terms of uncertainty analysis by the limits of uncertainty and sensitivity calculations within the underlying sectoral studies (described in Appendix B). All of the underlying studies examine outcomes across multiple climate projections (combinations of CMIP5 GCMs and RCPs), or develop impact damage functions that can be applied for multiple future climates; some assess differences in impacts across multiple socioeconomic assumptions; and a few examine limited parametric uncertainty in the estimation of economic impacts (for example, two alternative particulate matter and ozone precursor emissions as context for estimating the "climate penalty" in the formation of particulate matter and ozone in future meteorological conditions; two alternative longitudinal income elasticities for valuation of avoided mortality risk). As the underlying sectoral literature develops, it may also be possible to assess structural uncertainties within sectors, using multiple sectoral model formulations to estimate the same or

and/or Hispanic or Latino. It is acknowledged that there is no 'one size fits all' language when it comes to talking about race and ethnicity, and that no one term is going to be embraced by every member of a population or community. The use of BIPOC is intended to reinforce the fact that not all people of color have the same experience and cultural identity. This report therefore includes, where possible, results for individual racial and ethnic groups. Note the SV report reported results for this group as attributed to a "minority" category. The results are the same here but the category title has been updated.

[31] The R code, by default, calculates projected damages for all sectors in the tool. Alternatively, users have the option to select a specific set of sectors for which to calculate damages.

[32] The main output includes information about the underlying input scenario, for user reference.

similar impact categories, but currently most research is focused on expanding the scope of impact sector coverage rather than testing differences in estimates across multiple model formations.

Currently, a limited set of sectoral or aggregation studies attempt to propagate uncertainty across the major steps in climate impact assessment – one notable effort to do so is Hsiang et al. (2017) which estimates the joint uncertainty in impact estimates across the dimensions of emissions uncertainties (characterized by three RCPs); climate projections (characterized by a wide range of individual GCM inputs); and statistical econometric estimation of impacts for six sectors (agriculture, extreme temperature mortality, electricity demand, labor, violent and property crime, and coastal properties).

The FrEDI framework, however, is designed primarily to estimate the sensitivity of impact estimates to alternative individual choices for inputs, including varying adaptation responses, rather than propagating uncertainty across these dimensions. Attempting to propagate quantitative uncertainty estimates across analytic steps in the FrEDI framework, as currently configured, would involve mixing estimates of variability (e.g., across GCMs) with estimate of statistical uncertainty (e.g., for sector impacts that rely on statistically estimated exposure-response or stressor-response relationships, to the extent they are identified in the underlying literature), and could not be comprehensively applied across sectors. In addition, a joint estimate of uncertainty would necessarily ignore other sources of uncertainty that cannot be quantified (e.g., structural uncertainty associated with the choice of a single sector impacts model) and potential correlation in sources of uncertainty that may not be fully independent (e.g., many GCMs share a common structural foundation).

Consistent with the key goal of the framework to provide flexible and quick-turnaround capability for impact estimation, the FrEDI framework relies on an approach of identifying the key sources of uncertainty or variation, quantitatively assessing the impact of single sources of uncertainty where possible, and qualitatively characterizing the potential influence of other sources of uncertainty on the overall climate impact results. **Table 7** below provides a summary of this breakdown of quantitative and qualitative assessment of uncertainty associated with data sources, modeling, and analytic choices made in the development of the framework and the illustrative results presented in Chapter 3 and the appendices of this documentation report. Following the table, additional discussion is provided of several key uncertainties. Future work to address these uncertainties may further strengthen confidence in the estimates presented in this report but could also involve refinements to the framework to enhance capabilities to present uncertainty characterizations for individual sector studies, in cases where uncertainty is formally characterized provided in the underlying literature.

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

TABLE 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 from FrEDI, including discussion of sources of uncertainty that derive from pre-processing steps that are not inherent to the Framework. For each identified source of uncertainty, the table provides comments on the relative importance of the likely influence of that source of uncertainty as well as the capacity of the Framework to quantitatively assess influence on the economic impact results.

Source of Uncertainty	Analytical Step	Comments and Estimate of Influence of Uncertainty on Economic Impact Results
Greenhouse gas emissions associated with baseline and policy scenarios	Assessed outside of the framework	**Potentially large uncertainties, Framework not capable of estimating uncertainties.** Identifying the greenhouse gas emissions reductions associated with baseline and specified emissions reduction policies is challenging but is not estimated in FrEDI. The Framework is not capable of estimating the impact of this uncertainty on economic impact results. See additional discussion below.
Climate sensitivity to changes in greenhouse gas emissions	Assessed outside of the framework	**Major impact on central estimates.** Climate change scenarios are provided as an input to FrEDI. The Framework is designed to rapidly estimate multiple economic impact estimates using a wide range of climate scenarios, by running in batch mode. As illustrated by the case study results presented in Appendix C, 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 from the Framework. Also see additional discussion below.
Use of six climate models and six sea-level rise trajectories to assess variability in climate outcomes in the "impacts by degree" approach	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 CONUS domain, as well as other considerations such as consideration of model skill and independence (see the Technical Appendix to USEPA 2017a). These GCMs do not represent the full range of outcomes that could be considered for temperature and precipitation, and therefore the impact by degree datasets that emerge may be limited. The temperature binning/indexing approach effectively standardizes results for downstream temperature-based impact estimates, but the coincident precipitation outcomes for each degree of temperature vary widely. As a result, wide variability across GCMs might be expected for precipitation-dependent outcomes. Variability across GCMs at the local scale, in particular, for both temperature and precipitation can be substantial. In addition, for SLR scenarios, the current configuration of the Framework relates temperature to SLR in a deterministic fashion, but other research has quantified broad uncertainty bands for both GMSL and location specific relative SLR could occur, as summarized in Kopp et al. (2016). The FrEDI Framework could be run in batch mode to assess this component of uncertainty. See additional discussion below.
Climate hazard spatial patterns	Climate Hazard Projections,	**Unknown impact, unknown contribution to uncertainty.** Studies that underly the FrEDI framework use the detailed spatial results

Source of Uncertainty	Analytical Step	Comments and Estimate of Influence of Uncertainty on Economic Impact Results
	assessed within the Framework through user inputs	corresponding with the GCMs used in each study. Once processed for use in the framework, however, simplified relationships between global, CONUS, and regional scale temperatures are used that effectively reduce variability in climate outcomes that could be expected at fine spatial scale.
Socioeconomic and demographic change over time	Climate Impact Estimation, assessed within the Framework based on user inputs	**Unknown impact, limited ability to assess within the Framework**. FrEDI estimates climate change impacts using a consistent default population and GDP forecast, which can be modified based on user inputs to assess uncertainties in these projections. The ability to fully evaluate uncertainty in impacts associated with socioeconomic inputs is limited in FrEDI for four reasons: 1) The underlying sector studies may incompletely incorporate the effect of changes in population, GDP, demographic distribution, or other socioeconomic factors on impact estimates; 2) The underlying studies model impacts as a non-linear and/or dynamic process such that custom population and GDP scenarios cannot be fully assessed in FrEDI and year-specific adjustment factors must be used instead; 3) The underlying studies generally do not assess how socioeconomic factors affect adaptive capacity, which in turn can affect impact estimation; 4) Socioeconomic drivers may have important correlative dependency on climate scenarios, because of feedback of climate impacts and 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, but could be assessed within the Framework as literature expands and is added to FrEDI	**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 the models applied represent the best available information and the sectors chosen to reflect the best understood climate change impacts, and most of the models applied have been recently refined to reflect more recent data and improved understanding of impacts through peer review and other methods improvement processes.
Missing analysis of interactive or correlative effects	Climate Impact Estimation, not assessed	**Likely underestimate, 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.[33]

[33] See both Maxwell, K., S. Julius, A. Grambsch, A. Kosmal, L. Larson, and N. Sonti, 2018: Built Environment, Urban Systems, and Cities. In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II* [Reidmiller, D.R., C.W. Avery, D.R.

Source of Uncertainty	Analytical Step	Comments and Estimate of Influence of Uncertainty on Economic Impact Results
Estimation uncertainty for impact sector modeling	Climate Impact Estimation, not assessed	**Impact direction neutral, but estimation uncertainty could be substantial, depending on sector.** Each of the sectoral impact models applied within FrEDI estimates impacts with associated uncertainty. For sector models with econometric or epidemiological origins (e.g., Air Quality, Extreme Temperature, and Labor), a partial representation of this uncertainty can be characterized by statistical uncertainty around relevant parameter estimates. Further, the authors of the Climate Impact Lab (CIL) sector studies provided distributions of impact results which could be interpreted for estimation uncertainty. The Framework presents mean values, and statistical significance has been established for each model, so no underestimation or overestimation bias is implied, but the estimates are uncertain with varying levels of confidence. For sector models that rely on simulation approaches (e.g., High Tide Flooding, Coastal Properties, and Inland Flooding), the results are also uncertain but are generally not characterized by statistical methods. Estimates are either calibrated by or compared to current historical/baseline results, where possible, which increases confidence in the results, but they remain uncertain with mostly unknown impact on the results presented here.
Treatment of adaptation to climate impacts and consideration of adaptive capacity	Climate Impact Estimation, assessed within the Framework, but in a limited fashion	**Likely overestimation of impact for 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., High Tide Flooding). 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 adaptation is limited because of technological feasibility, difficulties in change human adaptive behavior, high upfront cost, or all three of these factors. See additional discussion of adaptation's influence on estimates in text below.

Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 438–478. doi: 10.7930/NCA4.2018.CH11 and Jacobs, J.M., M. Culp, L. Cattaneo, P. Chinowsky, A. Choate, S. DesRoches, S. Douglass, and R. Miller, 2018a: Transportation. In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II* [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 479–511. doi: 10.7930/NCA4.2018.CH12.

Source of Uncertainty	Analytical Step	Comments and Estimate of Influence of Uncertainty on Economic Impact Results
Impact of population migration that differs from the ICLUS 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 sector 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 from FrEDI.
Potential inconsistency between sector results with fully scalable and those with incompletely scalable socioeconomic inputs	Climate Impact Estimation, assessed within the Framework but in a limited fashion	**Impact direction unknown, probably minor.** Some sectors in the framework incorporate two types of socioeconomic input adjustments: direct impacts of population and GDP, and additional impacts associated with some sector and location specific adjustments such as age distribution of the subject population. The primary adjustments are "user-controlled", and their influence can be readily observed, but the secondary adjustments are not transparent and, while they remove overall bias, could be inconsistently applied. A sensitivity test was conducted, summarized in Appendix E for the Extreme Temperature sector, which shows that the impact of the primary adjustments is far larger than those of the secondary adjustments, showing that the potential for inconsistency varies in sign by region, but is likely to be small in magnitude. Other sectors which might be affected are Southwest Dust and Valley Fever, which have an overall smaller contribution to total estimated impacts than the Extreme Temperature sector.

GHG Emissions and Climate Scenarios: While emissions and climate scenarios are inputs to the FrEDI Framework, uncertainties in these components of climate impact studies should be acknowledged as contributing to uncertainty in the outputs of this Framework. Further, only six GCMs are used in most of the underlying sectoral impact modeling results that feed into the Framework. For those sectors where there is little variation in impacts resulting from the different GCM, such as Winter Recreation, there can be reasonable confidence when extrapolating to other, untested GCMs. For other sectors with more GCM-to-GCM variability, such as for climate impacts on the Rail sector, confidence in such extrapolation will be lower. More work understanding the causes of that variability, such as whether it is related to GCM-specific changes in precipitation or temperature changes in specific regions, could enable more sophisticated extrapolations.

Climate Drivers: FrEDI relies on estimation of impacts based on annual temperature indexing. While changes in daily or seasonal temperature, precipitation, and other climatic factors are used to drive the underlying sectoral models where it is relevant (e.g., Southwest Dust), these stressors other than annual temperature changes are only implicitly included within the temperature bins developed from each of the six GCMs considered. More detail on this point can be found in Sarofim et al. (2021a). Additionally, because not all GCMs reach six degrees by 2100, average impacts at higher temperatures are driven by a subset of GCMs that may not reflect average climate driver characteristics. This could lead to non-linearities at higher temperatures that are driven by the mix of available climate models rather than non-linearities in impact response.

Uncertainty in Warming Arrival Time: As described in Section 2 of this technical documentation, damage functions have typically been estimated using a single or limited number of emissions scenarios, and a limited number of climate models. However, there may be differences in a 2-degree scenario depending on how and when that level of warming is reached (Sarofim et al., 2021a). Aspects of this question have been addressed by several researchers (Tebaldi and Knutti 2018, Ruane et al., 2018, Baker et al., 2018, Tebaldi et al., 2020): generally, these studies find that the sensitivity of impacts for a given temperature level to the specific scenario is low compared to other sources of uncertainty, but that there are important sensitivities in the CO_2 concentration, aerosol concentration, and interannual variability across scenarios.[34] One physical difference that can arise when a temperature threshold is reached later in time is that the land-ocean differential would generally be expected to be smaller as a scenario approaches stabilization: this potential issue is partially addressed by using national rather than global temperatures for the binning. In general, while use of global temperatures improves the ability to associate results with the temperature targets discussed in climate policy, the use of national temperatures reduces scatter, improves fit, and allows better emulation of GCMs that might not have been used to generate the sector-specific damage functions. Note that there are some sectors where in theory an impact would be better associated with global temperatures than national temperatures, where the impacts are a function of large-scale weather pattern or ocean circulation changes.

Adaptation: Depending on the sector, FrEDI includes impact estimates that employ a variety of assumptions regarding adaptive responses to climate impacts. For some sectors, the Framework includes estimates that incorporate adaptation, in which they reflect the current understanding of the climate risk mitigating effects of adaptation in the literature. Much of the current literature reflects impact estimates developed for limited or no adaptation conditions. This is in part because the historical experience of climatic conditions such as those expected to be experienced in the future is limited, so mechanisms of adaptation can be poorly understood for some sectors. As a result, reliably quantified estimates of the effectiveness of adaptation are not currently available for all sectors addressed in this Framework. In addition, in many sectors adaptive action to date has been surprisingly slow, even where literature suggests that the economic benefits of taking action to mitigate climatic risks exceed the costs – for example, in response to coastal risks of accelerated storm surge and sea level rise (Lorie et al., 2020). For some sectors, including many of the infrastructure sectors and the Extreme Temperature Mortality sector, the Framework

[34] Additional sensitivity analyses of the impact of different numbers of year in the temperature bin, provided in Appendix F, indicate that the arrival year is not particularly sensitive to this factor. In the same Appendix, the sensitivity of results to the use of RCP4.5 (rather than RCP8.5) to parameterize the framework for a key sector (Roads) is assessed. The Roads sector relies on both temperature and precipitation climate inputs, the combination of which could see large differences in patterns at various temporal and spatial scales. The analysis concludes that while there are important differences among specific GCMs, for the ensemble mean and overall range of results across GCMs there is a small effect on the economic impact results.

provides the user an option to assess impacts under alternative human response scenarios, including no adaptation, reactive adaptation (to repair damage but without forward planning to avoid future damage), and proactive adaptation (including action and investment in risk mitigation based on some level of foresight of future conditions). For several sectors where the current scope of the Framework does not provide options to assess the effects of alternative adaptation assumptions, such as Labor or Winter Recreation, adaptation is partially represented in the underlying results used to create the damage functions. For example, the econometric methodology used in the Labor analysis would capture any extreme temperature adaptations employed by outdoor industries in the base period. Also, the Winter Recreation analysis included the use of artificial snow creation/blowing. For climate impacts on Air Quality, the Framework includes the two future relationships between climate and air quality derived in Nolte et al (2021), one based on a 2011 US emissions inventory and the other based on a 2040 US emissions inventory. The climate mortality penalty for the latter scenario is about half of the penalty for the former scenario. If precursor emissions were to be reduced further, that might further decrease the climate penalty. Nolte et al. (2021) did not consider elevated methane concentrations or changes in transboundary air pollution transport which could also influence the climate penalty.

The sectoral analyses of this report treat adaptation in unique ways, with some sectors directly modeling the implications of adaptation responses, and others implicitly incorporating well-established pathways for adapting to climate stress. For example, the Air Quality, Extreme Temperature Mortality, and Labor sectors all incorporate empirical analyses of individual, community, and infrastructure adaptation in estimating a climate stressor-response function, and so they reflect historical responses to these stressors. As climate stress worsens and expands geographically, wider adoption of historical adaptation actions (e.g., wider adoption of air conditioning as a response to extreme heat) therefore is implicitly incorporated in the estimated response function, and by extension in the results from the Framework. The Roads and Coastal Properties analyses employ a simulation modeling approach which allows for incorporation of baseline adaptation actions (e.g., in high-tide flooding a set of “reasonably anticipated actions” such as traffic re-routing are incorporated in the baseline – and continuation and expansion of existing beach nourishment at locations where it is currently practiced is incorporated in the coastal flooding analysis). These simulation modeling approaches also facilitate future adoption of more complex and extensive adaptive actions, such as changing maintenance practices and extending seawall and beach nourishment protections, which constitute new adaptation responses that are known to be cost-effective but which in some current situations have not yet been widely adopted.

Adaptation actions that go beyond historically implemented practices, however, require planning, potentially complex financing, and evaluation of efficacy with consideration of the specific human and natural environment contexts. Adaptation plans therefore are typically developed and implemented at local scales. As such, the general adaptation scenarios considered in the analyses of this report will not capture the complex issues that drive adaptation decision-making at regional and local scales. For example, the Coastal Properties sector study considers the cost effectiveness of adaptive responses to sea level rise inundation and storm surge damages by comparing the costs of protection to the value of those properties at risk. While many factors at the property, community, region, and national levels will determine adaptive responses to coastal risks, this sectoral analysis uses the simplistic cost/benefit metric to enable consistent comparisons for the entire coastline. However, the adaptation scenarios and estimates presented in all sections of this report should not be construed as recommending any specific policy or adaptive action.

2.7 Key Limitations of the Framework

The Temperature Binning Framework provides a method of utilizing existing climate change sectoral impact studies to create time independent estimates of the physical and economic impacts by degree of warming. EPA designed the Framework to readily synthesize the results of a broad range of peer-reviewed climate change impacts projections, and to support analysis of other climate change and socioeconomic scenarios not directly assessed in the supporting literature. Projected physical and economic impacts from the Framework are intended to provide insights about the potential magnitude of climate change impacts in the U.S. However, none of the estimates should be interpreted as definitive predictions of future impacts and damages. Instead, the intention is to produce estimates of future effects using a reliable and flexible method for generating rapid results, which can then be revisited and updated over time as science and modeling capabilities continue to advance.

In addition to the uncertainties in estimates identified in Section 2.6 above, the results provided by the FrEDI Framework should be used and interpreted with consideration of the following limitations, some of which may be addressed through future refinement of the Framework, particularly addition of new sectoral studies:

- **Coverage of Sectors and Impacts**: FrEDI incorporates a subset of all known climate change impacts, chosen based on current understanding, available data and methods, and demonstrated magnitudes of economic effect. EPA (2017a) further identifies additional sectors and impacts not addressed in the broader CIRA project, including cross-sectoral impacts, and incomplete coverage of effects within sectors – those are also omitted here. Examples of key missing sectors include the impacts of climate change on forestry, migration, broad-scale effects on ecosystem services and species, and political instability. Sectors that have already been modeled and incorporated into the Framework can be improved to capture more of the physical and/or economic effects, such as by expanding the population coverage and characterization of adaptation for extreme temperature-related mortality. Using more than one sectoral model to estimate impacts for a given sector would also lead to increased understanding of the results (and increased confidence, if the models are in agreement). Further, the sectoral studies largely omit potentially important indirect effects (e.g., how does road and electricity distribution infrastructure failure affect health and welfare, particularly during extreme events?), the potential for cascading failures, and the inability comprehensively to value all outcomes (e.g., the underestimation that results from using only cost to treat illness in some health sector studies, as opposed to the full willingness to pay to avoid sickness). As a result, the scope of estimates included in this Framework very likely underestimates impacts that could be reasonably expected under future climate scenarios.

- **Path Dependency:** Sectors where the impacts are a function of cumulative exposure can be more challenging to represent in a temperature binning context. For example, sea level rise is a function of the integration of heat absorption by the ocean and melting of land ice, and so is a more complex function of temperature over time, compared to health impacts from heat stress that occur in direct response to local ambient weather. There are approaches to addressing some of these difficulties: for example, financial smoothing is applied in the Framework for one-time adaptation costs or threshold damages to avoid discontinuities in the relationship between temperature and damages.

- **Rate of Change and Direct Effects of GHGs**: This approach does not capture impacts that are a function of rate of change, rather than absolute change (though there is a paucity of studies on that topic in general). Nor does it capture impacts that are a direct function of greenhouse gas concentrations, such as ocean acidification, CO_2 fertilization, or ozone resulting from methane oxidation in the atmosphere.[35] Impacts that are sensitive to non-GHG factors, such as aerosol emissions or land-use changes, will also be challenging to emulate. Inter-sectoral interactions (such as the land-water-energy nexus) and cascading risks would also be difficult to capture in this framework. Some of these challenges are surmountable – for example, Schleussner et al. (2016) shows temperature slices for coral reefs under assumptions of coral adaptation for both 2050 and 2100 in order to account for the ability of coral to adapt to slower rates of change, and O'Neill et al. (2017) created reasons for concern figures for rate-of-change and CO_2 concentration as a complement to the temperature-based reasons for concern – but require more complexity in approach.

- **Cross-Sectoral Impacts Modeling**: With some exceptions, the sectoral impact models that were simulated to develop functions used in FrEDI were run independently of each other. Some sectors, however, could reasonably interact with each other. These intersectoral effects are not reflected in the Framework.

- **Variability in Societal Characteristics**: The results from the Framework do not separately report impacts for overburdened populations for all sectors, only for the six sectors analyzed in EPA's Climate Change and Social Vulnerability report, nor does the Framework analyze how individual behavior affects vulnerability to climate. Results are aggregated across demographic groups.

- **Feedbacks**: The socioeconomic scenarios that drive the modeling analyses do not incorporate potential feedbacks from climate change impacts to the socioeconomic system (e.g., changes in albedo from land use change or increased GHG emissions resulting from vegetative changes) nor from sectoral damages to the economy (e.g., significant expenditures on protective adaptation measures, such as seawalls, would likely reduce available financial capital to the economy for other

[35] Note that the air quality estimates for ozone do not consider changes in methane emissions associated with greenhouse gas reduction policies, only the climate penalty on ozone formation associated with changes in meteorology for two overall conventional pollutant emissions scenarios

productive uses). Feedback effects of GHG mitigation policy on infrastructure, such as energy demand reduction, decarbonization policies, or the potential decentralization of the grid, are also omitted in the Framework (although climate induced changes in energy demand, such as for space heating and cooling, are incorporated in the Energy Demand and Supply sectoral study, see Appendix B for details). Also as discussed in the Uncertainties section above, the FrEDI Framework does not yet incorporate the feedback impact of income growth over time on adaptive capacity.

- **Geographic Coverage:** The primary geographic focus of this Framework is the contiguous U.S., excluding Hawai'i, Alaska, and the U.S. territories. This omission is particularly important given the unique climate change vulnerabilities of these high-latitude and/or island locales. In addition, some sectoral analyses assess impacts in a limited set of major U.S. cities (e.g., Extreme Temperature Mortality), and incorporation of additional locales would gain a more comprehensive understanding of likely impacts.
- **Changes in Other Drivers:** Some sectors in this analysis have significant non-climate drivers. For example, changes in land use and forest management could have substantial implications for the climate response of impacts such as wildfires or dust. If the underlying study did not consider such sensitivity analyses, the Framework cannot yet consider them.
- **Co-benefits and Ancillary Benefits and Costs of Climate Policy:** This Framework only examines the direct impacts of climate change. It does not, for example, estimate the benefits of reducing co-emitted air pollutants such as nitrogen oxides, volatile organic carbons, or particulate matter due to climate policy.

THREE | CLIMATE IMPACT ANALYSIS USING TEMPERATURE BINNING

This section demonstrates the capabilities of the Framework to evaluate climate impacts for the 17 sectors and 18 total available literature-based sector estimates that were included in the Framework as of the October 2021 publishing of the Technical Documentation.[36] In the original suite of sectors, extreme temperature mortality was based on the Mills et al. (2014) study, and the results in this section therefore include consideration of the impact based on that study. Subsequently the ATS Extreme Temperature and CIL Extreme Temperature sectors were added to FrEDI and provide more complete geographic coverage for temperature-related mortality impacts, but those results for the sector are not incorporated in this section. Specifically, this section provides examples of the ability of the Framework to evaluate sectoral impacts by degree (for CONUS and by region, as economic and physical impacts, and by adaptation assumption) and adjust impacts for socioeconomic conditions. These results are for illustration purposes only, do not reflect analysis of any particular policy or action, and should be interpreted with a consideration of the uncertainties described in Section 2.6. See Appendix E for more information on input scenarios used in this section.

3.1 CONUS Economic Impacts of Climate Change: Results by Degree

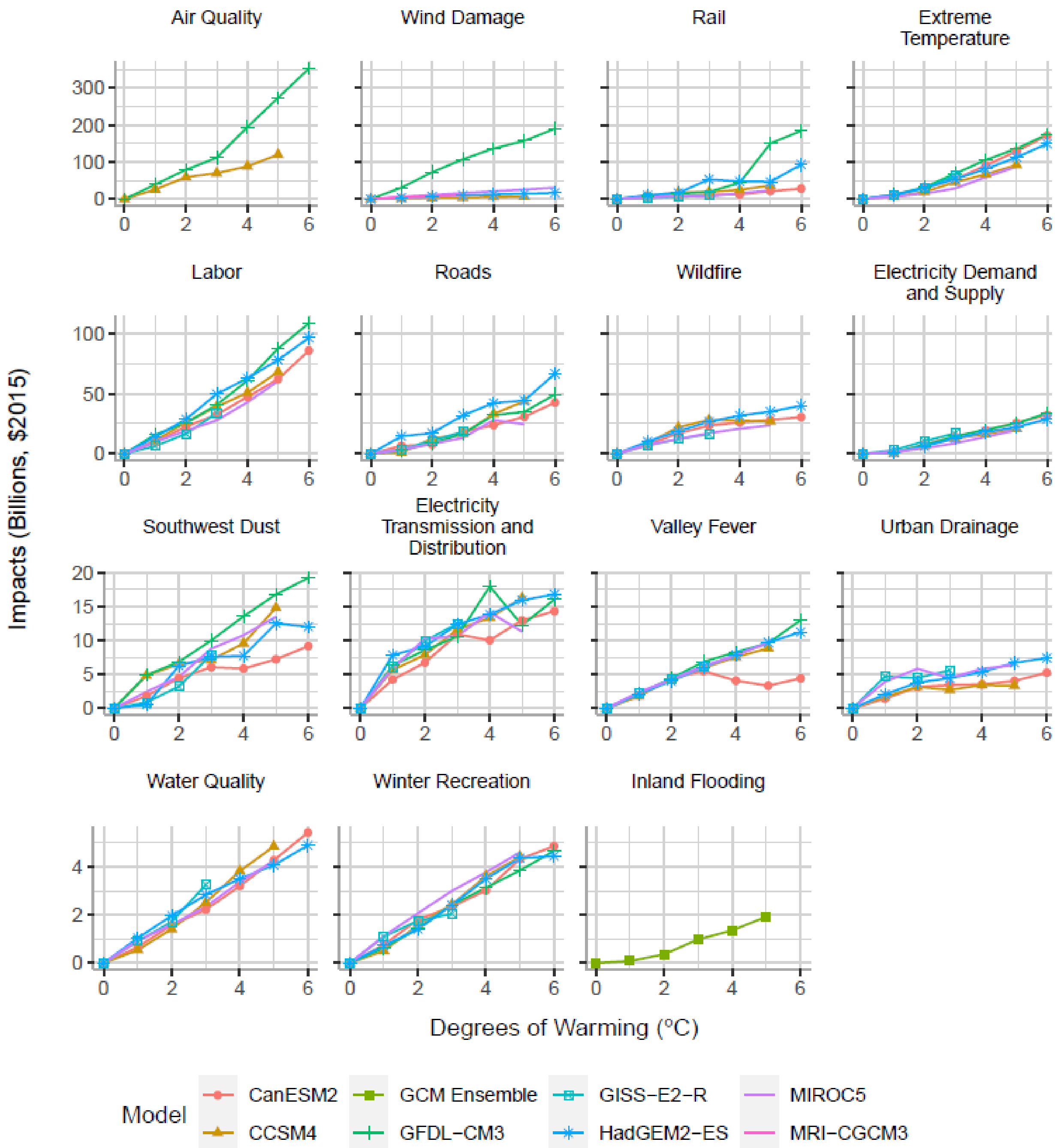
As discussed in Section 1, presenting impacts by degree of warming provides intuitive anchors for non-technical audiences and supports comparison across modeling efforts. Estimating impacts by degree is also the first step in developing impact trajectories for a custom temperature scenario. **Figure 6** and **Figure 7** shows CONUS-level annual impacts by degree and cm of GMSL rise, respectively, for each of the 18 originally processed sectors for each of the GCMs/SLR scenario used in the underlying study. Results reflect the "primary" adaptation scenario for sectors with multiple adaptation options available (see Section 2.2 for more details).

Figure 6 shows the FrEDI's ability to capture non-linearities in the relationship between temperature and impacts. While some sectors have consistently increasing impacts as temperatures increase, others taper off or accelerate at higher temperatures, particularly at 6 degrees. For most sectors there is a strong consistency across GCMs (see **Table 8** for more examples of the average and range of impacts across GCMs). Results across the GCMs generally have larger differences (as a percent of mean and in absolute terms) at higher degrees of warming. By producing both average impacts and GCM-specific results, the Framework allows for analysis of some of the uncertainties listed in Section 2.6, particularly around arrival times for degrees of warming and GHG emissions and climate scenarios.

[36] The results in this section do not include ATS Extreme Temperature, CIL Extreme Temperature, CIL Agriculture, CIL Crime, or Marine Fisheries. These sectors were added in subsequent versions of the FrEDI code and documentation as additional sectors were added to the Framework. As of July 2023 the Framework includes 22 unique sectors and 25 total study options – there are two options for Roads and three options for Extreme Temperature sectors. Note that the original Sarofim et al. (2021) paper which established a peer-reviewed basis for the conceptual framework of FrEDI included nine sectors.

Variation in results across GCMs is highest in sectors where impacts are driven by a climate stressor correlated with, but not directly linked to, mean temperature. Examples include sectors vulnerable to extreme temperatures (e.g., Extreme Temperature; Rail, which is sensitive to frequency of daily max temperature above a threshold), and those vulnerable to precipitation (e.g., Air Quality, which is sensitive to the frequency of days with rain, which affects particulate matter formation; Roads, where impacts are driven by extreme precipitation and freeze-thaw cycles; Urban Drainage, which is driven by extreme precipitation events; and Valley fever, which is sensitive to combinations of monthly temperature and precipitation that lead to aridity). In these cases, GCM-specific projections of temperature and precipitation can lead to differentiated results. For example, the GCM CanESM2 projects much wetter conditions than other models in Western U.S. at higher levels of warming, leading to a reduction in aridity and ultimately a lower projected Valley Fever impact than other GCMs.

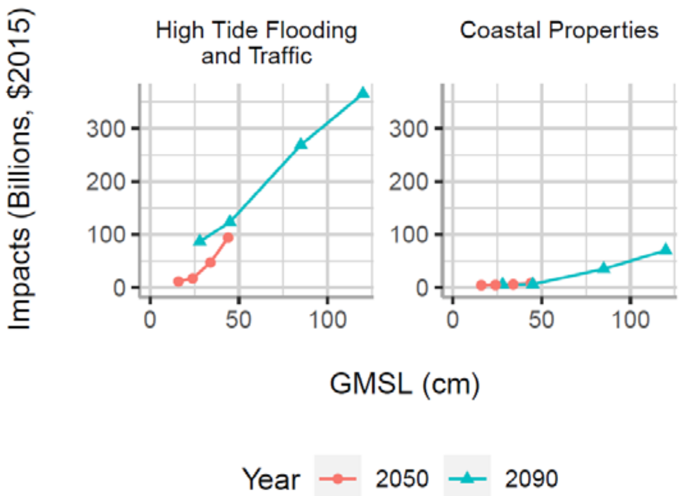
FIGURE 6. NATIONAL ECONOMIC IMPACTS BY DEGREE FOR TEMPERATURE-DRIVEN SECTORS



Impacts by CONUS degree of warming (Celsius) relative to the 1986-2005 baseline, under 2090 socioeconomic conditions, in millions of $2015, for comparability with Sarofim et al. (2021a) and EPA (2017a). Results for Extreme Temperature, Roads, Rail, and Electricity Transmission and Distribution Infrastructure reflect the primary adaptation scenarios (see Section 3.5). Each series represents the underlying GCM. Sectors are ordered by their average 5-degree impacts. Not all sectors include estimates for all models listed in the legend—for details on which models are included by sectors, see Appendix B. Note that the y-axis scalar varies by row. Figure produced using results from FrEDIv2.0.

GMSL heights associated with each integer degree of warming vary based on the pathways followed to reach the given temperature due to path dependencies in the derivation formula. For example, a scenario in which temperatures increase quickly then flatten out will have a different GMSL at the end of century than a scenario in which temperatures steadily increase (see Section 2.1 for more details on the temperature to GMSL relationship). Therefore, impacts by degree are less meaningful for the SLR-driven sectors and require a defined pathway. Instead, **Figure 7** presents impacts by GMSL for four of the underlying scenarios (30cm, 50cm, 100cm, and 150cm scenarios from Sweet et al. 2017) by arrival year (2050 and 2090).

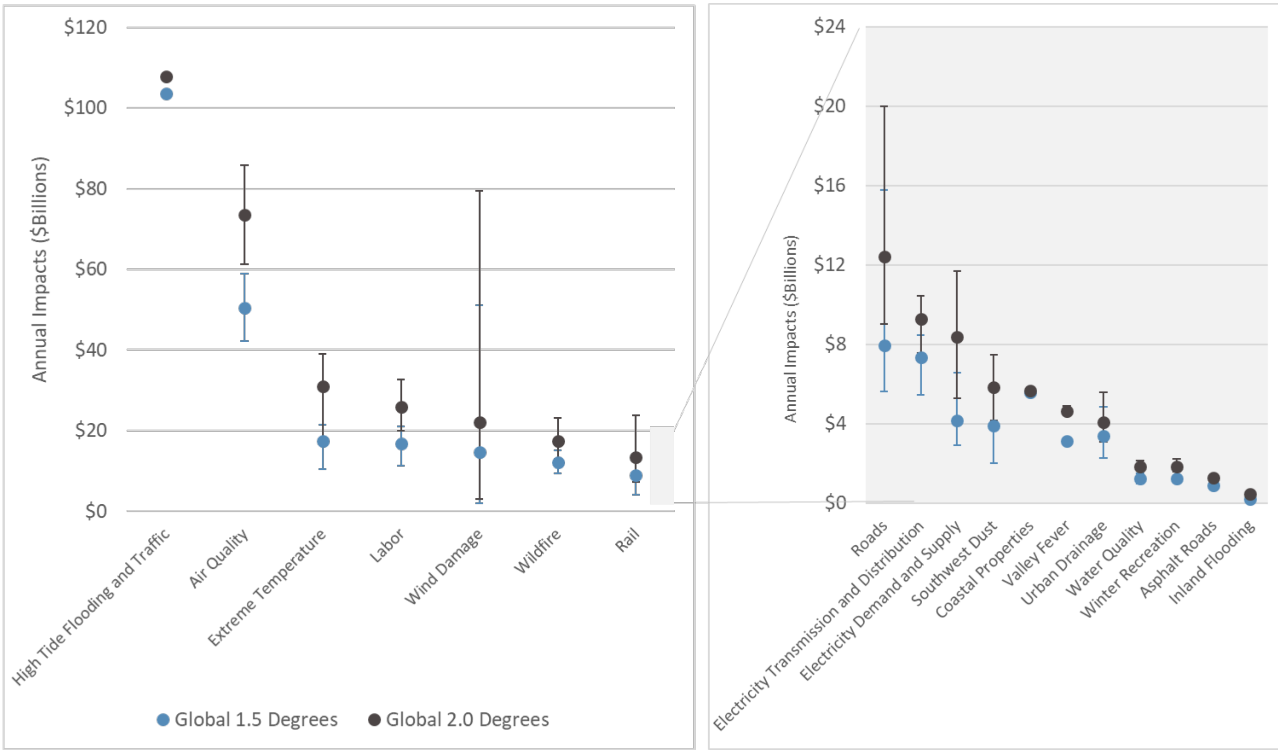
FIGURE 7. NATIONAL ECONOMIC IMPACTS BY CENTIMETER OF GMSL FOR SLR-DRIVEN SECTORS



Impacts by centimeter of GMSL rise relative to a year 2000 baseline, in millions of $2015. Each data point represents an annual impact based on one of four GMSL rise scenarios from Sweet et al. (used in the underlying models). The two series show results by year each GMSL is reached. Results for High Tide Flooding and Coastal Properties reflect the primary adaptation scenarios (see Section 3.5). Each series represents the underlying sea level rise scenario. Figure produced using results from FrEDIv2.0.

The Framework also produces impact estimates for non-integer degrees of warming by linearly interpolating between the integer-based results. One possible application of this capability is the analysis of impacts by degree in terms of global temperature change from a pre-industrial baseline. **Figure 8** shows impacts by sector under 2090 socioeconomic conditions at 1.5 and 2.0 degrees warming of *global temperatures relative to a pre-industrial baseline*, two thresholds commonly referenced in the literature and public discourse (e.g., IPCC 2018). This is accomplished in the Framework by converting the global temperatures to CONUS temperatures using the function described in Section 2.4 and Appendix D and adjusting for average warming up to the common baseline period (1986-2005) – 0.45 degrees Celsius. 1.5 and 2.0 degrees of global warming relative to pre-industrial are equivalent to 1.5 and 2.2 degrees of CONUS warming from the 1986-2005 baseline, respectively. GMSL at 1.5 and 2.0 degrees of global warming is path dependent, therefore the results for the SLR-driven sectors in Figure 8 follow two pathways defined relative to the Global Change Analysis Model v5.3 (GCAM) reference scenario (Calvin et al., 2019).[37]

FIGURE 8. PROJECTED NATIONAL IMPACTS FOR GLOBAL TEMPERATURE CHANGES RELATIVE TO PRE-INDUSTRIAL ERA



Impacts by sector for 1.5 and 2.0 degrees Celsius of warming globally relative to a pre-industrial baseline (1.5- and 2.2-degrees CONUS relative to 1986-2005) under 2090 socioeconomic conditions. Dots represent the average estimate across GCMs, and bars represent the range of GCM-specific results. Results for SLR-driven sectors (High Tide Flooding and Traffic and Coastal Properties) are estimated using the GCAM 90% emission reduction (ECS2.0) and 50% emission reduction (ECS2.0) to define pathways to 1.5 and 2.0 degrees of warming. The binning method for SLR-driven sectors produces one impact estimate per GMSL input, therefore ranges are not available. The plot on the right represents an inset of sectors with annual impacts <$20 billion. Figure produced using results from FrEDIv2.0.

3.2 Adjusting Economic Impacts for Socioeconomic Conditions

A key feature of the Framework is the ability to analyze impacts for any degree of warming that account for changing socioeconomic conditions, for example, both total population and the demographic composition of population at the time of evaluation. **Table 8** shows annual economic impacts at 2- and 3-degrees of CONUS warming under 2050, 2070, and 2090 socioeconomic conditions for temperature-driven sectors. In all sectors that include socioeconomic adjustments (the underlying studies for Asphalt Roads and Urban Drainage impacts do not model the influence of changing socioeconomic conditions), impacts are greater in the later year. For health sectors, where impacts are primarily driven by mortality, a function of population

[37] See Appendix C for more information about these scenarios. The pathway to 1.5 degrees of warming follows the 90-percent emissions reduction scenario (ECS2.0) and the pathway to 2.0 degrees of warming follows the 50-percent emissions reduction scenario (ECS2.0). These scenarios reach 1.66 and 1.98 degrees of global warming relative to the pre-industrial baseline by 2090.

and GDP per capita, estimated impacts increase by approximately 15 to 20 percent between 2070 and 2090 at the same degree of warming.[38] **Table 9** shows annual economic impacts for the SLR-driven sectors, for the same socioeconomic conditions and SLR-heights roughly aligning with the 2- and 3- degree thresholds shown in **Table 8**.

TABLE 8. PROJECTED NATIONAL ECONOMIC IMPACTS UNDER VARYING SOCIOECONOMIC CONDITIONS AND CLIMATES: TEMPERATURE-DRIVEN SECTORS

Impacts for temperature-driven sectors at 2- and 3-degrees of CONUS warming (Celsius) relative to the 1986-2005 baseline, under 2050, 2070, and 2090 socioeconomic conditions, in billions of $2015. Low and high GCM projected values shown below the average estimate. Note that impacts for Asphalt Roads, Inland Flooding, and Urban Drainage are not adjusted for any time dependencies based on the data available from the underlying studies. Table produced using results from FrEDIv2.0.

	2-Degrees		3-Degrees	
Sector	**2050 conditions**	**2070 conditions**	**2070 conditions**	**2090 conditions**
Air Quality	$49.3 *$42.7 to $55.9*	$59.2 *$50.8 to $67.7*	$77.7 *$60.1 to $95.2*	$90.8 *$70.0 to $111.7*
Asphalt Roads	$1.2 *$1.1 to $1.3*		$1.6 *$1.4 to $1.7*	
Electricity Demand and Supply	$5.5 *$3.4 to $7.8*	$6.5 *$4.0 to $9.4*	$12.0 *$7.9 to $15.4*	$13.3 *$8.7 to $17.0*
Electricity Transmission and Distribution	$6.7 *$5.2 to $7.9*	$7.7 *$5.9 to $9.0*	$10.1 *$9.3 to $11.0*	$11.4 *$10.6 to $12.5*
Extreme Temperature	$18.3 *$10.3 to $22.4*	$22.0 *$12.4 to $27.0*	$44.6 *$24.5 to $58.5*	$52.3 *$28.8 to $68.8*
Inland Flooding[a]	$0.4		$1.0	
Labor	$14.0 *$10.0 to $17.4*	$18.2 *$13.0 to $22.6*	$29.3 *$21.8 to $39.0*	$37.2 *$27.7 to $49.6*
Rail	$6.4 *$3.2 to $9.9*	$8.9 *$4.5 to $13.6*	$15.2 *$5.2 to $39.9*	$20.3 *$7.0 to $53.2*
Roads	$10.4 *$7.3 to $16.3*	$10.6 *$7.5 to $16.8*	$18.7 *$12.9 to $31.3*	$19.0 *$13.1 to $31.8*
Southwest Dust	$3.6 *$2.2 to $4.6*	$4.5 *$2.7 to $5.8*	$6.7 *$5.1 to $8.4*	$7.9 *$6.1 to $10.0*
Urban Drainage	$4.1 *$3.2 to $5.8*		$4.1 *$2.7 to $5.6*	
Valley Fever	$2.9 *$2.8 to $3.0*	$3.6 *$3.4 to $3.7*	$5.2 *$4.7 to $5.8*	$6.1 *$5.5 to $6.9*
Water Quality	$1.5 *$1.2 to $1.7*	$1.6 *$1.3 to $1.9*	$2.5 *$2.1 to $3.1*	$2.6 *$2.2 to $3.2*
Wildfire	$11.7 *$8.7 to $15.7*	$14.1 *$10.4 to $18.8*	$19.2 *$14.0 to $24.1*	$22.3 *$16.3 to $28.1*
Wind Damage	$20.3 *$2.8 to $72.4*		$29.8 *$4.3 to 107.6*	

[38] The Air Quality results presented here employ the 2011 emissions option. A 2040 emissions option, which accounts for the implementation of a suite of regulatory policies on stationary and mobile emissions sources by 2040, is also available for analysis within the Framework. Results for the 2040 emissions option result in a roughly 30 to 50% lower "climate penalty" of temperature and precipitation changes on the economic impact of air pollution on health than for the 2011 emissions option, and both sets of results are presented in Appendix B.

Sector	2-Degrees		3-Degrees	
	2050 conditions	2070 conditions	2070 conditions	2090 conditions
Winter Recreation	$1.5 *$1.3 to $1.9*	$1.6 *$1.4 to $2.0*	$2.4 *$2.0 to $2.9*	$2.4 *$2.0 to $3.0*

Notes:
a. The underlying Inland Flooding study provides only one value, which represents a GCM ensemble.

TABLE 9. PROJECTED NATIONAL ECONOMIC IMPACTS UNDER VARYING SOCIOECONOMIC CONDITIONS AND CLIMATES: SLR-DRIVEN SECTORS

Impacts for SLR-driven sectors at 25- and 40-cm of GMSL relative to the 2000 baseline, under 2050, 2070, and 2090 socioeconomic conditions, in billions of $2015. Table produced using results from FrEDIv2.0.

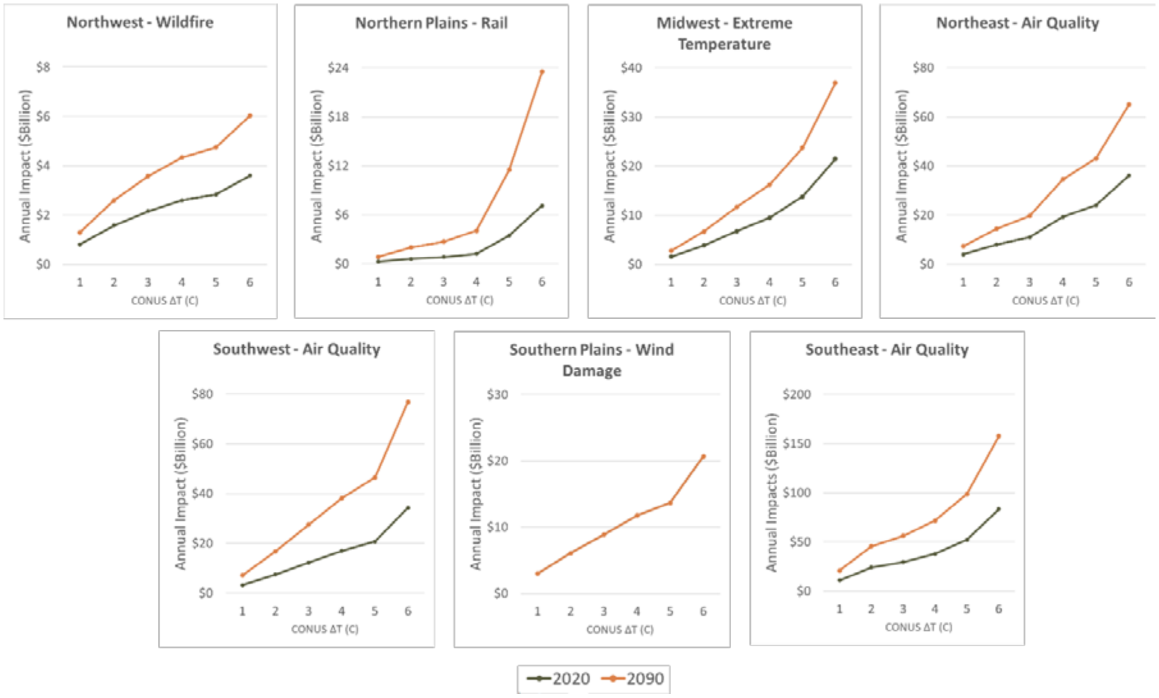
	25cm GMSL[a]		40cm GMSL[b]	
	2050 conditions	2070 conditions	2070 conditions	2090 conditions
Coastal Properties	$4.7	$5.1	$6.2	$5.7
High Tide Flooding and Traffic	$16.1	$46.9	$80.3	$111.6

Notes:
a. Pathway assumptions for 2050: Reference scenario, ECS5.0 (2.3 degrees of warming) and 2070: 90-percent emissions reduction scenario, ECS2.0 (1.4 degrees of warming).
b. Pathway assumptions for 2070: Reference scenario, ECS5.0 (3.5 degrees of warming) and 2090: 90-percent emissions reduction scenario, ECS2.5 (2.0 degrees of warming).

3.3 Regional Economic Impacts of Climate Change: Results by Degree

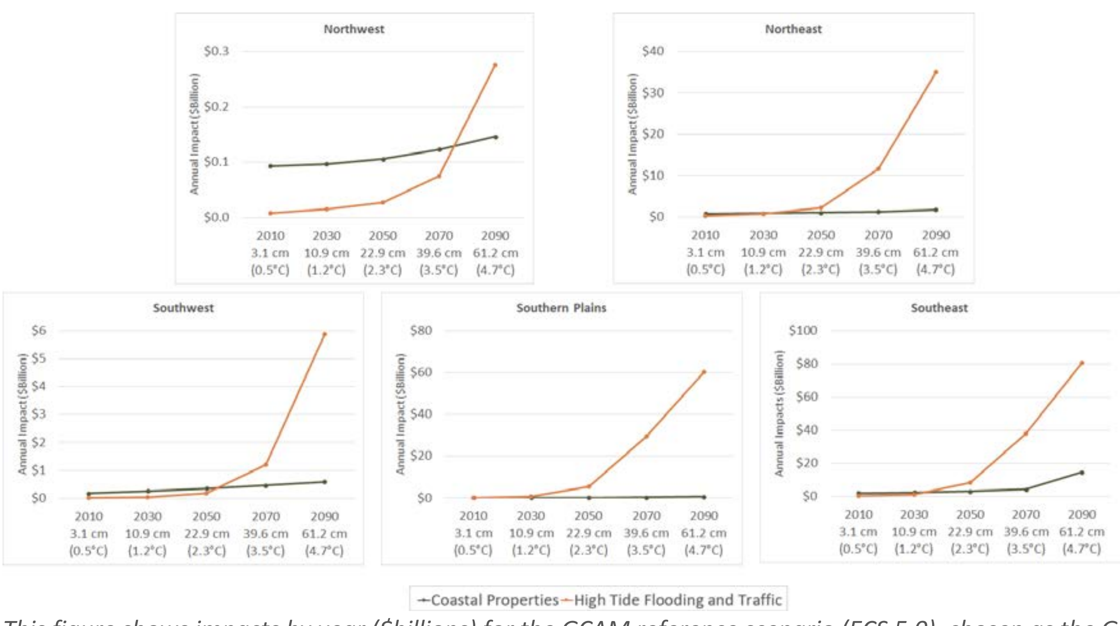
The Framework produces impact projections at the regional level which can help inform potential adaptation planning and communicate risks. **Figure 9** presents examples of impacts by degree for the sectors with the highest impacts at 2-degrees of warming in each region, for temperature-driven sectors. Air Quality, the sector with the largest estimated national damages at 2-degrees, is the largest sector regionally for the Southwest and Southeast. When looking across regions, the projected magnitude of the largest sectors varies significantly: Air Quality impacts in the Southeast reach over $70 billion per year by end of century, while the largest sector in the Northwest (Wildfire) reaches just over $6 billion annually. The GCM averages in **Figure 9** also highlight the ability of the Framework to capture non-linearities in the relationship between temperature and economic impacts. **Figure 10** presents results for the SLR-driven sectors for coastal regions under conditions comparable to the by-degree impacts used in **Figure 9**.

FIGURE 9. LARGEST PROJECTED REGIONAL ECONOMIC IMPACTS FOR TEMPERATURE-DRIVEN SECTORS BY DEGREE



This figure shows impacts by degree of CONUS warming in Celsius relative to the 1986-2005 baseline (in billions of $2015) for the largest economic impact sector in each region. Results represent the average across GCMs and are shown for 2020 and 2090 socioeconomic conditions. Note that the scales of the y-axes vary by panel. Figure produced using results from FrEDIv2.0.

FIGURE 10. REGIONAL ECONOMIC IMPACTS FOR SLR-DRIVEN SECTORS



This figure shows impacts by year ($billions) for the GCAM reference scenario (ECS 5.0), chosen as the GCAM scenario with the largest range of temperatures for comparison to ***Figure 9****. In each year, the associated GMSL rise and CONUS temperature changes are listed. Note that the scales of the y-axes vary by panel. Figure produced using results from FrEDIv2.0.*

3.4 Physical Impacts of Climate Change: Results by Degree

The Framework also produces physical impact measures for sectors where economic impacts are estimated through multipliers on physical outcomes (see the last column of **Table 6** in Section 2.3). Physical impact measures provide another method of communicating climate impacts: for example, premature mortality can be an easier concept for some audiences to grasp compared to the VSL. As with economic impacts, physical impacts are also adjusted for socioeconomic conditions (primarily through population and demographic composition). **Table 10** shows the available physical impacts at each degree of warming under 2090 socioeconomic conditions. These impacts scale linearly with the analogous economic impacts either through VSL (premature mortality), wildfire suppression costs (acres burned), or weather exposed (high-risk) industry wages (work hours lost).

TABLE 10. PROJECTED NATIONAL ANNUAL PHYSICAL IMPACTS BY DEGREE: 2090 SOCIOECONOMIC CONDITIONS

Available physical impacts in the Framework include premature mortality, acres burned, and work hours lost. Impacts assume 2090 socioeconomic conditions. Annual impacts presented by CONUS degree change (Celsius) from the 1986-2005 baseline. Table produced using results from FrEDIv2.0.

Physical Value	Sector		Degree Change (CONUS in Celsius)					
			1	2	3	4	5	6
Premature Mortality (# of deaths)	Air Quality	Total	2,150	4,542	5,962	9,295	12,923	23,143
		Ozone	506	1,102	1,489	2,205	3,020	3,590
		$PM_{2.5}$	1,644	3,440	4,473	7,089	9,903	19,553
	Extreme Temperature	Total	633	1,688	3,432	5,305	7,336	10,852
		Cold-related	-32	-49	-57	-64	-70	-71
		Heat-related	666	1,736	3,489	5,368	7,406	10,923
	Southwest Dust		169	169	348	519	622	850
	Valley Fever		19	134	276	395	459	531
	Wildfire		69	481	1,007	1,386	1,650	1,769
Acres Burned	Wildfire		2,302,194	2,666,904	3,030,676	3,388,595	3,613,215	4,307,421
Work Hours Lost (thous.)	Labor		146,480	306,183	493,191	700,401	943,401	1,284,056
Note: Values presented are direct outputs from the Framework. Results do not reflect an implied precision in the estimates or a determination of significant figures. Negative values for cold-related premature mortality represent a reduction from the baseline.								

3.5 Risk Reduction through Adaptation: Results by Degree

As noted in Section 2.2, the Framework incorporates a capacity to generate and report analytically consistent results by degree for multiple adaptation scenarios, to the extent adaptation scenarios were analyzed and reported in the underlying literature. In general, adaptation options are available at three levels: No Adaptation (sometimes better characterized as historical levels of adaptation, depending on the sector); Reactive Adaptation, where adaptive action is taken but without advance planning or foresight; and Proactive Adaptation, where all cost-effective adaptations, including those involving planning and foresight about future climate conditions, are undertaken. The general adaptation scenarios considered in the analyses of this report will not capture the complex issues that drive adaptation decision-making at regional and local scales. As such, the adaptation scenarios and estimates presented in all sections of this report should not be construed as recommending any specific policy or adaptive action.

There are six sectors currently processed for the Framework where an adaptation option is operable, most of these are infrastructure sectors: Coastal Properties, Electricity Transmission and Distribution Infrastructure, Extreme Temperature, High Tide Flooding and Traffic, Rail, and Roads. The capacity to consider adaptation scenarios enables analysis of the value of adaptation in reducing future climate damages, reflecting the impact of different assumptions about how effectively society might adapt as climate changes manifest. Similar to results summarized in Section 3.1, adaptation scenario results can be generated by degree and GCM, for custom climate inputs, and for custom socioeconomic scenario inputs.

Illustrative results for the six sectors with adaptation options are presented in **Table 11**, and in bar chart form in **Figure 11**. Both exhibits use 2090 socioeconomic scenario inputs, and present average results across GCMs, but **Table 11** provides results for six CONUS integer degree bins (and comparable GMSL thresholds), while **Figure 11** focuses on the 2-degree bin results. Shaded rows in **Table 11** indicate the "primary" adaptation response assumption as identified in the underlying literature. In the infrastructure sectors, a "No Adaptation" assumption is generally considered to reflect little or no implementation of potentially cost-effective options to minimize damage, so while it is informative, it may not be considered the most likely response in the long-term. On the other end of the spectrum of adaptation response, a "Proactive" assumption requires collective planning, upfront expense for future benefit (therefore requiring financing), and sometimes requiring perfect foresight. Therefore, this scenario may not be considered the most likely response.[39] For the Mills et al. (2014) Extreme Temperature sector, the adaptation option is characterized as an illustrative sensitivity analysis, assuming that all of the 49 largest U.S. cities are assumed to have the mortality incidence function of one of the hottest and best adapted U.S. cities (Dallas, TX) – but without consideration of the likely costs incurred to achieve lower susceptibility, such as increased deployment of air conditioning, or other physiological or technical barriers to achieving the high level of adaptation capacity observed in Dallas. As a result, the Adaptation scenario for Extreme Temperature is not considered to be the primary result, or most likely response, for all cities.

Results in **Table 11** follow expected patterns of damage magnitude. Estimates are higher for higher degrees of warming, and lower as adaptation effort increases. One exception is seen in the result for Reactive and Proactive Adaptation in the Coastal Properties sector, for the 1- and 2-degree bins, where Proactive Adaptation scenario results are slightly larger than Reactive Adaptation scenario results. In this sector, reactive adaptation is limited to structure elevation, which is a very cost-effective method for mitigating storm surge risk, but which does not address permanent inundation of properties from gradual sea level

[39] Note that including ancillary protection of properties with sea walls in the "reasonably anticipated" category, consistent with the underlying Fant et al. (2021) study, may seem inconsistent with the classification of sea walls as "proactive" adaptation in the coastal properties sector. As outlined in the Fant et al. (2021) high-tide flooding paper, however, the impact of this inconsistency is slight - Figure 3 and accompanying text in that paper notes that alternative routing reduces the no adaptation impacts by 77%, while the marginal additional impact of ancillary sea wall protection increases the total to an 80% reduction.

rise. Proactive Adaptation, however, includes the option to armor shorelines with seawalls – protecting properties from both storm surge and permanent inundation, but at higher cost.[40] In the low temperature bins, the underlying model chooses armoring in the Proactive Scenario, but with low levels of SLR, the full expected benefits are not realized unless higher temperatures (and sea levels) are realized. For 3-degree and higher bins, however, the results revert to the expected pattern, and Proactive Adaptation results represent the lowest estimated damages. Overall, the results presented in **Table 11** and **Figure 11** support the conclusion that adaptation assumptions are influential to damage results.

TABLE 11. PROJECTED ANNUAL IMPACTS BY ADAPTATION SCENARIO

This table presents annual impacts by sector and adaptation scenarios for integer degree changes in CONUS temperature (1 to 6 degrees Celsius) from the 1986-2005 baseline, under 2090 socioeconomic conditions for temperature-driven sectors and by GMSL in 2090 for SLR-driven sectors (see note a for information on the assumed pathways from GCAM). Impacts are presented in billions of $2015. Table produced using results from FrEDIv2.0.

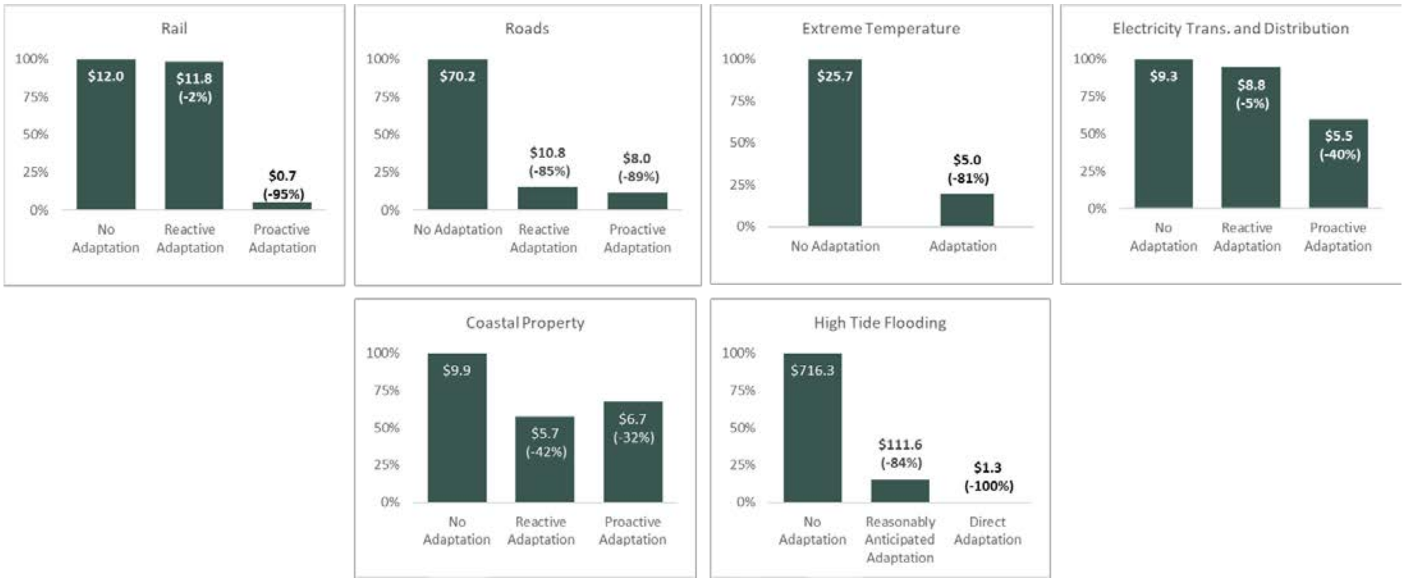
		CONUS Degree Change in Celsius					
Sector	**Adaptation Scenario**	**1**	**2**	**3**	**4**	**5**	**6**
Electricity Transmission and Distribution	No Additional Adaptation	$6.3	$9.3	$12.6	$16.1	$19.0	$22.6
	Reactive Adaptation	$6.0	$8.8	$11.4	$13.9	$13.8	$15.7
	Proactive Adaptation	$4.4	$5.5	$6.3	$7.9	$8.3	$10.1
Extreme Temperature	No Additional Adaptation	$9.6	$25.7	$52.3	$80.8	$111.8	$165.3
	Adaptation	$1.1	$5.0	$13.9	$27.1	$45.1	$77.4
Rail	No Additional Adaptation	$5.8	$12.0	$22.6	$34.7	$69.4	$127.1
	Reactive Adaptation	$6.3	$11.8	$20.3	$29.0	$55.7	$102.0
	Proactive Adaptation	$0.2	$0.7	$1.8	$3.2	$4.3	$6.9
Roads	No Additional Adaptation	$14.7	$70.2	$152.0	$268.5	$371.4	$467.2
	Reactive Adaptation	$5.3	$10.8	$19.0	$31.7	$35.5	$52.7
	Proactive Adaptation	$5.6	$8.0	$6.1	$6.8	$5.1	$5.2
		GMSL (cm)[a]					
Sector	**Adaptation Scenario**	**35**	**40**	**45**	**50**	**55**	**60**
Coastal Properties	No Additional Adaptation	$9.5	$9.9	$10.9	$17.0	$23.2	$31.1
	Reactive Adaptation	$5.6	$5.7	$6.1	$9.6	$13.1	$17.6
	Proactive Adaptation	$6.6	$6.7	$7.0	$7.2	$7.5	$7.8
High Tide Flooding and Traffic	No Additional Adaptation	$664.2	$716.3	$799.5	$900.3	$1,004.1	$1,134.7
	Reasonably Anticipated Adaptation	$103.6	$111.6	$124.4	$141.8	$159.7	$182.2
	Direct Adaptation	$1.2	$1.3	$1.5	$2.0	$2.4	$3.0

Note: Shaded rows are "primary" results, or best representative of a continued "business as usual" adaptation response.

a. Pathways selected based on proximity to listed GMSL heights in 2090: 35cm – 90-percent emissions reduction (ECS2.0); 40cm – 90% emissions reduction (ECS2.5); 45cm – Reference (ECS2.5); 50cm – 70% emissions reduction (ECS4.0); 55cm – 70% emissions reduction (ECS5.0); 60cm – Reference (ECS5.0)

[40] The "higher cost" conclusion is based on costs of adaptation used in the underlying sector study, see Neumann et al. (2021).

FIGURE 10. PROJECTED ANNUAL IMPACTS BY ADAPTATION SCENARIO AS A PERCENT OF NO ADAPTATION IMPACTS



For sectors where the underlying sectoral study simulates multiple adaptation scenarios, the plots in this figure present impacts under each scenario as a percent of no adaptation impacts (e.g., where no adaptation equals 100 percent). Labels show total impacts in billions of $2015, and for the adaptation scenarios, labels show percent decrease in impacts relative to no adaptation. Impacts for temperature-driven sectors are estimated for a 2-degree Celsius temperature change (CONUS) relative to the 1986-2005 baseline and 2090 socioeconomic conditions. Impacts for SLR-driven sectors are estimated for the 90% emissions reduction scenario (ECS2.5), which results in 40cm of GMSL and a 2.0-degree Celsius temperature change (CONUS). Figure produced using results from FrEDIv2.0.

3.6 Distributional Analyses of Risk Reductions for Two Illustrative Scenarios

As noted in Section 2.4, the Framework incorporates a capacity to generate and report results of disproportionate exposure and distributional physical effects across four categories of potentially overburdened populations. This capability connects to FrEDI results for a subset of sectors (Air quality (mortality (ages 65+) and childhood asthma cases); Extreme Temperature; Labor; Roads; High Tide Flooding; and Coastal Properties) and four dimensions of overburdened populations (Low Income; Black, Indigenous, and People of Color (BIPOC); No High School Diploma; and 65 and Older) and also includes the ability to assess multiple specific racial and ethnic subdivisions of the BIPOC category. Details of the methods and data used to develop metrics of disproportionate exposure and the distribution of impacts across demographic groups are provided in Appendix G, with full details in EPA (2021).

Results from the FrEDI-SV module can be generated for three types of metrics:

1. **Impacts**: absolute impacts on overburdened populations
2. **Risk**: difference in risk, a measure of disproportionality, as used in the EPA SV Report
3. **Rates**: relative impacts on overburdened populations, displayed as rates

Illustrative results for the Air Quality sector are presented in **Figures 12 and 13.** These graphics are drawn from a case study with two custom temperature trajectories:

1. A **Reference** temperature trajectory based on SSP370, a CMIP6 scenario combining the socioeconomic narrative of SSP3 with an emissions trajectory producing radiative forcing of 7.0 W/m^2 by 2100
2. A **1.5 Degree** temperature trajectory based on the emissions reduction targets necessary to limit global mean temperature increase to 1.5 degrees from pre-industrial levels

Figure 12 shows the **difference in risk** of new childhood asthma cases for overburdened populations relative to their reference populations under the 1.5 Degree scenario for CONUS. Because the calculations in the Air Quality – Childhood Asthma sector measure impacts on children, the 65 and Older and No High School diploma groups are omitted.

FIGURE 12. DIFFERENCE IN RISK[41] OF CHILDHOOD ASTHMA FOR OVERBURDENED POPULATIONS IN 2090 UNDER 1.5 DEGREE EMISSIONS REDUCTION SCENARIO – CONUS

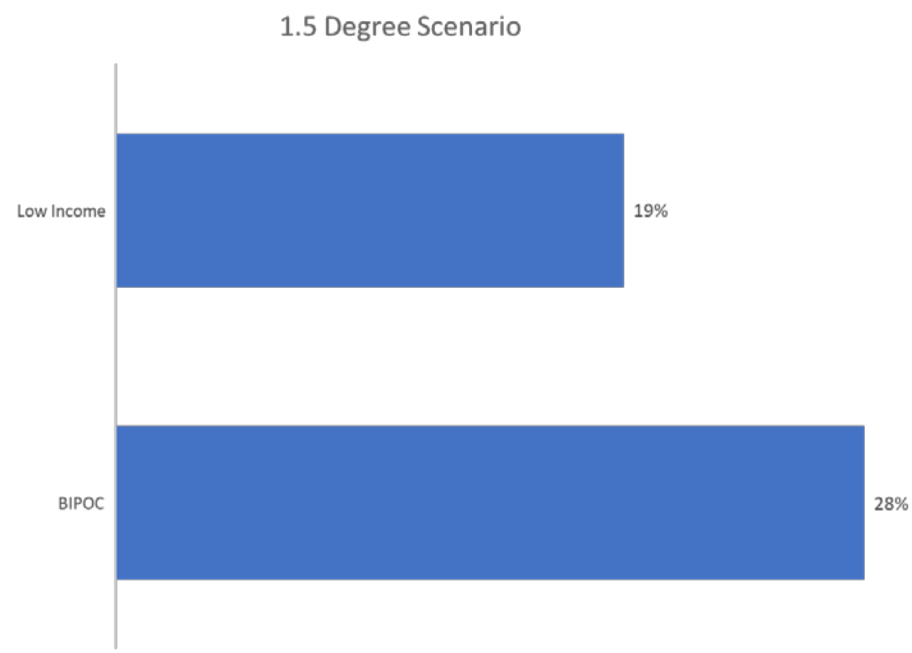
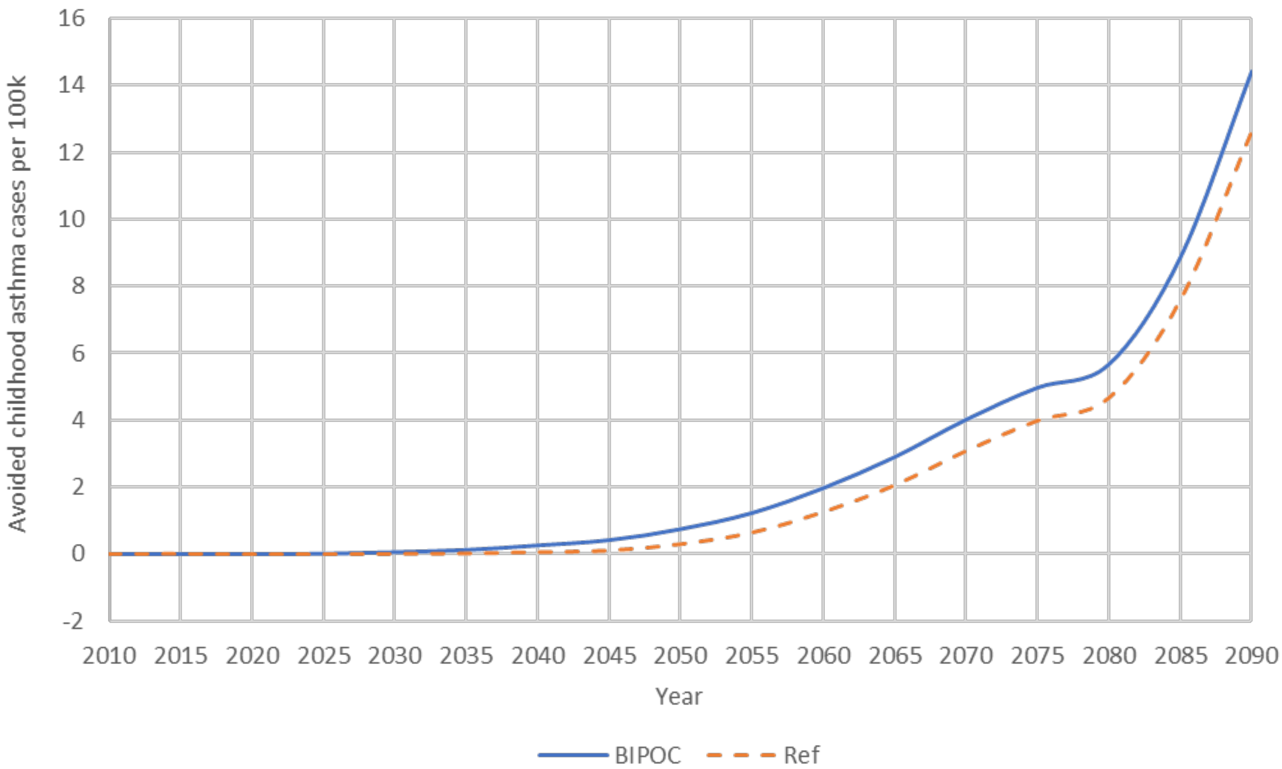


Chart showing the difference in likelihood of living in areas with the highest projected increases in new childhood asthma cases from climate-driven changes in $PM_{2.5}$ between overburdened groups and reference populations for a scenario based on the emissions reduction targets needed to hold global temperature increase to 1.5 degrees from a pre-industrial baseline.

[41] Note that magnitude of impacts should be considered alongside difference in risk when comparing projected outcomes for overburdened groups for different driver values (e.g. in the same year for different scenarios). Difference in risk is a relative measure comparing overburdened and reference population likelihoods of living in tracts projected to experience impacts in the highest tercile for a given driver value. A decrease in disproportionality for a given population group does not necessarily indicate a decrease in average impacts for that group.

Figure 13 compares the **rates** of new childhood asthma cases per 100 thousand people in BIPOC populations under the 1.5 Degree scenario for CONUS. In this graphic, "reference" refers to the reference population (non-BIPOC) compared to the results for the BIPOC population.

FIGURE 13. AVOIDED CHILDHOOD ASTHMA CASES PER 100K IN BIPOC POPULATIONS AND THE REFERENCE POPULATION UNDER 1.5 DEGREE EMISSIONS REDUCTION SCENARIOS - CONUS



Graph showing the rates of avoided new childhood asthma cases from climate-driven changes in $PM_{2.5}$ per 100 thousand people in BIPOC and reference populations for a temperature trajectory based on the emissions reduction targets to meet a 1.5 degree target relative to a reference temperature trajectory based on SSP370.

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