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Supplementary Material for the Regulatory Impact Analysis for the Supplemental Proposed Rulemaking, "Standards of Performance for New, Reconstructed, and Modified Sources and Emissions Guidelines for Existing Sources: Oil and Natural Gas Sector Climate Review"

EPA External Review Draft of Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances

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Report on the Social Cost of Greenhouse Gases:

Estimates Incorporating Recent Scientific Advances

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List of Abbreviations

AR	Assessment Report of the United Nations Intergovernmental Panel on Climate Change
BRICK	Building Blocks for Relevant Ice and Climate Knowledge
CH_4	Methane
CIAM	Coastal Impact and Adaptation Model
CMIP	Coupled Model Intercomparison Project
CO_2	Carbon Dioxide
DICE	Dynamic Integrated Climate and Economy
DSCIM	Data-driven Spatial Climate Impact Model
ESM	Earth System Models
ECS	Equilibrium Climate Sensitivity
E.O.	Executive Order
FACTS	Framework for Assessing Changes To Sea-level
FaIR	Finite Amplitude Impulse Response
FUND	Climate Framework for Uncertainty, Negotiation, and Distribution
GHG	Greenhouse Gas
GDP	Gross Domestic Product
GIVE	Greenhouse Gas Impact Value Estimator
GMSL	Global Mean Sea Level
GMST	Global Mean Surface Temperature
IAM	Integrated Assessment Model
IWG	Interagency Working Group on the Social Cost of Greenhouse Gases
MAGICC	Model for the Assessment of Greenhouse Gas Induced Climate Change
N_2O	Nitrous Oxide
PAGE	Policy Analysis of the Greenhouse Gas Effect
PPP	Purchasing Power Parity
RC	Reduced Complexity
RCP	Representative Concentration Pathway
SC	Social Cost
SLR	Sea-level Rise
SP	Socioeconomic Projections
SSP	Shared Socioeconomic Pathways
TCR	Transient Climate Response

Executive Summary

This report presents new estimates of the social cost of carbon (SC-CO_2), social cost of methane (SC-CH_4), and social cost of nitrous oxide (SC-N_2O), collectively referred to as the "social cost of greenhouse gases" (SC-GHG). These estimates reflect recent advances in the scientific literature on climate change and its economic impacts and incorporate recommendations made by the National Academies of Science, Engineering, and Medicine (National Academies 2017). The SC-GHG allows analysts to incorporate the net social benefits of reducing emissions of greenhouse gases (GHG), or the net social costs of increasing such emissions, in benefit-cost analysis and, when appropriate, in decision-making and other contexts. The SC-GHG is the monetary value of the net harm to society from emitting a metric ton of that GHG to the atmosphere in a given year. The SC-GHG, therefore, also reflects the societal net benefit of reducing emissions of the GHG by a metric ton. The SC-GHG is the theoretically appropriate value to use when conducting benefit-cost analyses of policies that affect GHG emissions.

Since 2008, the EPA has used estimates of the SC-GHG in analyses of actions that affect GHG emissions. The values used by the EPA from 2009 to 2016, and since 2021, have been consistent with those developed and recommended by the Interagency Working Group on the SC-GHG (IWG), and the values used from 2017-2020 were consistent with those required by Executive Order (E.O.) 13783. During that time, the National Academies conducted a comprehensive review of the SC-CO_2 and issued a final report in 2017 recommending specific criteria for future updates to the SC-CO_2 estimates, a modeling framework to satisfy the specified criteria, and both near-term updates and longer-term research needs pertaining to various components of the estimation process. The IWG was reconstituted in 2021 and E.O. 13990 directed it to develop a comprehensive update of its SC-GHG estimates, recommendations regarding areas of decision-making to which SC-GHG should be applied, and a standardized review and updating process to ensure that the recommended estimates continue to be based on the best available economics and science going forward.

The EPA is a member of the IWG and is participating in the IWG's work under E.O. 13990. While that process continues, this EPA report presents a set of SC-GHG estimates that incorporates numerous methodological updates addressing the near-term recommendations of the National Academies. The report takes a modular approach in which the methodology underlying each of the four components, or modules, of the SC-GHG estimation process – socioeconomics and emissions, climate, damages, and discounting – is developed by drawing on the latest research and expertise from the scientific disciplines relevant to that component. The socioeconomic and emissions module relies on a new set of probabilistic projections for population, income, and GHG emissions developed under the Resources for the Future Social Cost of Carbon Initiative (Rennert et al. 2022a). The climate module relies on the Finite Amplitude Impulse Response (FaIR) model (Millar et al. 2017; Smith et al. 2018, IPCC 2021b), a widely used Earth system model recommended by the National Academies, which captures the relationships between GHG emissions, atmospheric GHG concentrations, and global mean surface temperature. The socioeconomic projections and outputs of the climate module are used as inputs to the damage module to estimate monetized future damages from temperature changes. Based on a review of available studies and

approaches to damage function estimation, the report uses three separate damage functions to form the damage module. They are:

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

The discounting module discounts the stream of future climate damages back to the year of emissions using a set of dynamic discount rates that have been calibrated following the Newell et al. (2022) approach, as applied in Rennert et al. (2022a, 2022b). This approach uses the Ramsey (1928) discounting formula in which the parameters are calibrated such that (1) the decline in the certainty-equivalent discount rate matches the latest empirical evidence on interest rate uncertainty estimated by Bauer and Rudebusch (2020, 2021) and (2) the average of the certainty-equivalent discount rate over the first decade matches a near-term consumption rate of interest. Uncertainty in the starting rate is addressed by using three near-term target rates (1.5, 2.0, and 2.5 percent) based on multiple lines of evidence on observed market interest rates. This approach results in three dynamic discount rate paths and is consistent with the National Academies (2017) recommendation to use three sets of Ramsey parameters that reflect a range of near-term certainty-equivalent discount rates and are consistent with theory and empirical evidence on consumption rate uncertainty. Finally, the value of aversion to risk associated with damages from GHG emissions is explicitly incorporated into the modeling framework following the economic literature.

The estimation process generates nine separate distributions of estimates – the product of using three damage modules and three near-term target discount rates – of the social cost of each gas in each emissions year. To produce a range of estimates that reflects the uncertainty in the estimation exercise while providing a manageable number of estimates for policy analysis, in this report the multiple lines of evidence on damage modules are combined by averaging the results across the three damage module specifications. Table ES.1 summarizes the resulting SC-CO_2, SC-CH_4, and SC-N_2O estimates for emissions years 2020 through 2080.

The modeling implemented in this report reflects conservative methodological choices, and, given both these choices and the numerous categories of damages that are not currently quantified and other model limitations, the resulting SC-GHG estimates likely underestimate the marginal damages from GHG pollution. The EPA will continue to review developments in the literature, including more robust methodologies for estimating the magnitude of the various direct and indirect damages from GHG emissions, and look for opportunities to further improve SC-GHG estimation going forward.

Table ES.1: Estimates of the Social Cost of Greenhouse Gases (SC-GHG), 2020-2080 (2020 dollars)

Emission Year	SC-CO$_2$ (2020 dollars per metric ton of CO$_2$)			SC-CH$_4$ (2020 dollars per metric ton of CH$_4$)			SC-N$_2$O (2020 dollars per metric ton of N$_2$O)		
	2.5%	2.0%	1.5%	2.5%	2.0%	1.5%	2.5%	2.0%	1.5%
2020	120	190	340	1,300	1,600	2,300	35,000	54,000	87,000
2030	140	230	380	1,900	2,400	3,200	45,000	66,000	100,000
2040	170	270	430	2,700	3,300	4,200	55,000	79,000	120,000
2050	200	310	480	3,500	4,200	5,300	66,000	93,000	140,000
2060	230	350	530	4,300	5,100	6,300	76,000	110,000	150,000
2070	260	380	570	5,000	5,900	7,200	85,000	120,000	170,000
2080	280	410	600	5,800	6,800	8,200	95,000	130,000	180,000

Values of SC-CO$_2$, SC-CH$_4$, and SC-N$_2$O are rounded to two significant figures. The annual unrounded estimates are available in Appendix A.4 and at: www.epa.gov/environmental-economics/scghg.

The heading "SC-GHG and Near-term Ramsey Discount Rate" spans across all rate columns.

1 Background

A robust and scientifically founded assessment of the positive and negative impacts that an action can be expected to have on society facilitates evidence-based policy making. Estimates of the social cost of carbon (SC-CO$_2$), social cost of methane (SC-CH$_4$), and social cost of nitrous oxide (SC-N$_2$O) allow analysts to incorporate the net social benefits of reducing emissions of each of these greenhouse gases, or the net social costs of increasing such emissions, in benefit-cost analysis, and when appropriate, in decision making and other contexts.[1] Collectively, these values are referred to as the "social cost of greenhouse gases" (SC-GHG) in this document. The SC-GHG is the monetary value of the future stream of net damages associated with adding one ton of that GHG to the atmosphere in a given year. The SC-GHG, therefore, also reflects the societal net benefit of reducing emissions of the gas by one ton. The social benefits of abatement are an aggregated measure of the affected individuals' willingness to pay to avoid those damages. The SC-GHG is the marginal social benefit of GHG abatement and is, therefore, the theoretically appropriate value to use when conducting benefit-cost analyses of policies that affect GHG emissions.[2] Estimates of the marginal social cost will differ by the type of GHG (such as CO$_2$, CH$_4$, and N$_2$O) and by the year in which the emissions change occurs.

In principle, the SC-GHG includes the value of all climate change impacts (both negative and positive), including (but not limited to) changes in net agricultural productivity, human health effects, property damage from increased flood risk, changes in the frequency and severity natural disasters, disruption of energy systems, risk of conflict, environmental migration, and the value of ecosystem services. In practice, because of data and modeling limitations, which prevent full representation of harmful climate impacts, estimates of the SC-GHG are a partial accounting of climate change impacts and, as such, lead to underestimates of the marginal benefits of abatement.

1.1 Overview of SC-GHG Estimates Used in EPA Analyses to Date

The academic literature has published estimates of the social cost of carbon and other GHGs since at least the early 1990s. As early as 2002 researchers began conducting reviews that combined lines of evidence across early SC-CO$_2$ estimates (Clarkson and Deyes 2002). The EPA began regularly incorporating SC-CO$_2$ estimates in regulatory impact analyses following a 2008 court ruling in which an agency was ordered to

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[1] Note, for example, that EPA has recommended use of SC-GHG estimates in environmental impact statements under NEPA when appropriate. See e.g., Letter from EPA to USPS, on the Final Environmental Impact Statement for Next Generation Delivery Vehicle Acquisitions, Feb. 2, 2022.

[2] These estimates of social damages should not be confused with the estimated costs of attaining a predetermined emissions or warming limit. Specifically, there is another strand of research that investigates the costs of setting a specific climate target (e.g., capping emissions or temperature increases to a certain level). The expected marginal cost of GHG abatement associated with meeting a specific climate target can be useful in evaluating policy cost-effectiveness but is not an alternative way to value damages from GHG emissions in benefit-cost analysis. For more on how these concepts (e.g., a predetermined target-based approach and a damage (SC-GHG) based approach) can be used when designing climate policy and in policy evaluation, see, for example, Hänsel et al. (2020); Stern et al. (2022); Aldy et al. (2021); and Gundlach and Livermore (2022).

consider the $SC\text{-}CO_2$ in the rulemaking process. Specifically, the U.S. Ninth Circuit Court of Appeals remanded a fuel economy rule to the Department of Transportation for failing to consider the value of reducing CO_2 emissions when determining the appropriate level of the fuel economy standard, stating that "while the record shows that there is a range of values, the value of carbon emissions reduction is certainly not zero."[3] The $SC\text{-}CO_2$ estimates initially presented in EPA analyses in 2008 and early 2009 were derived from the academic literature.[4]

Beginning in September 2009, EPA's regulatory impact analyses applied $SC\text{-}CO_2$ estimates that were developed through a U.S. Government interagency working group (IWG) process. The IWG was launched in early 2009, under the leadership of the Office of Management and Budget (OMB) and the Council of Economic Advisers (CEA), to ensure that Federal agencies had access to the best available information when quantifying the benefits of reducing CO_2 emissions in benefit-cost analyses. The IWG included technical experts from the EPA and other federal agencies. The IWG first developed an interim set of $SC\text{-}CO_2$ estimates based on an average of estimates published in the peer reviewed academic literature.[5] The EPA chose to use these interim estimates in multiple regulatory impact analyses and sought public comments to inform the estimates for future use.[6] In 2010, the IWG published a Technical Support Document (TSD) with a set of four updated $SC\text{-}CO_2$ estimates recommended for use in regulatory analyses in addition to guidance on using the estimates (IWG 2010). Three of these values were based on the average $SC\text{-}CO_2$ from three widely cited integrated assessment models (IAMs) in the peer-reviewed literature – DICE, PAGE, and FUND[7] – at constant discount rates of 2.5, 3, and 5 percent. The fourth value was included to represent the potential for lower-probability, higher-impact outcomes from climate change, that would be particularly harmful to society and thus relevant to the public and policymakers. For this purpose, it selected the $SC\text{-}CO_2$ value for the 95th percentile at a 3 percent discount rate. Absent

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[3] *Ctr. for Biological Diversity v. Nat'l Highway Traffic Safety Admin.*, 538 F.3d 1172, 1200 (9th Cir. 2008).

[4] For more information, see "Technical Support Document on Benefits of Reducing GHG Emissions" (https://www.regulations.gov/document/EPA-HQ-OAR-2008-0318-0078), prepared for EPA's July 2008 Advanced Notice of Proposed Rulemaking for Regulating Greenhouse Gas Emissions Under the Clean Air Act, and EPA's May 2009 Regulatory Impact Analysis for the Renewable Fuel Standard Program (RFS2) Proposed Rule.

[5] The IWG used a meta-analysis of $SC\text{-}CO_2$ estimates (Tol 2008) as the starting point for the development of the interim estimates recommended in 2009. With that starting point, the IWG filtered the existing $SC\text{-}CO_2$ estimates in the meta-analysis by using those that (1) were derived from peer-reviewed studies; (2) did not weight the monetized damages to one country more than those in other countries (i.e., no equity weighting); (3) used a "business as usual" climate scenario; and (4) were based on the most recent published version of each of the three major integrated assessment models (IAMs): FUND, PAGE, and DICE. See EPA and DOT (2009) for more discussion of how the filtered estimates were combined to form a set of five recommended interim values.

[6] See, for example, EPA and DOT's joint September 2009 Proposed Rulemaking to Establish Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards (EPA and DOT 2009).

[7] The DICE (Dynamic Integrated Climate and Economy) model by William Nordhaus evolved from a series of energy models and was first presented in 1990 (Nordhaus and Boyer 2000, Nordhaus 2008). The PAGE (Policy Analysis of the Greenhouse Effect) model was developed by Chris Hope in 1991 for use by European decision-makers in assessing the marginal impact of carbon emissions (Hope 2006, Hope 2008). The FUND (Climate Framework for Uncertainty, Negotiation, and Distribution) model, developed by Richard Tol in the early 1990s, was originally used to study international capital transfers in climate policy and was subsequently widely used to study climate impacts (e.g., Tol 2002a, Tol 2002b, Anthoff et al. 2009, Tol 2009).

formal inclusion of risk aversion in the modeling, considering values above the mean in a right skewed distribution with long tails acknowledges society's preference for avoiding risk.

The EPA chose to update the set of SC-CO_2 estimates used in regulatory analyses following a May 2013 update of the IWG SC-CO_2 estimates (IWG 2013). The 2013 IWG SC-CO_2 update incorporated new versions of the IAMs used in the peer-reviewed literature but did not revisit other IWG modeling decisions (i.e., the discount rates or harmonized inputs for socioeconomic and emission scenarios and equilibrium climate sensitivity). Improvements in the way damages are modeled were confined to those that had been incorporated into the latest versions of the models by the developers themselves in the peer-reviewed literature.[8]

In June 2015, the EPA began using estimates of SC-CH_4 and SC-N_2O from Marten et al. (2015), which were consistent with the methodology underlying the IWG's estimates of the SC-CO_2 estimates. The Marten et al. estimates were first applied in sensitivity analyses in regulatory impact analyses of proposed rulemakings with CH_4 and N_2O emission impacts.[9] Following the completion of an external peer review of the application of these estimates to federal regulatory analysis, the estimates were used in the main analysis of other proposed rulemakings with CH_4 emissions impacts (EPA 2015a, 2015b).[10] In August 2016, the Marten et al. SC-CH_4 and SC-N_2O estimates were adopted by the IWG in an addendum to the IWG's TSD (IWG 2016a, 2016b).[11] The IWG recommended these estimates as a method for improving the analyses of regulatory actions that are projected to influence CH_4 or N_2O emissions in a manner consistent with how CO_2 emission changes were being valued.

Over the course of developing and updating the SC-GHG estimates that have been used in EPA analyses, there were extensive opportunities for public input on the estimates and underlying methodologies. There was a public comment process associated with each proposed EPA rulemaking that used the estimates, and OMB initiated a separate comment process on the IWG TSD in 2013. Commenters offered a wide range of perspectives on all aspects of the process, methodology, and final estimates, and submitted diverse suggestions for improvements. The U.S. Government Accountability Office (GAO) reviewed the development of the IWG SC-CO_2 estimates and concluded that the IWG processes and methods reflected three principles: consensus-based decision making, reliance on existing academic literature and models, and disclosure of limitations and incorporation of new information (GAO 2014).

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[8] The IWG subsequently provided additional minor technical revisions in November of 2013 and July of 2015, as explained in Appendix B of the 2016 TSD (IWG 2016a).

[9] The SC-CH_4 and SC-N_2O estimates were first used in sensitivity analysis for the Proposed Rulemaking for Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles–Phase 2 (EPA and DOT 2015).

[10] For a discussion of public comments received on the valuation of non-CO_2 GHG impacts in general and the use of the Marten et al. (2015) estimates, see, e.g., EPA (2012a, 2012b, 2016a, 2016b), EPA and DOT (2016).

[11] In 2021, the EPA developed analogous estimates of the social cost of hydrofluorocarbons (SC-HFCs) that are consistent with the methodology underlying the SC-CO_2, SC-CH_4, and SC-N_2O estimates. See, for example, EPA's final Regulatory Impact Analysis for Phasing Down Production and Consumption of Hydrofluorocarbons (HFCs) for more information (EPA 2021a).

In 2015, as part of the IWG response to the public comments received in the 2013 solicitation, the IWG announced a National Academies review of the IWG estimates (IWG 2015). Specifically, the IWG asked the National Academies to conduct a multi-discipline, two-phase assessment of the IWG estimates and offer advice on approaching future updates to ensure that the estimates continue to reflect the best available science and methodologies. The National Academies' interim (Phase 1) report (National Academies 2016a) recommended against a near-term update of the $SC\text{-}CO_2$ estimates within the existing modeling framework. For future revisions, the National Academies recommended a broader update of the climate system module consistent with the most recent, best available science and offered recommendations for how to enhance the discussion and presentation of uncertainty in the $SC\text{-}CO_2$ estimates. In addition to publishing estimates of $SC\text{-}CH_4$ and $SC\text{-}N_2O$, the IWG's 2016 TSD revision responded to the National Academies' Phase 1 report recommendations regarding the presentation of uncertainty. The revisions included: an expanded presentation of the SC-GHG estimates that highlights a symmetric range of uncertainty around estimates for each discount rate; new sections that provide a unified discussion of the methodology used to incorporate sources of uncertainty; a detailed explanation of the uncertain parameters in the FUND and PAGE models; and making the full set of $SC\text{-}CO_2$ estimates easily accessible to the public on OMB's website.

In January 2017, the National Academies released their final report, *Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide* and recommended specific criteria for future updates to the $SC\text{-}CO_2$ estimates, a modeling framework to satisfy the specified criteria, and both near-term updates and longer-term research needs pertaining to various components of the estimation process (National Academies 2017). A description of the National Academies' recommendations for near-term updates is provided in Section 1.2 below. Shortly thereafter, in March 2017, President Trump issued Executive Order (E.O.) 13783, which called for the rescission and review of several climate-related Presidential and regulatory actions as well as for a review of the SC-GHG estimates used for regulatory impact analyses.[12] Further, E.O. 13783 disbanded the IWG, withdrew the previous TSDs, and directed agencies to "ensure" SC-GHG estimates used in regulatory analyses "are consistent with the guidance contained in OMB Circular A-4", "including with respect to the consideration of domestic versus international impacts and the consideration of appropriate discount rates" (E.O. 13783, Section 5(c)). The EPA's benefit-cost analyses following E.O. 13783 used SC-GHG estimates that attempted to focus on the specific share of physical climate change damages in the U.S. as captured by the models (which do not reflect many pathways by which climate impacts affect the welfare of U.S. citizens and residents) and were calculated using two default discount rates recommended by OMB Circular A-4 (2003), 3 percent and 7 percent.[13]

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[12]https://www.federalregister.gov/documents/2017/03/31/2017-06576/promoting-energy-independence-and-economic-growth

[13]The EPA's regulatory analyses under E.O. 13783 included sensitivity analyses based on global SC-GHG values and using a lower discount rate of 2.5%. OMB Circular A-4 (2003) recognizes that special considerations arise when applying discount rates if intergenerational effects are important. In the IWG's 2015 *Response to Comments*, OMB— as a co-chair of the IWG—made clear that "Circular A-4 is a living document," that "the use of 7 percent is not considered appropriate for intergenerational discounting," and that "[t]here is wide support for this view in the academic literature, and it is recognized in Circular A-4 itself." OMB, as part of the IWG, similarly repeatedly confirmed that "a focus on global SCC estimates in [regulatory impact analyses] is appropriate" (IWG 2015). See Sections 1.3 and 2.3 for further discussion on both issues.

All other methodological decisions and model versions used in SC-GHG calculations under E.O. 13783 remained the same as those used by the IWG in 2010 and 2013, respectively.

On January 20, 2021, President Biden issued E.O. 13990 which established an IWG and directed the group to develop an update of the SC-GHG estimates that reflect the best available science and the recommendations of the National Academies (2017).[14] In February 2021, the IWG recommended the interim use of the most recent SC-GHG estimates developed by the IWG prior to the group being disbanded in 2017, adjusted for inflation (IWG 2021). As discussed in the February 2021 TSD, the IWG concluded that these interim estimates reflected the immediate need to have SC-GHG estimates available for agencies to use in regulatory benefit-cost analyses and other applications that were developed using a transparent process, peer reviewed methodologies, and the science available at the time of that process. The February 2021 update also recognized the limitations of the interim estimates and encouraged agencies to use their best judgment in, for example, considering sensitivity analyses using lower discount rates. The IWG published a Federal Register notice on May 7, 2021, soliciting comment on the February 2021 TSD and on how best to incorporate the latest peer-reviewed scientific literature in order to develop an updated set of SC-GHG estimates. The EPA has applied the IWG's interim SC-GHG estimates in analyses published since the release of the February 2021 TSD (see, e.g., EPA (2021b, 2021c)) and has reviewed the comments submitted to the IWG in developing this report.

1.2 Recommendations from the National Academies of Sciences, Engineering, and Medicine

As previously mentioned, in 2015, the IWG requested that the National Academies review and recommend potential approaches for improving its SC-CO_2 estimation methodology. In response, the National Academies convened a multidisciplinary committee, called the Committee on Assessing Approaches to Updating the Social Cost of Carbon. In addition to evaluating the IWG's overall approach to SC-CO_2 estimation, the committee reviewed its choices of IAMs and damage functions, climate science assumptions, future baseline socioeconomic and emission projections, presentation of uncertainty, and discount rates.

In its final report (National Academies 2017), the National Academies committee recommended that the IWG pursue an integrated modular approach to the key components of SC-CO_2 estimation to allow for independent updating and review and to draw more readily on expertise from the wide range of scientific disciplines relevant to SC-CO_2 estimation. Under this approach, each step in SC-CO_2 estimation is developed as a module—socioeconomic projections, climate science, economic damages, and discounting—that reflects the state of scientific knowledge in the current peer-reviewed literature. In the longer term, it recommended that the IWG communicate research needs and priorities to its member agencies to stimulate research on ways to improve accounting of interactions and feedbacks between these components. In addition, the committee noted that, while the IWG harmonized key inputs across three IAMs, shifting to the use of a single climate module in the nearer-term (2-3 years) and eventually transitioning to a single framework for all modules will enhance transparency, improve consistency with the underlying science, and allow for more explicit representation of uncertainty. It recommended these

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[14]https://www.federalregister.gov/documents/2021/01/25/2021-01765/protecting-public-health-and-the-environment-and-restoring-science-to-tackle-the-climate-crisis

three criteria also be used to judge the value of other updates to the methodology. It also recommended that the IWG update SC-CO_2 estimates at regular intervals, suggesting a five-year cycle.

Regarding the key components of the SC-CO_2, the committee recommended the following improvements:

> ***Socioeconomic and emissions projections:*** Use accepted statistical methods and elicit expert judgment to project probability distributions of future annual growth rates of per-capita gross domestic product (GDP) and population, bearing in mind the potential correlation between economic and population projections. Use expert elicitation, guided by information on historical trends and emissions consistent with different climate outcomes, to project emissions for each forcing agent of interest, conditional on population and income scenarios. Additional recommendations were offered pertaining to the time horizon, inclusion of future policies, disaggregation of scenarios, and feedbacks from the damage module to the socioeconomic module.

> ***Climate science:*** Adopt or develop a simple Earth system model (such as the Finite Amplitude Impulse Response (FaIR) model) to capture the relationships between CO_2 emissions, atmospheric CO_2 concentrations, and global mean surface temperature change over time while accounting for non-CO_2 forcing and allowing for the evaluation of uncertainty. Adopt or develop a sea level rise component in the climate module that: (1) accounts for uncertainty in the translation of global mean temperature to global mean sea level rise and (2) is consistent with sea level rise projections available in the literature for similar forcing and temperature pathways. The committee also noted the importance of generating spatially and temporally disaggregated climate information as inputs into damage estimation. It recommended the use of linear pattern scaling (which estimates linear relationships between global mean temperature and local climate variables) to achieve this goal in the near-term.

> ***Economic damages:*** Improve and update existing formulations of individual sectoral damage functions when feasible; characterize damage function calibrations quantitatively and transparently; present spatially disaggregated market and nonmarket damages by region and sector in both monetary and natural units (incremental and total) and discuss how they scale with temperature, income, and population; and recognize any correlations between formulations when multiple damage functions are used.

> ***Discounting:*** Account for the relationship between economic growth and discounting; explicitly recognize uncertainty surrounding discount rates over long time horizons using a Ramsey-like approach; select parameters to implement this approach that are consistent with theory and evidence to produce certainty-equivalent discount rates consistent with near-term consumption rates of interest; use three sets of Ramsey parameters to generate a low, central, and high certainty-equivalent near-term discount rate, and three means and ranges of SC-CO_2 estimates; discuss how the SC-CO_2 estimates should be combined with other cost and benefit estimates that may use different discount rates in regulatory analysis.

Additional details on the National Academies' near-term recommendations are provided in Section 2 below. The National Academies' final report also provided longer-term recommendations pertaining to each module and identified research priorities for addressing these recommendations.

In focusing on the four categories above, the National Academies left various topics for future research. For example, the report pointed to future research that might enable more robust methods of capturing the benefits of reducing climate risks. While the National Academies report did not explicitly address methods to account for the disproportionate climate damages that may accrue to lower-income individuals in SC-GHG estimates, it did outline ways to present evidence on the possible distributional effects of climate change. The National Academies point to the importance of presenting spatially disaggregated results that could, in turn, enable methods that would better identify vulnerable populations and those most at risk. Additional discussion of these dimensions can be found in Section 3.3 of this report.

1.3   Accounting for Global Damages

Benefit-cost analyses of U.S. Federal regulations have traditionally focused on the benefits and costs that accrue to individuals that reside within the country's national boundaries and that accrue to regulated industries, regardless of the nationality of the owners of affected physical assets.[15] This approach reflects the fact that for most regulations, those are the two groups primarily affected. It does not reflect any other scientific, legal, or other rationale. The default recommendation in OMB's Circular A-4 (2003) is that, an "analysis should focus on benefits and costs that accrue to citizens and residents of the United States."[16] However, OMB Circular A-4 states that when a regulation is likely to have international effects, "these effects should be reported"; and though the guidance recommends this be done separately, the guidance also explains that "[d]ifferent regulations may call for different emphases in the analysis, depending on the nature and complexity of the regulatory issues."[17] The National Academies advised that "[i]t is important to consider what constitutes a domestic impact in the case of a global pollutant that could have international implications that affect the United States" (National Academies 2017, p. 13). There are many reasons, as summarized in this section – and as articulated by OMB and in IWG TSDs (IWG 2010, 2013, 2016a, 2016b, 2021) and the 2015 Response to Comments (IWG 2015) – why the EPA uses the global value of climate change impacts when analyzing policies that affect GHG emissions, which have global effects. Courts have upheld the use of global estimates of the SC-GHG, partially in recognition of

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[15] It is customary in the benefit-cost analyses of U.S. Federal regulations to include the full compliance costs that accrue to entities operating in the U.S,, even if those costs are fully or partially borne by owners, employees, or consumers that reside outside of the U.S.

[16] OMB's Circular A-4 (2003) provides guidance to Federal agencies on the development of regulatory analysis conducted pursuant to Executive Order (E.O.) 12866.

[17] Circular A-4 also explains "You will find that you cannot conduct a good regulatory analysis according to a formula. Conducting high-quality analysis requires competent professional judgement." For example, as noted above, benefit-cost analyses have historically often included compliance costs that are ultimately borne by owners, employees, or customers that reside outside of the U.S. It may therefore also be relevant that Circular A-4 generally recommends consistency in the analytical treatment of costs and benefits. ("The same standards of information and analysis quality that apply to direct benefits and costs should be applied to ancillary benefits and countervailing risks" (OMB 2003).)

the diverse ways in which U.S. interests, businesses, and residents are impacted by global climate change.[18]

Unlike many environmental problems where the causes and impacts are distributed more locally, GHG emissions are a global externality making climate change a true global challenge. GHG emissions contribute to damages around the world regardless of where they are emitted. The global nature of GHG pollution and its impacts means that U.S. interests are affected by climate change impacts through a multitude of pathways and these need to be considered when evaluating the benefits of GHG mitigation to the U.S. population. For example, climate change will directly impact U.S. interests that are located abroad (such as U.S. citizens, investments, military bases and other assets, and resources in the global commons (e.g., through changes in fisheries' productivity and location)). An estimated 9 million U.S. citizens lived abroad as of 2020,[19] and the U.S. direct investment abroad position totaled $6.15 trillion at the end of 2020.[20] Nearly 40% of U.S. pension assets' equity holdings are in foreign stocks.[21] Climate impacts occurring outside of U.S. borders have a direct impact on these U.S. citizens and the investment returns on those assets owned by U.S. citizens and residents. In addition, the U.S. has over 500 military sites abroad across 45 foreign countries.[22] Climate change impacts (such as sea level rise) occurring in these locations already affect U.S. military infrastructure and will continue to lead to increased expenditures to maintain bases' viability and readiness (USGCRP 2018a). Failure to do so can lead to impacts on mission execution and increased security risks. As one example, "…the United States has important defense assets located in…the Marshall Islands, and Palau, all of which are vulnerable to these [climate] hazards. Additionally, competitors such as China may try to take advantage of climate change impacts to gain influence" (DoD 2021). The timing and severity of climate events are already affecting missions in some cases and these risks are expected to increase. For example, in the Marshall Islands, the Ronald Reagan Ballistic Missile Defense Test Site, "a pillar of U.S. Strategic Command" used for detecting foreign missile launches, may be "uninhabitable in mere decades" according to a recent study conducted by the Center for Climate and Security's Military Expert Panel (CCS 2018).

The U.S. economy is also inextricably linked to the rest of the world. The U.S. exports over $2 trillion worth of goods and services a year and imports around $3 trillion.[23] According to recent data, over 20% of

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[18] Zero Zone, Inc. v. Dep't of Energy, 832 F.3d 654, 678-79 (7th Cir. 2016) (rejecting a petitioner's challenge to DOE's use of a global social cost of carbon in setting an efficiency standard under the Energy Policy and Conservation Act, holding that DOE had reasonably identified carbon pollution as "a global externality" and concluding that, because "national energy conservation has global effects, . . . those global effects are an appropriate consideration when looking at a national policy.").

[19] U.S. Department of State's Bureau of Consular Affairs, https://travel.state.gov/content/dam/travel/CA-By-the-Number-2020.pdf.

[20] BEA Direct Investment by Country and Industry 2020, https://www.bea.gov/news/2021/direct-investment-country-and-industry-2020.

[21] Based on Thinking Ahead Institute's 2022 Global Pension Assets Study , available at: https://www.thinkingaheadinstitute.org/research-papers/global-pension-assets-study-2022/.

[22] Based on data from U.S. DOD BASE STRUCTURE REPORT – FISCAL YEAR 2018 BASELINE: A SUMMARY OF THE REAL PROPERTY INVENTORY DATA. See Figure 1.
https://www.acq.osd.mil/eie/Downloads/BSI/Base%20Structure%20Report%20FY18.pdf

[23] BEA National Income and Product Accounts Table 1.1.5.

American firms' profits are earned on activities outside the country.[24] Climate impacts that occur outside U.S. borders will impact the welfare of individuals and the profits of firms that reside in the U.S. because of their connection to the global economy. This will occur through the effect of climate change on international markets, trade, tourism, and other activities. Supply chain disruptions are a prominent pathway through which U.S. business and consumers are, and will continue to be, affected by climate change impacts abroad. The impact of international supply chain disruptions can be severe. For example, severe flooding in Thailand in 2011 disrupted production of components for global companies including computer disk drives and cars (USGCRP 2018a, DoD 2021). As a result, U.S. consumers faced higher prices for many electronic goods. The U.S.-based firm Western Digital alone posted $199 million in losses and a 51% drop in hard drive shipments, and U.S. vehicle production had to be temporarily halted or reduced considerably by at least two manufacturers (USGCRP 2018a). As climate change increases the severity and frequency of extreme weather events, it increases the risk of supply chain disruptions. Recent research finds the "probability of a hurricane of sufficient intensity to disrupt semiconductor supply chains may grow two to four times by 2040" and the "probability heavy rare earths production is severely disrupted from extreme rainfall may increase 2 to 3 times by 2030."[25]

Additional climate change-induced international spillovers can occur through pathways such as damages across transboundary resources, economic and political destabilization, and global migration that can lead to adverse impacts on U.S. national security, public health, and humanitarian concerns (DoD 2014, CCS 2018). As articulated in a landmark 2007 study by retired three- and four-star Generals and Admirals - and echoed in the Department of Defense's (DoD) 2014 Quadrennial Defense Review – the projected effects of climate change act as a "threat multiplier" that will exacerbate many stressors and instabilities that already exist in some of the most volatile regions of the world (CNA 2007, DoD 2014). A follow-up study emphasized that beyond being a threat multiplier, climate change impacts will also "serve as catalysts for instability and conflict" (CNA 2014). For example, in Sub-Saharan Africa regional environmental stressors exacerbated by climate change can help to transform resource competition into ethnopolitical conflict and enable the involvement of transnational terrorist groups (such as Al Qaeda in the Islamic Maghreb (AQIM) in Mali in 2012) (CNA 2014). More recent DoD reports reiterate these concerns, concluding that the impacts of climate change "could stress economic and social conditions that contribute to mass migration events or political crises, civil unrest, shifts in the regional balance of power, or even state failure," with results that affect the national interests of the U.S. (DoD 2021). The key takeaway from the National Intelligence Council's (NIC) 2021 National Intelligence Estimate is that "climate change will increasingly exacerbate risks to US national security interests as the physical impacts increase and geopolitical tensions mount about how to respond to the challenge" (NIC 2021). The NIC finds "the increasing physical effects of climate change are likely to exacerbate cross-border geopolitical flashpoints as states take steps to secure their interests", and as intensifying physical effects "out to 2040 and beyond will be most acutely felt in developing countries, which we assess are also the least able to adapt to such changes…[t]hese physical effects will increase the potential for instability and possibly internal conflict in

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[24] Bureau of Econ. Analysis, National Income and Product Accounts Table 6.16D, https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=survey.

[25] https://www.mckinsey.com/business-functions/sustainability/our-insights/could-climate-become-the-weak-link-in-your-supply-chain.

these countries, in some cases creating additional demands on US diplomatic, economic, humanitarian, and military resources" (NIC 2021).

As described by the National Academies (2017), to correctly assess the total damages to U.S. citizens and residents, one must account for these spillover effects on the U.S. For more discussion and examples of international spillover effects, including the ways that climate change spillovers are exacerbating existing risks and creating new security, health, and humanitarian challenges for U.S. interests, see for example, NIC (2021), DoD (2021), USGCRP (2018a), Freeman and Guzman (2009), Howard and Livermore (2021), Schwartz (2021), and IPCC (2022).

A robust estimate of climate damages to U.S. citizens and residents that accounts for the myriad of ways that global climate change reduces the net welfare of U.S. populations does not currently exist in the literature. At present, the only quantitative characterizations of U.S. damages from GHG emissions are based on the share of modeled damages that physically occur within U.S. national borders as represented in current IAMs. Such estimates provide an underestimate of the climate change damages to the citizens and residents of the U.S. because these models do not fully capture the range of climate change impacts and exclude important regional interactions and spillovers discussed above. In addition, a 2020 GAO study observed that "[a]ccording to the National Academies, the integrated assessment models were not premised or calibrated to provide estimates of the social cost of carbon based on domestic damages, and more research would be required to update the models to do so" (GAO 2020). Further, the National Academies observed that existing models "focus primarily on global estimates and do not model all relevant interactions among regions.…More thoroughly estimating a domestic SC-CO$_2$ would therefore need to consider the potential implications of climate impacts on, and actions by, other countries, which also have impacts on the United States" (National Academies 2017, p. 13).

In addition to accounting for the ways that climate change impacts occurring outside of U.S. borders affect U.S. populations, it is also important to consider how changes in U.S. emissions affect the GHG emissions of other countries. This is relevant because the global nature of greenhouse gases means that damages caused by a ton of emissions in the U.S. are felt globally and that a ton emitted in any other country harms those in the U.S. This is a classic public goods problem because each country's reductions benefit everyone else and no country can be excluded from enjoying the benefits of other countries' reductions. As discussed by EPA and other members of the IWG in the 2015 response to comments (IWG 2015), in this situation, the only way to achieve an efficient allocation of resources for emissions reduction on a global basis—and so benefit the U.S. and its citizens and residents —is for all countries to consider estimates of global marginal damages. Therefore, international GHG mitigation activities taken in response to U.S. policies that reduce emissions will also provide a benefit to U.S. citizens and residents. A wide range of scientific and economic experts have emphasized the issue of reciprocity as support for assessing global damages of GHG emissions in domestic policy analysis (e.g., Kopp and Mignone 2013, Pizer et al. 2014, Howard and Schwartz 2017, Pindyck 2017, 2021, Revesz et al. 2017, Carleton and Greenstone 2022). Kotchen (2018) demonstrates how a country's decision to internalize global damages in domestic policymaking can be individually rational (i.e., in the country's own self-interest) because of the

reciprocally induced emissions reductions occurring in other countries.[26] Carleton and Greenstone (2022) discuss examples of how accounting for global damages in past U.S. regulatory analyses may have contributed to additional international action. Houser and Larson (2021) estimate that under the Paris Agreement, other countries pledged to reduce 6.1 to 6.8 tons for every ton pledged by the U.S.

Assessing global marginal damages of GHG emissions in U.S. analyses of regulatory and other actions allows the U.S. to continue to actively encourage other nations, including emerging economies, to also assess global climate damages of their policies and to take significant steps to reduce emissions. Many countries and international institutions have either already explicitly adapted the IWG's estimates of global damages in their domestic analyses (e.g., Canada[27], Israel[28]), developed their own estimates of global damages (e.g., Germany[29]), or have taken note of the IWG estimates in their assessments of climate policies (e.g., India's National Green Tribunal[30], the Australian Capital Territory[31], New Zealand[32], and the International Monetary Fund[33]). In 2016, Mexico announced its intention to "align approaches [with the

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[26] Kotchen (2018) not only details the "efficiency argument in support of all countries internalizing the GSCC [global social cost of carbon] for domestic policy," but Kotchen (2018) also introduces the concept of countries having a "preferred" social cost of carbon (PSCC) for setting global climate policy and shows that all countries' PSCC exceeds the marginal damages to its own populations. The PSCC is shaped by a country's expected benefits from other countries' emission reductions. Kotchen's study shows that in some countries the PSCC can even exceed the value of global marginal damages (e.g., in small island nations for whom the benefits of stringent worldwide abatement based on a high PSCC would exceed the increase in its own abatement costs due to a high PSCC). Kotchen offers illustrative estimates of the PSCC for several countries and regions based on research using a regionalized version of the DICE model (Nordhaus 2015). In this analysis Kotchen finds the U.S. PSCC to be nearly 75% of the value of global marginal damages. And as Kotchen has further clarified, "depending on the U.S. government's diplomatic strategies, its expectations of international reciprocity, and the international distribution of costs, it can be rational for the United States to adopt the full global SCC values for use in policy-making." (Kotchen 2021, comment number OMB-2021-0006-0018, available at: https://www.regulations.gov/comment/OMB-2021-0006-0018). Such arguments for accounting for the global value of climate change impacts in analysis of policies affecting U.S. GHG emissions, based on the U.S. derived benefits from reciprocally induced emission reductions elsewhere, are distinct from and additional to arguments above based on spillover effects and U.S. interests beyond our geographic borders.

[27] Envt. & Climate Change Canada, Technical Update to Environment and Climate Change Canada's Social Cost of Greenhouse Gas Estimates at 13 (2016), http://publications.gc.ca/collections/collection_2016/eccc/En14-202-2016-eng.pdf.

[28] Israel Ministry of Envtl. Protection, Green Book on External Costs of Air Pollutants (2020), https://www.gov.il/BlobFolder/publicsharing/pc_external_costs_of_air_pollution/he/public_comments_2020_Ext ernal _air_pollution_costs_pc_accessible.docx

[29] See GAO (2020) for a discussion of Germany's SC-GHG values.

[30] Additional Report of Committee on Environmental Damage Assessment Due to Air Pollution Caused on Account of Explosion & FIR…in the Matter of OA No. 22 of 2020, at 12 (2020), https://cpcb.nic.in/NGT/ADDITIONAL_REPORT_Air_OA_22_of_2020-SEP-2020.pdf.

[31] Austl. Cap. Terr. Env't, Plan. and Sustainable Dev. Directorate, ACT Climate Change Strategy 2019-2025 (2019), https://perma.cc/487H-BHHC; *see also* Rovingstone Adv. Pty Ltd., A Social Cost of Carbon for the ACT, Report Prepared for the ACT Government (2021), https://www.climatechoices.act.gov.au/__data/assets/pdf_file/0006/1864896/a-social-cost-of-carbon-in-the-act.pdf (recommending adopting the U.S. valuations of the social cost of carbon).

[32] Ministry of Transp., Preliminary CBA for Vehicle Fuel Efficiency Standard (2018), https://perma.cc/Y7SS-3AG2.

[33] Benedict Clements et al., IMF, Energy Subsidy Reform: Lessons and Implications at 8 (2013), https://www.imf.org/en/Publications/Books/Issues/2016/12/31/Energy-Subsidy-Reform-Lessons-and-Implications-40410 .

U.S. and Canada] to account for the social cost of carbon and other greenhouse gas emissions when assessing the benefits of emissions-reducing policy measures"[34], and references to global estimates of climate damages can be found in Mexican regulatory analyses in 2017.[35] However, the bilateral technical discussions to help implement the announced plan did not occur over 2017-2021 during the time U.S. federal regulatory analyses stopped focusing on SC-GHG estimates that reflect global damages.

EPA and other members of the IWG found previously and restated in their February 2021 TSD that because of the distinctive global nature of climate change that analysis of Federal regulations and other actions should center on a global measure of SC-GHG (IWG 2021). This is the same approach that was recommended by OMB and other members of the IWG and used by EPA and other agencies in regulatory analyses from 2009 to 2016. It is also consistent with guidance in OMB Circular A-4 that "[d]ifferent regulations may call for different emphases in the analysis, depending on the nature and complexity of the regulatory issues," and National Academies' guidance that "it is important to consider what constitutes a domestic impact in the case of a global pollutant that could have international implications that impact the United States." In the case of this global pollutant, for all the reasons articulated in this section, the assessment of global net damages of GHG emissions allows analysts to fully disclose and contextualize the net climate benefits of domestic policies that reduce GHG emissions. The extent that analysis relying on these SC-GHG estimates is considered in setting the stringency of future regulatory actions and other policy decisions would be guided by the statutes under which those decisions are promulgated.[36,37] The EPA will continue to review developments in the literature, including more robust methodologies for estimating the magnitude of the various direct and indirect damages to U.S. populations from climate impacts occurring abroad and reciprocal international mitigation activities.

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[34] https://obamawhitehouse.archives.gov/the-press-office/2016/06/29/leaders-statement-north-american-climate-clean-energy-and-environment

[35] See, e.g., Secretaria del Medio Ambiete y Recursos Naturals, Que Establece Los Limites Maximos Permisible de Emision de Monoxido de Carbono....Anexo: Beneficios (2017), https://perma.cc/N6YHZYTM (citing the Working Group's estimates); Secretaria del Medio Ambiente y Recursos Naturales, Aviso Mediante elCual Se Dan a Conocer los Parametros para el Calculo de las Emisiones de Bioxido de Carbono (CO2) en los Vehiculos Automotores Ligeros Nuevos con Peso Bruto Vehicluar Que No Exceda Los 3857 Kilogramos, Que Utilizan Gasolina o Diesel como Combustible Cuyo Ano-Modelo SEA 2017 (June 15, 2016), https://perma.cc/HV8H-62GU (referencing "beneficios globales para las emisiones evitadas de CO2").

[36] For example, as the Supreme Court stated in *Motor Vehicle Manufacturers Ass'n. v. State Farm Mutual Auto. Ins. Co*., 463 U.S. 29, 41-43 (1983): "Normally, an agency rule would be arbitrary and capricious if the agency has relied on factors which Congress has not intended it to consider, entirely failed to consider an important aspect of the problem, offered an explanation for its decision that runs counter to the evidence before the agency, or is so implausible that it could not be ascribed to a difference in view of the product of agency expertise." This requires agencies to "examine the relevant data and articulate . . . a rational connection between the facts found and the choice made."

[37] Public comments received on the February 2021 TSD argue that key U.S. statutes explicitly require or allow consideration of global climate damages in decision making. See, e.g., discussion within comments submitted by the Institute for Policy Integrity and the attachments and literature cited therein (comment number OMB-2021-0006-0074, available at: https://www.regulations.gov/comment/OMB-2021-0006-0074) (discussing, for example, how the National Environmental Policy Act requires that "public laws of the United States shall be interpreted and administered in accordance with the policies set forth in this chapter, and all agencies of the Federal Government shall…recognize the worldwide and long-range character of environmental problems").

2 Methodological Updates

The SC-GHG is commonly estimated with the use of integrated assessment models (IAM). In the broadest sense IAMs are "approaches that integrate knowledge from two or more domains into a single framework" (Nordhaus 2017a). The literature on "IAMs" is vast and spans many sciences, e.g., earth sciences, biological sciences, environmental engineering, economics, and sociology. IAMs have been used to study environmental problems and their connection to economic systems for nearly 40 years (e.g., Freeman 1979, 1982; Mendelsohn 1980; Nordhaus 1993a, 1993b). The National Academies defined IAMs used to study climate change as "computational models of global climate change that include representation of the global economy and greenhouse gas emissions, the response of the climate system to human intervention, and impacts of climate change on the human system" (National Academies 2017). These IAMs vary significantly in structure, geographic resolution, the degree to which they capture feedbacks within and between natural and economic systems and include valuation, and application. Those that are used to estimate the SC-GHG are reduced-form in nature and combine climate processes, economic growth, and feedback between the climate and the global economy into a single modeling framework, providing a holistic view of the system, and include a valuation of climate change damages. Other climate change IAMs, often called detailed-structure IAMs, include structural representations of the global economy with a high level of regional and sectoral detail, and were originally developed for analyzing the impact of policy and technology on greenhouse gas emissions (e.g., Edmonds and Reilly, 1983). These types of IAMs are increasingly being used to examine different climate change impact sectors and interactions between sectors and regions but do not yet comprehensively link physical impacts to monetized economic damages as needed for SC-GHG estimation (National Academies 2017).

As illustrated in Figure 2.1, the steps necessary to estimate the SC-GHG with a climate change IAM can generally be grouped into four modules: socioeconomics and emissions, climate, damages, and discounting. The emissions trajectories from the socioeconomic module are used to project future temperatures in the climate module. The damage module then translates the temperature and other climate endpoints (along with the projections of socioeconomic variables) into physical impacts and associated monetized economic damages, where the damages are calculated as the amount of money the individuals experiencing the climate change impacts would be willing to pay to avoid them. To calculate the marginal effect of emissions, i.e., the SC-GHG in year t, the entire model is run twice – first as a baseline and second with an additional pulse of emissions in year t. After recalculating the temperature effects and damages expected in all years beyond t resulting from the adjusted path of emissions, the losses are discounted to a present value in the discounting module. Much of the uncertainty in the estimation process can be incorporated using Monte Carlo techniques by taking draws from probability distributions that reflect the uncertainty in parameters.

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

The SC-GHG estimates in this report no longer rely on the three IAMs (i.e., DICE, FUND, and PAGE) used in previous SC-GHG estimates. Instead, this report uses a modular approach to estimating the SC-GHG, consistent with the National Academies' near-term recommendations. That is, the methodology underlying each component, or module, of the SC-GHG estimation process draws on expertise from the scientific disciplines relevant to that component. Under this approach, each step in the SC-GHG estimation improves consistency with the current state of scientific knowledge, enhances transparency, and allows for more explicit representation of uncertainty. This section discusses the methodological updates in each of the four National Academies' recommended modules in addition to other updates in the modeling framework, such as the explicit incorporation of risk aversion.

Figure 2.1: The Four Components of SC-GHG Estimation[38]
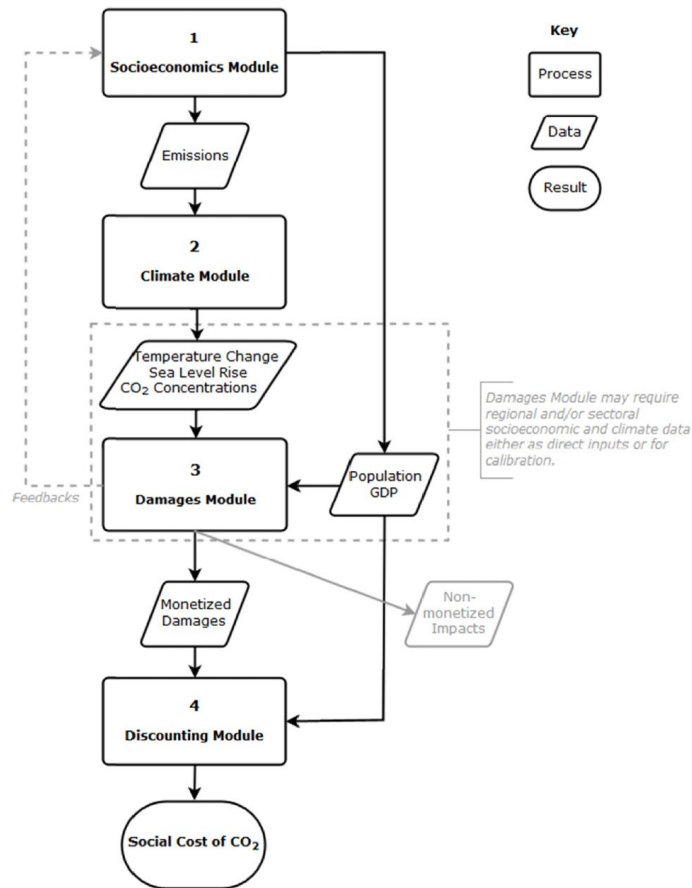
Source: National Academies of Sciences, Engineering, and Medicine (2017)

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[38] In Figure 2.1, the different shading for non-monetized impacts signifies that those impacts are outside the scope of the modeling and is not intended to suggest that non-monetized impacts are less relevant than monetized impacts.

2.1 Socioeconomic and Emissions Module

The first step in the SC-GHG estimation process is the development of projections of socioeconomic variables and GHG emissions at the spatial and temporal resolution required by the climate and damage modules. Socioeconomic trajectories are closely tied to climate damages because, holding all else equal, increases in population and income will increase GHG emissions and lead to a greater willingness to pay to avoid climate change impacts. Within the SC-GHG estimation process, projections of GHG emissions serve as inputs to the climate module, and projections of GDP and population serve as inputs to the damage function and discounting modules. Disaggregation of these inputs is required when greater spatial and/or temporal resolution is required for the damage module. Finally, because GHG emissions and their effects are long lived, it is necessary to project these variables far into the future and address the many complex uncertainties associated with such projections.

SC-GHG estimates used in the EPA's analyses to date have relied on the socioeconomic and emissions projections selected by the IWG in 2010. The IWG elected to use socioeconomic and emissions projections based on deterministic scenarios that, at the time, were recently updated, grounded in multiple well-recognized models, used in climate policy simulations, and spanned a plausible range of outcomes for these variables. The socioeconomic and emission projections included five deterministic reference scenarios based on the Stanford Energy Modeling Forum EMF-22 modeling exercise (Clarke, et al. 2009; Fawcett, et al. 2009). Four of these scenarios represented business-as-usual (BAU) trajectories, while the fifth scenario assumed that substantive actions would be adopted to reduce future emissions. The SC-GHG estimates gave equal weight to each scenario. The IWG also elected to use a time horizon extending to 2300 to try to capture the vast majority of discounted climate damages. Running the IAMs through 2300 required extrapolations of the projections after 2100, the last year available for projections from the EMF-22 models.[39]

The National Academies 2017 final report included several recommendations for how to approach updating the socioeconomic module to reflect newer information. The National Academies (2017) recommended that socioeconomic scenarios used to estimate the SC-GHG should: "extend far enough in the future to provide inputs for estimation of the vast majority of discounted climate damages"; "take account of the likelihood of future emissions mitigation policies and technological developments"; "provide the sectoral and regional detail in population and GDP necessary for damage calculations"; and, "to the extent possible…incorporate feedbacks from the climate and damages modules that have a significant impact on population, GDP, or emissions" (National Academies, 2017, p. 15). The National Academies acknowledged that it would not be possible to meet all these criteria in the near term.

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[39] These inputs were extrapolated from 2100 to 2300 as follows: (1) population growth rate declines linearly, reaching zero in the year 2200; (2) GDP/ per capita growth rate declines linearly, reaching zero in the year 2300; (3) the decline in the fossil and industrial carbon intensity (CO_2/GDP) growth rate over 2090-2100 is maintained from 2100 through 2300; (4) net land use CO_2 emissions decline linearly, reaching zero in the year 2200; and (5) non-CO_2 radiative forcing remains constant after 2100. See IWG (2010) for more discussion of each of these assumptions. In 2016, the IWG added more specificity to the assumptions regarding post-2100 baseline CH_4 and N_2O emissions in order to calculate SC-CH_4 and SC-N_2O. See IWG (2016b) for more details.

However, the report suggested initial steps for how to achieve these goals and overcome several limitations in the methodology used to date. Specifically, they recommend:

(1) working with demographers to extend existing probabilistic population projections beyond 2100, validated and adjusted by expert judgment;

(2) generating probabilistic projections of annual growth rates of per-capita GDP with an appropriate statistical technique, informed by expert judgment;

(3) using a set of emissions projections generated by an expert elicitation, conditioned by the set of scenarios of future population and income; and

(4) developing projections of sectoral and regional GDP and regional population using scenario libraries, published projections, detailed-structure economic models, or other sources.

Resources for the Future Socioeconomic and Emissions Projections (RFF-SPs). Based on a review of available sources of long-run projections for socioeconomic variables and GHG emissions necessary for damage calculations, the socioeconomic and emissions projections recently developed under the Resources for the Future Social Cost of Carbon Initiative (Rennert et al. 2022a) stand out as being most consistent with the National Academies' recommendations. These projections (hereafter collectively referred to as the RFF-SPs) are an internally consistent set of probabilistic projections of population, GDP, and GHG emissions (CO_2, CH_4, and N_2O) to 2300. Consistent with the National Academies' recommendation, the RFF-SPs were developed using a mix of statistical and expert elicitation techniques to capture uncertainty in a single probabilistic approach, taking into account the likelihood of future emissions mitigation policies and technological developments, and provide the level of disaggregation necessary for damage calculations. Unlike other sources of projections, they provide inputs for estimation to 2300 without further extrapolation assumptions. Conditional on the modeling conducted for this report, this time horizon is far enough in the future to capture the majority of discounted climate damages (see discussion in Section 3). Including damages beyond 2300 would increase the estimates of the SC-GHG. As discussed in Section 2.5, the use of the RFF-SPs allows for capturing economic growth uncertainty within a calibrated utility approach to discounting.

The RFF-SPs were developed as follows. The country-level population projections are based on Raftery and Ševčiková's (2021) extension to the Bayesian methodology that the United Nations has used since 2015 for population forecasting (UN 2015). The extension combines the United Nations statistical approach with expert review and elicitation to extend the projections to 2300.

The economic growth projections extend research by Müller et al. (2022), who refined a foundational statistical methodology for generating internally consistent long-term probabilistic growth projections at the country level. Specifically, Müller et al. were the first to extend the approach provided in Müller and Watson (2016) for estimating global economic growth. These probabilistic economic growth projections are combined with the results of a formal expert elicitation of 10 leading growth economists, conducted individually via videoconference in 2019-2020. As part of the elicitation, the experts first quantified their uncertainty for a set of calibration questions, the results of which were used to performance-weight the experts in their final combination. The elicitation focused on quantifying uncertainty for a representative frontier of economic growth in OECD countries. The combined results from the experts were then used to inform econometric projections based on the Müller et al. (2022) model of an evolving frontier (also based on the OECD), in turn providing country-level, long-run probabilistic projections.

GHG emissions are projected using expert elicitation techniques.[40] A separate panel of 10 experts[41] was asked to provide uncertainty quantiles for four emissions variables in five benchmark years and to indicate the sensitivity of the CO_2 emissions responses to five GDP per capita trajectories.[42] Responses were requested under a case incorporating views about changes in technology, fuel use, and other conditions, including the evolution of future policy.[43] The projections from the RFF-SPs represent a state-of-the-art set of probabilistic socioeconomic and emissions scenarios based on high-quality data, robust statistical techniques, and expert elicitation. In addition, they cover a sufficient time horizon for estimating the SC-GHG and incorporate uncertainty over future background policies. As such, the RFF-SPs are consistent with the National Academies' recommendations on socioeconomic and emissions scenarios.

Other Sources of Socioeconomic and Emissions Projections. The RFF-SPs represent a significant advancement over the now outdated and deterministic EMF-22 scenarios and offer improvements over other recently developed socioeconomic and emissions projections. The only other probabilistic projections identified in this review are a library of scenarios generated using MIT's Emissions Prediction and Policy Analysis (EPPA) Model, coupled with expert elicitation (Abt Associates 2012, Marten 2014). These projections have the advantage that they rely on a comprehensive computable general equilibrium (CGE) model that captures key feedbacks and interdependencies across the sources of uncertainty. However, they were generated in 2012 and do not incorporate changes in the economy, emissions trends, and policies adopted over the past decade.

Other socioeconomic and emissions projections developed since the EMF-22 exercise are deterministic and do not provide global projections over a time horizon sufficient for SC-GHG estimation. The most prominent deterministic projections come from the database of Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs).[44] The SSPs and RCPs are the result of a scenario development effort that started in the late 2000s to replace the Special Report on Emission Scenarios (SRES) scenarios from the 1990s (used in the IPCC Third Assessment Report). The two components, SSPs and RCPS, were designed to be complementary. RCPs set pathways for GHG concentrations and,

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[40] For greenhouse gases other than CO_2, CH_4, and N_2O that are needed as inputs to FaIR (e.g., CF_4, C_2F_6, HFCs, CFCs, HCFCs), emissions are projected using SSP2-4.5 from AR6. This scenario is also used to calibrate FaIR1.6.2 and is nearest to the RFF-SP median emissions for carbon dioxide and methane.

[41] The experts were nominated by their peers and/or by members of the RFF Scientific Advisory Board, and have expertise in, and have undertaken, long-term projections of the energy-economic system under a substantial range of climate change mitigation scenarios. More information about the experts is provided in Rennert et al. (2022a).

[42] Specifically, the experts were asked to provide quantiles (minimum, 5th, 50th, 95th, maximum, as well as additional percentiles at the expert's discretion) for (1) fossil fuel and process-related CO_2 emissions; (2) changes in natural CO_2 stocks and negative-emissions technologies; (3) CH_4; and (4) N_2O, for five benchmark years: 2050, 2100, 2150, 2200, and 2300.

[43] See Rennert et al. (2022a) for a detailed discussion of the survey methodology and the full elicitation protocol.

[44] Some organizations also regularly produce forecasts of key socioeconomic variables and emissions, but these tend to be only for a few decades or some countries or regions (e.g., IEA, EIA). Some IAM researchers have constructed deterministic projections using disparate sources. For example, the inputs used in the latest version of the DICE model, DICE 2016, include economic growth projections based on a survey by Christensen et al. (2018), population data from the United Nations, and CO_2 emissions projections from Carbon Dioxide Information Analysis Center, with simple assumptions for extending each series post-2100 (Nordhaus 2017b).

effectively, the amount of warming that could occur by the end of the century.[45] Many possible socio-economic futures may lead to the same RCP, so the SSPs are scenarios of projected socioeconomic global changes through 2100, based on potential future changes in quantitative elements, including population, education, urbanization, GDP, and technology. There are five SSPs, each consisting of a set of quantified measures of development and an associated narrative storyline. The storylines provide a qualitative description of plausible future conditions that drive the quantitative elements. Pairings of these illustrative SSP scenarios with RCPs have been widely used by the IPCC, the global scientific community, and researchers spanning a wide range of disciplines. For modeling exercises requiring emissions projections beyond 2100, such as for SC-GHG estimation, researchers commonly use emissions extensions provided by the Reduced Complexity Model Intercomparison Project (Nicholls et al. 2020). When population and economic growth projections beyond 2100 are necessary, researchers have used various methods to extend the SSPs to 2300, ranging from simple extrapolation assumptions (e.g., CIL 2022, Benveniste et al. 2020)[46] to empirically derived projection methods (e.g., Kikstra et al. 2021).[47] Use of deterministic scenarios, such as the SSP-RCP pairings, would prevent the SC-GHG estimates from capturing important aspects of climate risk, including its relationship to broader socioeconomic uncertainty, and from valuing that risk in a way that is consistent with economic theory and observed human behavior related to risk aversion.

Figure 2.1.1 and Figure 2.1.2 present the RFF-SP projections of population and economic growth through 2300. These figures also include a comparison to the SSPs that have been used in IPCC reports and other applications.[48] The SSP projections beyond 2100 (dashed) are based on the extrapolation method used in Benveniste et al. (2020) for all SSPs. To illustrate the sensitivity to this assumption, projections based on the SSP extrapolation method employed by the Climate Impact Lab (CIL 2022) are also displayed for SSP2 and SSP3. The mean (black solid line) and median (black dotted line) of the RFF-SP population projections follow an increasing trajectory through 2100, consistent but slightly higher than the SSP2 and SSP5 projections, peaking at 11.2 billion people (Figure 2.1.1). This is followed by a slow decline to under 10 billion by 2300. Except for SSP1—which follows an optimistic storyline on sustainability and stabilizing population—all the SSPs lie within the RFF-SP distribution throughout the modeling horizon—with SSP3 in the upper tails of the distribution.

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[45] Four RCPs were used in the IPCC Fifth Assessment Report (2014a) that span a range of radiative forcing (watts per m^2) in 2100 and are named for that forcing above the pre-industrial level (RCP2.6, RCP4.5, RCP6.0 and a high-end no-mitigation RCP8.5). The SSPs took longer to develop. The SSPs were published in 2016 and updated in 2018. The are available at: https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=10. The SSPs and some additional RCPs are being used in the IPCC Sixth Assessment Report (2021a). The three additional RCPs include RCP1.9 (which focuses on limiting warming to below 1.5C), RCP3.4 (an intermediate pathway between RCP2.6 and RCP4.5), and RCP7.0 which represents medium-to-high end of emissions range and is a baseline outcome rather than a mitigation target.

[46] In the components of their modeling that require extrapolation of GDP and population beyond 2100, when using SSPs, Climate Impact Lab (CIL 2022) modeling assumed GDP per capita growth and the level of global population remain constant at 2100 levels through 2300. Benveniste et al. (2020) generates country level extensions to 3000, based on the assumption that population growth declines linearly to 0 in 2200, and is held constant thereafter; GDP per capita growth is assumed to decline linearly reaching 0 in 2300.

[47] Kikstra et al. (2021) develop regional extensions based on the assumption that regional GDP per capita and population growth rates (in PAGE model regions) converge toward the global mean.

[48] Figures 2.1.1 and 2.1.2 contain all Tier 1 SSPs from IPCC AR6. Tier 2 scenarios, such as SSP4, were not considered.

Figure 2.1.1: Global Population under RFF-SPs and SSPs, 1950-2300
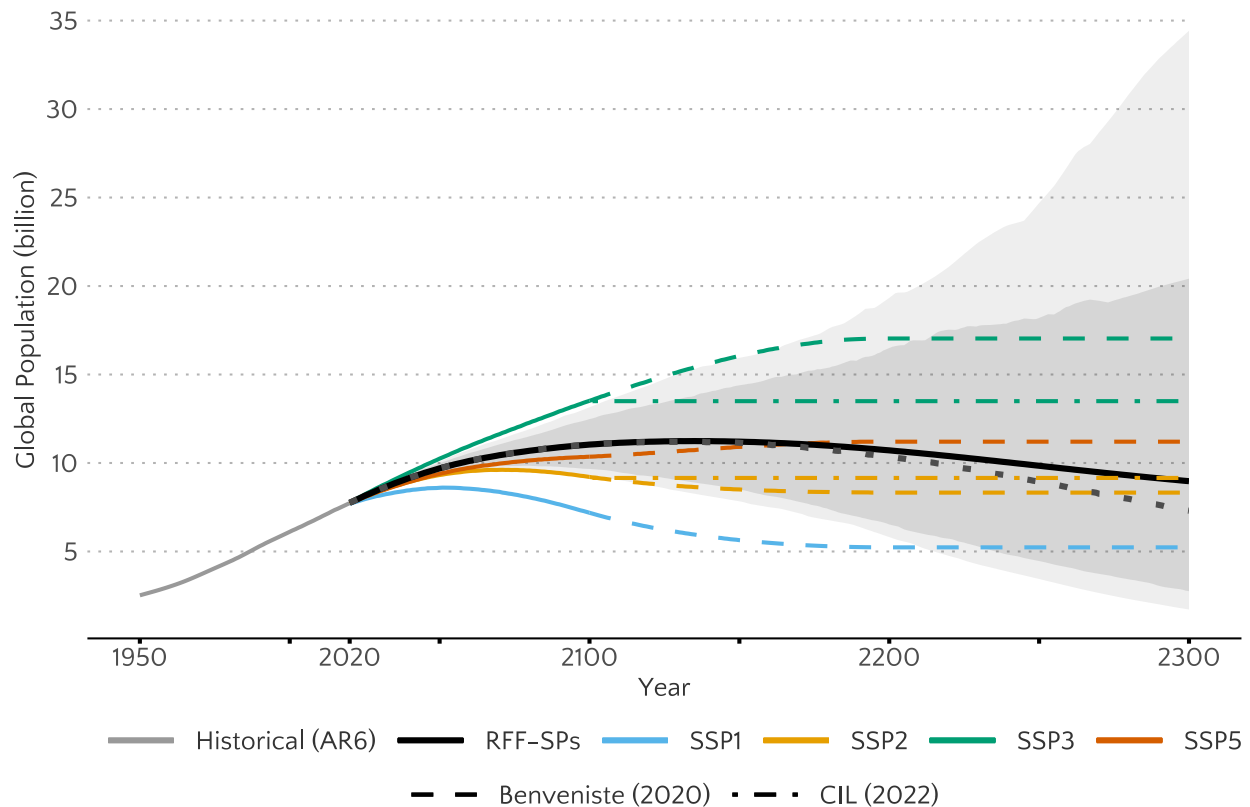
RFF-SP projections based on RFF-SPs (Rennert et al. 2022a). Black lines represent mean (solid) and median (dotted) lines along with 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges. SSP data through 2100 from International Institute for Applied Systems Analysis (IIASA) SSP Database (Riahi et al. 2017). SSPs beyond 2100 (dashed) are based on two recent extrapolation methods: Benveniste et al. (2020) and CIL (2022).

Figure 2.1.2 presents the economic growth projections from the RFF-SPs along with comparisons to the SSPs in AR6.[49] The mean (black solid line) and median (black dotted line) economic growth rates are relatively flat until 2100 at 1.6% and then decline through-out the next century. The mean economic growth rate levels off again after 2200 at 1.1%. The RFF-SP economic growth projections are lower but most consistent with SSP2, i.e., the "middle of the road" scenario in which economic trends follow historical patterns. All the SSP storylines lie within the RFF-SP distribution throughout the modeling horizon. One notable difference between the RFF-SPs and the SSPs is the high near-term growth rates in the SSPs. Published in 2017, the SPPs economic growth projections are based on historical data through 2010. Between 2005 and 2010 the historical average annual growth rate was nearly 3%. The SSPs predicted an average annual growth rate between 2010 and 2019 of 2.89–2.96% (Riahi et al. 2017), whereas in the past decade average global per capita growth rates have been closer to 2% (World Bank

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[49] The growth rates (and the uncertainty bounds around the RFF-SPs) shown in Figure 2.1.2 are plotted in a time-averaged manner to accurately present the underlying year-on-year correlations that exist within each scenario/storyline.

2021). The estimated growth-rates in the RFF-SPs are long-run growth rates, built to eliminate short-run fluctuations.

Figure 2.1.2: Long-run Projections of Growth in Global Income per Capita under RFF-SPs and SSPs, 2020-2300
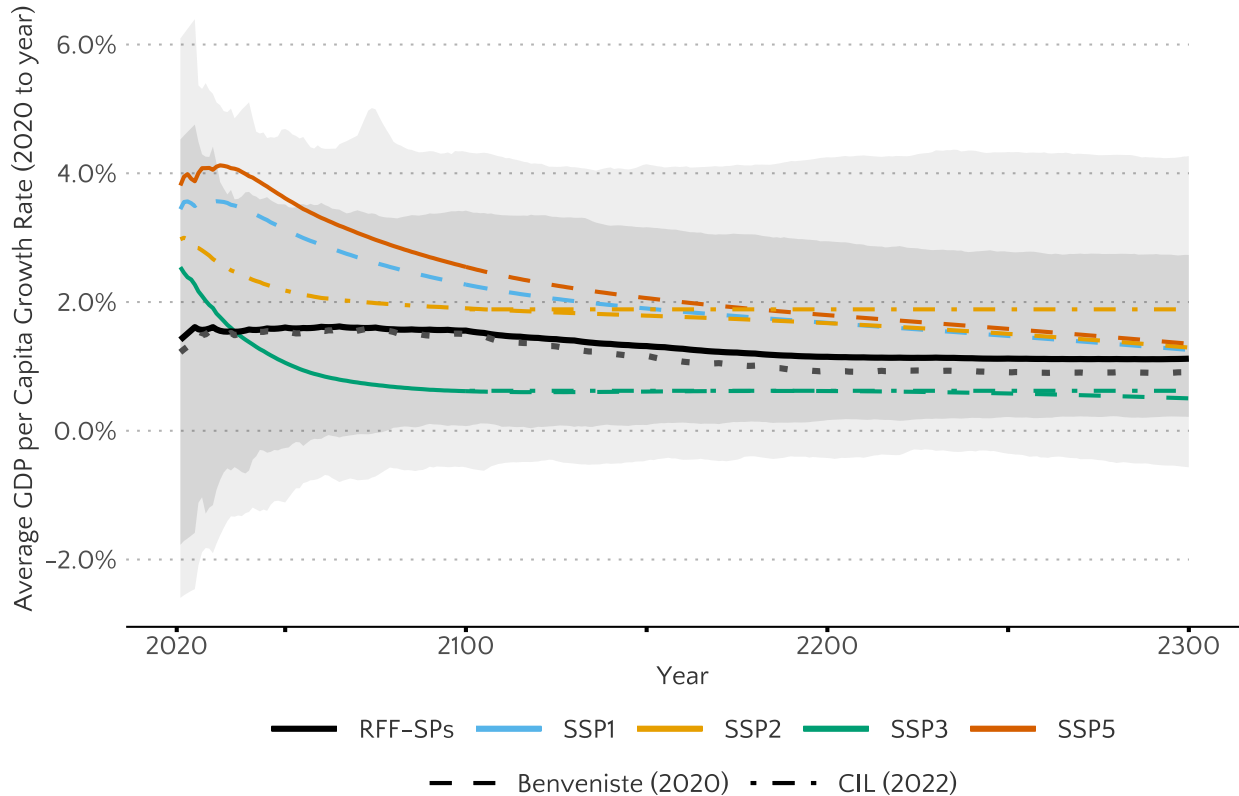
RFF-SP projections based on RFF-SPs (Rennert et al. 2022a). Black lines represent mean (solid) and median (dotted) growth rates along with 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges. SSP data through 2100 from International Institute for Applied Systems Analysis (IIASA) SSP Database (Riahi et al. 2017), OECD Env-Growth model based projections. SSPs beyond 2100 (dashed) are based on two recent extrapolation methods: Benveniste et al. (2020) and CIL (2022). The growth rates (and the uncertainty bounds around the RFF-SPs) are plotted in a time-averaged manner to accurately present the underlying year-on-year correlations that exist within each scenario/storyline.

Although the RFF-SPs displayed in the figures above are mostly consistent with the SSPs, there are notable advantages to the RFF-SPs. First, the economic growth and population projections are based on recent peer-reviewed statistical methodologies for generating long-term projections. These statistical projections represent advancements in the literature since the publication of the SSPs in 2017 and incorporate additional historical data beyond those used to calibrate the SSPs. Second, the RFF-SPs formally characterize the uncertainty in economic growth and population over time (less is known about the far-future than is known about the near-future). The SSPs are a set of deterministic scenarios and intentionally developed without probabilities attached to them, making them less suitable for addressing uncertainty. Third, the RFF-SPs provide projections over a much longer time horizon (out to 2300), which is relevant for capturing more of the discounted damages from climate change, whereas the SSPs provide projections out to 2100. Each of these advantages were highlighted by the National Academies (2017) as important elements in developing improved projections of socioeconomic variables and emissions. Thus,

the RFF-SPs more closely implement the near-term recommendations from the National Academies on economic growth and population projections than do the SSPs.

In the SSPs and the mean RFF-SPs, global emissions of CO_2 peak at some point this century and decline toward zero emissions (in some cases negative emissions). These emission peaks for the SSPs are based on simplistic assumptions about net emissions reaching zero in 2250. The RFF-SP projections are based on expert elicitation, where the experts were asked to incorporate their views on the evolution of future policy. This is consistent with the National Academies' (2017) recommendations to "take account of the likelihood of future emissions mitigation policies." Because the RFF-SPs are probabilistic they reflect the uncertainty in future policy and when this peak would occur. In the mean RFF-SP projection the peak occurs this decade. In some of the higher emissions scenarios this peak in emissions does not occur until near the end of the century.

Figure 2.1.3 presents the RFF-SP projections for CO_2 emissions through 2300 along with a comparison to a range of SSP-RCPs from AR6 (Figure A.5.1 and Figure A.5.2 in the Appendix present the same information for CH_4 and N_2O emissions through 2300). For SSP-RCP pairings presented in the figure, emissions projections beyond 2100 are based on the commonly used extensions provided by the Reduced Complexity Model Intercomparison Project (Nicholls et al. 2020). The post-2100 SSP projections are based on simplistic assumptions about when global emissions reach zero (2055 for SSP1-1.9, 2075 for SSP1-2.6, 2250 for SSP2-4.5, SSP3-7.0, and SSP5-8.5) and how global emissions reach this point after 2100. In the mean RFF-SPs (black solid line) global CO_2 emissions continue to rise in the term near but peak at 42 $GtCO_2$ in 2026. Both the RFF-SP median and the mean track closely with SSP2-4.5, which is often described as a "middle of the road" SSP storyline. The SSP5-8.5 projection is the only SSP-RCP pairing with CO_2 emissions projections outside the 1st to 99th percentile range of RFF-SPs. The RCP8.5 emissions scenario is a high emissions scenario in absence of climate change policies (Riahi et al. 2017).[50] As mentioned above, the RFF-SPs explicitly account for the likelihood of future climate policies.[51] While the SSP-RCP scenarios offer plausible storylines that imbed these assumptions within their trajectories, the RFF-SPs have a significant advantage in that they assign probabilities to these future policies and their outcomes, account for adoption of cleaner technologies and fuel sources, and explicitly link socioeconomic growth scenarios to emissions.[52]

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[50] While all the RCP emissions scenarios peak and begin to decline by, or shortly after, the end of the century, it is important to note that CO_2 concentrations, and therefore temperatures, will not stabilize until CO_2 emissions decline to zero (Matthews and Caldeira 2008).

[51] Specifically, Rennert et al (2022a) states: "…experts viewed low economic growth as likely to reduce emissions overall but also lead to reduced global ambition in climate policy and slower progress to decarbonization. For median economic growth conditions, experts generally viewed policy and technology evolution as the primary driver of their emissions distributions, often offering a median estimate indicating reductions from current levels but with a wide range of uncertainty. Several experts said high economic growth would increase emissions through at least 2050, most likely followed by rapid and complete decarbonization, but with a small chance of substantial continued increases in emissions."

[52] Throughout all stages of the SC-GHG modeling process, we compared the intermediate and final outputs across the SSP-RCP socioeconomic and emissions storylines and the RFF-SP probabilistic scenarios. In all cases (global mean surface temperature, sea level rise, and even the final SC-GHG estimates) the RFF-SPs lie within the full range of the SSP-RCP storylines and are most consistent with the SSP2-RCP4.5 pairing.

Figure 2.1.3: Net Annual Global Emissions of Carbon Dioxide (CO_2) under RFF-SPs and SSPs, 1900-2300
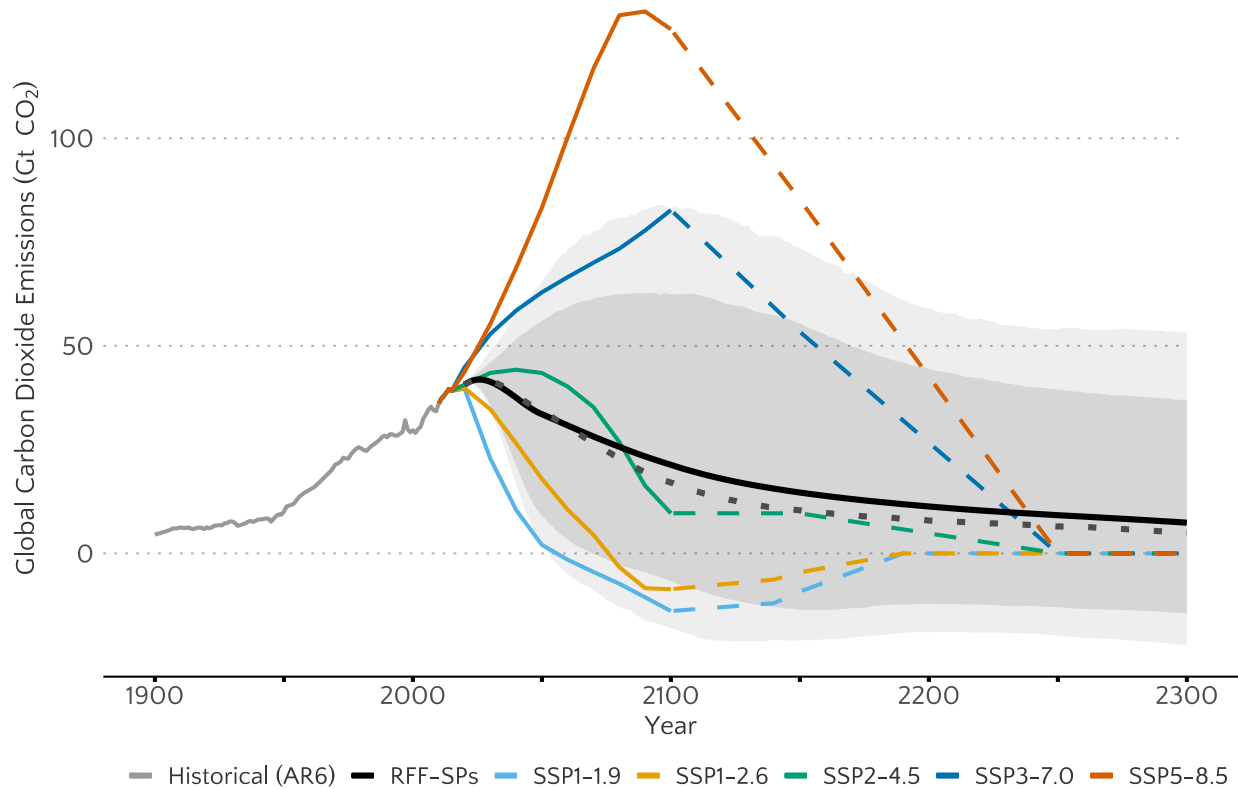
RFF-SP projections based on RFF-SPs (Rennert et al. 2022a). Black lines represent the mean (solid) and median (dotted) CO_2 emissions projections along with 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges. SSP data through 2100 are from the International Institute for Applied Systems Analysis (IIASA) SSP Database (Riahi et al. 2017). SSPs beyond 2100 (dashed lines) are based on the commonly used extensions provided by the Reduced Complexity Model Intercomparison Project (Nicholls et al. 2020).

In both the RFF-SPs and the SSPs, projections of global GDP are calculated using purchasing power parity (PPP). This represents a shift from the EMF-22 projections used to date, in which global GDP was based on combining regional GDPs using market exchange rates (MER). As discussed in the IWG's 2010 TSD, PPP takes into account the different price levels and different baskets of goods consumed across countries, so it more accurately describes relative standards of living across countries. PPP-adjusted measures are increasingly available and used in climate economics research. For example, Nordhaus has argued since 2007 that "PPP measures are superior to MER measures for representing relative incomes and outputs" (Nordhaus 2007), and the update to his DICE model in 2016 included a shift from MER to PPP exchange rates (Nordhaus 2017a, 2017b). Similarly, Anthoff and Emmerling (2019) maintain that "…using nominal or market exchange rates would overstate the (current) degree of inequality between countries compared to the measurements using PPPs." The shift to PPP-based projections in the RFF-SPs, therefore, represents another advancement in the science underlying the SC-GHG framework presented in this report.

2.2 Climate Module

The next step in the SC-GHG estimation process is to estimate the effect of emissions on physical climate variables, such as temperature, and to ensure that the outputs from the climate model are at the spatial and temporal resolution required by the damage module. This means the climate module must:

(1) translate GHG and other forcing agent emission projections into atmospheric concentrations, accounting for the uptake of CO_2 by the land biosphere and the ocean and the removal of other greenhouse gases through atmospheric reactions, deposition, and/or other mechanisms;
(2) translate concentrations of greenhouse gases and other forcing agents into radiative forcing;
(3) translate forcing into global mean surface temperature response, accounting for heat uptake by the ocean, and
(4) generate other climatic variables, such as sea level rise (SLR), that may be needed by the damage module.[53]

Together, with the projections of associated socioeconomic variables, the results from the climate module serve as inputs to the damage module.

As discussed in section 1.1, the methodology underlying SC-GHG estimates used in the EPA's analyses to date has included a representation of climate and other earth system dynamics as provided in the default version of the DICE, FUND, and PAGE IAMs. The only climate variable that was harmonized across these three previous models was equilibrium climate sensitivity (ECS) – a measure of the globally averaged temperature response to increased radiative forcing (generally, the equilibrium temperature response resulting from a doubling of atmospheric CO_2 concentrations). Each IAM was run using a probability distribution for the ECS, calibrated to the Intergovernmental Panel on Climate Change's (IPCC) Fourth Assessment Report (AR4) (IPCC 2007a) findings using the Roe and Baker (2007) distribution.[54] All other aspects of the modeling – such as the representation of the carbon cycle and its parameterization, sea-level rise, regional downscaling of temperature, and treatment of non-CO2 greenhouse gases – varied across the three IAMs and were used as the model developers had designed them.

To implement a modular approach to updating the representation of climate and other Earth system dynamics in SC-GHG estimation, it is helpful to review the available climate models capable of meeting the climate module requirements outlined above, the conclusions of recent scientific assessments published since the IPCC's AR4 report, the public comments received on individual EPA proposed rulemakings and the IWG's February 2021 TSD (IWG 2021), and the National Academies (2017) recommendations related to the climate module.

The conclusions of recent scientific assessments (e.g., IPCC 2014a, 2018, 2019a, 2019b, 2021a; USGCRP 2016, 2018a; and the National Academies 2016b, 2019) bolster the science underlying the modeling of

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[53] This module could in future iterations also generate estimates of other climatic variables (e.g., precipitation changes) as well as non-climate mediated impacts of GHG emissions if needed as inputs to future damage functions. As discussed in Section 3.3, the only non-climate mediated effect included in SC-GHG estimates used by the EPA to date are plant fertilization effects from elevated CO_2 concentrations. Other non-climate mediated effects of GHG emissions that have not yet been incorporated into SC-GHG estimation are discussed in Section 4.2.

[54] The IPCC's Fourth Assessment Report (IPCC 2007b) was the most current IPCC assessment available at the time when the IWG calibrated the ECS distribution.

climate dynamics. Recently, in August 2021, the IPCC released the Working Group (WG) 1 contribution to the IPCC Sixth Assessment Report (AR6) (IPCC 2021a). The IPCC (2021a) report brings together the most up-to-date physical understanding of the climate system and climate change. The report includes updated IPCC AR6 consensus statements on key climate parameters that are relevant for SC-GHG estimation, including equilibrium climate sensitivity and transient climate response. For equilibrium climate sensitivity (ECS)[55], the AR6 assessment finds, with high confidence, that the best estimate is 3°C with a likely range of 2.5°C to 4°C.[56] AR6 also concludes that "it is virtually certain that ECS is larger than 1.5°C, but currently it is not possible to rule out ECS values above 5°C" (IPCC 2021a). For the transient climate response (TCR), AR6 finds that the best estimate of TCR is 1.8°C, and it is very likely between 1.2 and 2.4°C.[57] Additional discussion of scientific updates in AR6 is provided in the Appendix. In particular, Section A.1 contains a summary of the IPCC's understanding of CO_2, CH_4, and N_2O greenhouse gas radiative efficiency, atmospheric lifetimes, and chemistry in AR6 relative to AR4, which was the basis of the simplified lifetime and forcing equations underlying the IWG estimates used by the EPA and other federal agencies to date.

Reduced-complexity climate models (RC models) offer meaningful improvements over the current representation of climate dynamics in existing IAMs (Nicholls et al. 2020). RC models are highly parameterized, computational emulators of the climate system. RC models are different from the highly complex and computationally demanding Earth system models (ESMs), which are the state-of-the-art tools for climate projections. However, the use of RC models may be preferred over ESMs for certain applications for at least three reasons: (1) the computational efficiency of the RC models allows for hundreds or thousands of simulations in a relatively short timeframe, (2) the adjustability of model parameters allows for the exploration of uncertainty, and (3) because RC models do not model year-to-year variability they allow for the estimation of the difference between emission scenarios that would be smaller than that variability (Sarofim et al. 2021a). RC models have a long history of use in climate science assessments, IAM modeling applications, and analyses of climatic processes. They are ubiquitously used to support model inter-comparisons and diagnostics because of their ability to emulate different ESM components and variables, explore uncertainties in key climate parameters, analyze scenarios to provide concentration and temperature inputs to IAMs and other models, and estimate climate sensitivity when

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[55] ECS is defined as "the equilibrium (steady state) change in the surface temperature following a doubling of the atmospheric carbon dioxide (CO_2) concentration from pre-industrial conditions" (IPCC 2021a).

[56] The AR6 assessment finds "[b]ased on multiple lines of evidence, the very likely range of equilibrium climate sensitivity is between 2°C (high confidence) and 5°C (medium confidence). The AR6 assessed best estimate is 3°C with a likely range of 2.5°C to 4°C (high confidence), compared to 1.5°C to 4.5°C in AR5, which did not provide a best estimate" (IPCC 2021a). In IPCC statements, the terms "likely", "very likely" and "virtually certain" are defined to correspond to probabilities of at least 66% (16.6-83.3 percentile), 90% (5-95 percentile), and 99% (0.5-99.5 percentile), respectively (IPCC 2007c). In IPCC reports a level of confidence is expressed using five qualifiers (very low, low, medium, high, and very high) based on the type, amount, quality, and consistency of evidence (e.g., mechanistic understanding, theory, data, models, expert judgement) and on the degree of agreement across multiple lines of evidence. Statements in the AR6 WG1 report that include "best estimate" are not specific on its definition.

[57] TCR is defined as "the surface temperature response for the hypothetical scenario in which atmospheric carbon dioxide (CO_2) increases at 1% yr-1 from pre-industrial to the time of a doubling of atmospheric CO2 concentration" (IPCC 2021a), thereby being a measure of the speed as well as the magnitude of the climate response. AR6 states that "Based on process understanding, warming over the instrumental record and emergent constraints the best estimate TCR is 1.8°C, it is likely 1.4 to 2.2°C and very likely 1.2 to 2.4°C" (IPCC 2021a).

coupled with historical climate observations (Nicholls et al. 2020, Nicholls et al. 2021, Sarofim et al. 2021a).

One of the most widely used RC models is the Finite amplitude Impulse Response (FaIR) climate model (Millar et al. 2017, Smith et al. 2018) to generate projections of global mean surface temperature (GMST) change. The FaIR model was originally developed by Richard Millar, Zeb Nicholls, and Myles Allen at Oxford University, as a modification of the approach used in IPCC AR5 to assess the GWP and GTP (Global Temperature Potential) of different gases. It is open source, widely used (e.g., IPCC 2018, IPCC 2021b), and was highlighted by the National Academies (2017) as an RC model that satisfies their recommendations for a near-term update of the climate module in SC-GHG estimation. Specifically, it translates GHG emissions into mean surface temperature response following the steps outlined above and represents the current understanding of the climate and GHG cycle systems and associated uncertainties within a probabilistic framework. The FaIR model's projections of future warming are consistent with more complex, state of the art ESMs and can, with high confidence, be used to accurately characterize current best understanding of uncertainty, is easily implemented, and is transparently documented.

The updated SC-GHG estimates presented in this report rely on FaIR version 1.6.2 as used by the IPCC (2021a, 2021b). An alternative version of the model, FaIR 2.0, was recently published (Leach et al. 2021) that offers some advantages with respect to simplicity and the inclusion of a flexible, state-dependent methane lifetime, but is less preferable for SC-GHG estimation at this time because it is not yet able to track ocean heat uptake (which is used as an input to help project future sea level rise in some models such as BRICK); importantly the calibration of its uncertain parameters is based on historical data but has not yet been adjusted to be consistent with the AR6 evaluation of climate characteristics such as the IPCC assessed likely range of 2.5 to 4°C for the climate sensitivity. FaIR 1.6.2 also has advantages over the latest versions of other RC models, including the Model for the Assessment of Greenhouse Gas Induced Climate Change (MAGICC; Meinshausen et al. 2011) and the Hector model, a U.S. Government-developed model (Hartin et al. 2015).[58] MAGICC is widely used in science research, policy analysis, IPCC reports, and the latest version, MAGICC 7.5.1, has been calibrated to AR6 findings. However, the model itself is not open source and, therefore, less preferable to FaIR in terms of transparency and reproducibility. The Hector model has some additional complexity and features that could be helpful in future SC-GHG updates. For example, it can emulate ocean acidification, permafrost, and land carbon cycles (Woodard et al. 2021). However, Hector has not yet been calibrated to the AR6 assessed climate characteristic ranges, and the current version of Hector has no suggested parameter sets for use in uncertainty analysis. Table 2.2.1 shows summary statistics for the ECS from the FaIR 1.6.2 model used in this report and other RC models

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[58] FaIR and MAGICC were among the four RC models examined in IPCC (2021a), along with Oscar (Gasser et al. 2020), and Cicero-SCM (Skeie et al. 2021). Each of these were calibrated based on agreement with observations such as historical temperatures, ocean heat uptake, CO_2 concentrations, and airborne fraction. The WG1 report compares distributions from the calibrated models to assessed values of metrics such as ECS and TCR. The latter two RC models are dropped from detailed consideration in this report because Cicero-SCM does not have a carbon cycle representation, and Oscar did not match projected future temperatures from the Coupled Model Intercomparison Project (CMIP) and other projections. Thompson (2018) also identified FaIR, MAGICC, and Hector as being good fits to the National Academies' recommended criteria for the climate module.

and compares them to IPCC statements. For reference, Table 2.2.1 also includes the assumed distribution used in IWG SC-GHG estimates to date. Table 2.2.2 shows similar information for the TCR.

Taken together, FaIR 1.6.2 is a fitting RC model to serve as the basis for an updated climate module in SC-GHG estimation. It provides, with high confidence, an accurate representation of the latest scientific consensus on the relationship between global emissions and global mean surface temperature under the wide range of socioeconomic emissions scenarios discussed in Section 2.1. It also offers a code base that is fully transparent and available online (unlike MAGICC), and the uncertainty capabilities in FaIR 1.6.2 have been calibrated to the most recent assessment of the IPCC (which importantly narrowed the range of likely climate sensitivities relative to prior assessments) (unlike FaIR2.0 or Hector at the present time).

Table 2.2.1: Summary Statistics for Equilibrium Climate Sensitivity under Reduced-Complexity Climate Models and IPCC statements

	Percentiles and Other Summary Statistics						
	5%	16.6%	Mode[a]	Median (50%)	Mean	83.3%	95%
FaIR 1.6.2[d]	2.05	2.37	2.78	2.95	3.18	3.87	5.03
FaIR 2.0.0 (Leach et al. 2020)	1.94	2.36		3.24		4.74	6.59
MAGICC7 (IPCC 2021a)	1.93			2.97			4.83
Hector2.5 (Nicholls et al. 2021)	1.84	2.16		2.85		3.90	5.45
AR6 statement (2022)	2.00	2.50		3.00[b]		4.00	5.00
AR5 statement (2014)	> 1.00	1.50				4.50	< 6.00
IWG to date (Roe & Baker (2007), calibrated to AR4) (2010)	1.72	2.00	2.34	3.00	3.50	4.50	7.14
AR4 statement (2007)		2.00		3.00[c]		4.50	

[a] Mode calculated after rounding to 2 decimal places.
[b] AR6 offers a "best estimate" but is not specific on which statistic for central value most closely corresponds to "best".
[c] AR4 offers a "most likely" value. As noted in IWG (2010), strictly speaking, "most likely" refers to the mode of a distribution rather than the median, but common usage would allow the mode, median, or mean to serve as candidates for the central or "most likely" value and the IPCC report is not specific on this point.
[d] Results from FaIR 1.6.2 were estimated using the 2,237 constrained parameter sets.

Table 2.2.2: Summary Statistics for Transient Climate Response under Reduced-Complexity Climate Models and IPCC Statements

	Percentiles and Other Summary Statistics						
	5%	16.6%	Mode[a]	Median (50%)	Mean	83.3%	95%
FaIR 1.6.2[b]	1.36	1.49	1.60	1.81	1.85	2.20	2.46
FaIR 2.0.0 (Leach et al. 2020)	1.30	1.48		1.79		2.15	2.44
MAGICC7 (IPCC 2021a)	1.27			1.88			2.61
Hector2.5 (Nicholls et al. 2021)	1.42	1.58		1.82		2.08	2.29
AR6 statement (2022)	1.20	1.40		1.80		2.20	2.40
AR5 statement (2014)		1.00				2.50	3.00
AR4 statement (2007)	1.00						3.00

[a] Mode calculated after rounding to 2 decimal places.

[b] Results from FaIR 1.6.2 were estimated using the 2,237 constrained parameter sets.

Figure 2.2.1 shows the projected future atmospheric concentration[59] of CO_2 through 2300 based on the RFF-SP emissions projections that are used as inputs into FaIR 1.6.2. Atmospheric concentrations increase over time due to the accumulation of annual emissions, with excess CO_2 from the atmosphere moving into the ocean and ecosystems slowly over time until eventually a new equilibrium is reached.[60] Figure 2.2.2 shows the corresponding projection of global mean surface temperature. The ranges in these figures reflect uncertainty in both emissions and physical climate processes that are consistent with the latest projections coming out of the Sixth Assessment Report (IPCC 2021a).

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[59] Atmospheric concentration refers to the amount of a gas in the atmosphere. For CO_2, it is measured in parts per million (ppm). Pre-industrial concentrations of CO_2 were 280 ppm, and concentrations this high have not been seen in at least 2 million years.

[60] Figures A.5.3 and A.5.4 in the Appendix show projected atmospheric concentrations of methane (CH_4) and nitrous oxide (N_2O). CH_4 and N_2O concentrations are higher than at any time in at least 800,000 years. While CO_2, once emitted into the atmosphere through combustion, is not destroyed but rather moves between the ocean, ecosystems, and atmosphere, other gases like CH_4 and N_2O are destroyed through reactions in the atmosphere.

Figure 2.2.1: Global Atmospheric Concentrations of Carbon Dioxide (CO₂), 1900-2300
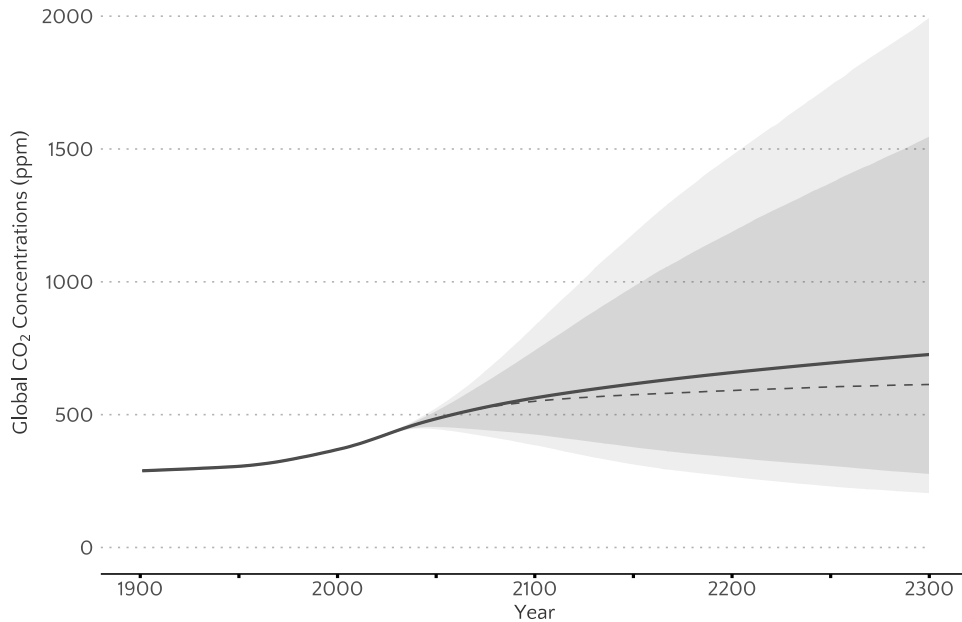
Future atmospheric concentrations of carbon dioxide (CO₂) are based on the range of annual emissions projections from the sampled RFF-SP scenarios used as inputs into FaIR 1.6.2. FaIR 1.6.2 is run with the full, AR6 calibrated (constrained) uncertainty distribution. Therefore, the uncertainty ranges in this figure represent both emissions and physical carbon cycle uncertainty. Mean (solid) and median (dashed) lines are shown along with the 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges.

Figure 2.2.2: Global Mean Surface Temperature Change, 1900-2300
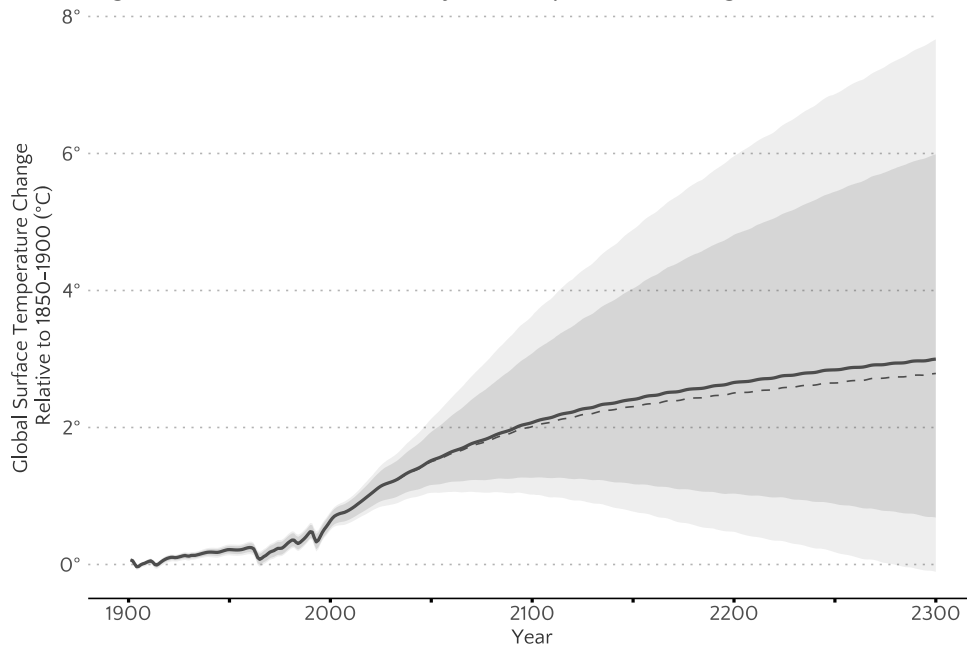
The range of global mean surface temperature change relative to pre-industrial (1850-1900) as calculated by FaIR 1.6.2 corresponding to the CO₂ concentrations from Figure 2.2.1 and the accompanying figures for CH₄ and N₂O in the Appendix. Uncertainty comes from emissions uncertainty from the RFF-SP projections and physical climate uncertainty from FaIR. Mean (solid) and median (dashed) lines are shown along with the 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges.

Because the SC-GHG is calculated based on the impact of a marginal pulse of emissions, it is particularly relevant to investigate how the climate model responds to small changes in emissions. The response of the climate to a pulse of GHG emissions (i.e., CO_2, CH_4, or N_2O) is calculated by using a reference scenario (baseline) and subtracting the temperatures of that reference scenario from a second scenario (perturbed) that is identical in all dimensions except for the marginal increase in emissions for the one year and one gas being examined (i.e., all characteristics of the model run, emissions levels of other gases, etc., are held constant for the duration of the perturbed model run). Figure 2.2.3 shows the temperature response resulting from a pulse of CO_2 emissions in 2030 under the three RC models considered in this report.[61] The FaIR, MAGICC, and Hector model outputs all exhibit similar dynamics in the timing of peak warming in response to a pulse of emissions. For most gases, a pulse of emissions leads to a peak in temperature within a few years following the pulse of emissions. Then, as the radiative forcing declines and the ocean heat uptake increases, the marginal increase in temperature begins to decline at an increasing rate. However, as illustrated in Figure 2.2.3, the temperature response to a pulse of CO_2 is a little more complicated. When the rate of decrease in radiative forcing slows such that the rate of decline in ocean heat uptake exceeds it, atmospheric warming resumes leading to a sustained increase in temperature.[62] The temperature dynamics of these models represents a significant scientific advancement over the temperature responses underlying the climate components of the three IAMs used in the IWG SC-GHG estimates. Specifically, Dietz et al. (2021) showed that the initial response of DICE, FUND, and PAGE to a pulse of CO_2 emissions was slower than the response of FaIR calibrated to 256 models involved in the fifth phase of the Coupled Model Intercomparison Project (CMIP5[63]), demonstrating that FaIR and related models can better emulate the high-resolution global climate models. This is an important feature when estimating the SC-GHG as discussed in Section 2.4 (near term marginal damages are discounted less than damages far in the future). Additionally, Dietz et al. (2021) found that for the long-term response (200 years after the pulse) FUND and DICE 2016 were higher than the FaIR emulations and the response of PAGE was consistently lower. (See Figure A.5.7 in the Appendix.)

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[61] Figures A.5.5 and A.5.6 in the Appendix show the temperature response resulting from a pulse of CH_4 and N_2O emissions.

[62] A more detailed explanation of the temporal temperature response resulting from a pulse of greenhouse gas emissions is as follows. The atmospheric concentration response from an emissions release is the highest at time zero and declines thereafter as the gas either decomposes in the atmosphere or cycles into other reservoirs. The radiative forcing is directly related to the increased concentration. However, the temperature response is a function of the accumulation of energy due to the radiative forcing, minus the heat that the ocean takes up as the atmosphere warms and the increased heat that is radiated to space due to a warmer planet. For most gases, this balance between radiative heating from the gas and heat uptake by the ocean leads to a peak in temperature within a few years of the emission as the radiative forcing declines and the ocean heat uptake increases. The decline in temperature lags the decline in radiative forcing, as the heat that went into the ocean is eventually released. However, the response to a pulse of CO_2 is a little more complicated: because the elevated concentrations resulting from a pulse of CO_2 emissions decreases quickly to start as CO_2 cycles into the ecosystems and surface oceans, but then the decrease slows as the timescale becomes dominated by deep ocean mixing and slows further when it is dominated by sedimentation. When the rate of decrease in radiative forcing slows such that the rate of decline in ocean heat uptake exceeds it, atmospheric warming resumes creating a second peak in temperature (Millar et al. 2017).

[63] CMIP is the Coupled (sometimes, Climate) Model Intercomparison Project. CMIP creates a framework for consistent application of climate models to a common set of scenarios, and with a common set of outputs, to facilitate assessment of these models and provide consistent inputs to impacts assessments. CMIP5 is the fifth phase of CMIP and was timed to provide important scientific input to the IPCC AR5 assessment.

As described in Section 2.3, all three of the approaches to damage function estimation in this report use only GMST as an input to the damage module. For the two more disaggregated approaches, any needed regional or more finely spatially disaggregated temperature projections are created internal to the damage module.

Figure 2.2.3: Global Mean Surface Temperature Anomaly from a Pulse of Carbon Dioxide (1GtC) by Model, 2020-2300
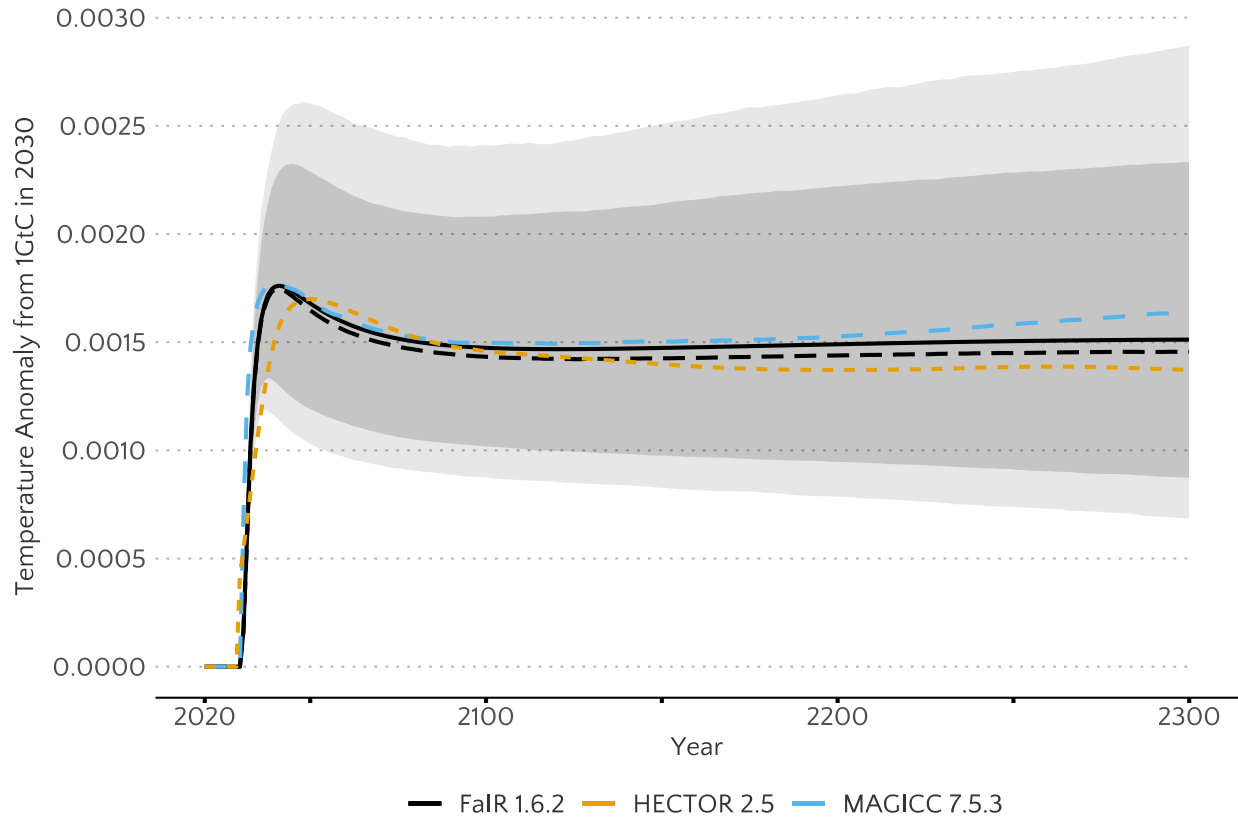
The mean global temperature response resulting from a pulse of emissions of CO₂ in 2030 as projected by FaIR1.6.2, Hector 2.5, and MAGICC 7.5.3. This represents the difference between a reference scenario (using SSP2-RCP4.5 for the figure) and the same scenario including the pulse of emissions. The emission pulse size is 1 GtC for carbon dioxide. Mean (solid) and median (dashed) lines are shown along with the 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges.

Sea Level Rise. In addition to temperature change, two of the three damage modules used in this report require global mean sea level (GMSL) projections as an input to estimate coastal damages. Those two damage modules use different models for generating estimates of GMSL. Both are based off reduced complexity models that can use the FaIR temperature outputs as inputs to the model and generate projections of GMSL accounting for the contributions of thermal expansion and glacial and ice sheet melting based on recent scientific research. Absent clear evidence on a preferred model, the SC-GHG estimates presented in this report retain both methods used by the damage module developers.

The first damage module used in this report (discussed in Section 2.3.1) projects GMSL using an implementation of the Framework for Assessing Changes To Sea-level (FACTS). FACTS is a flexible computational framework, that can mix and match components of different models in order to further explore uncertainty that is being used for the IPCC AR6 SLR projections (IPCC 2021c, Garner et al. 2021).[64] In this damage module, FACTS is used to project sea level rise, relying on the parameterizations based on the two approaches that the IPCC characterized as "medium confidence", and assuming that those two approaches were equally likely. This leads to a slightly narrower projected SLR range than the likelihood bounds from the IPCC medium confidence approach (given two distributions, the IPCC used the outermost probability for any given likelihood estimate). The choice of using only the medium confidence parameterizations leads to the lowest future sea level rise projections available from the FACTS model; the parameterization excludes the possible contributions from marine ice cliff instability (MICI) and from ocean forcing on basal melt rates that was also assessed to be low confidence by the IPCC.

The additional sea level rise resulting from the emissions pulse is estimated using what is known as a "semi-empirical"[65] sea level model (Kopp et al. 2016), which was cited by the National Academies as a potential approach for estimating sea level rise from an emissions pulse (National Academies 2017). The semi-empirical model is driven by the same probabilistic GMST projections from FaIR used in the non-coastal sectors. It is calibrated based on historical data and has its own probability distribution that is generally lower than that seen in the FACTS projections. The FACTS projections account for a best understanding of future contributions to SLR from numerous sources but cannot be applied to an individual emissions pulse. Thus, to bias-correct the semi-empirical model's projections, each probabilistic draw is quantile-mapped to an equivalent probabilistic draw of the FACTS projections within each SSP-RCP. The magnitude of the SLR impact of an emissions pulse is not changed, but the baseline SLR in the absence of the pulse is adjusted such that it is consistent with the probabilistic distribution from FACTS for each SSP-RCP. To model SLR in the RFF-SPs, for which no FACTS projections are available for bias correction, an additional quantile-mapping step is taken. This is detailed in CIL (2022).

The second SLR model used in this report, Building Blocks for Relevant Ice and Climate Knowledge (BRICK), is a semi-empirical modeling framework that simulates GMSL. Changes in global mean surface temperature drive changes in GMSL. The model includes contributions to GMSL from the Greenland and Antarctic ice sheets, thermal expansion, glaciers and ice caps, and land water storage (Wong et al. 2017, Vega-Westhoff et al. 2019). The parameterizations for the BRICK model include assumptions about

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[64] Additional information about the IPCC AR6 SLR projection methods can be found at: https://sealevel.nasa.gov/data_tools/17.

[65] Semi-empirical models are a form of reduced complexity process models. These models are known as semi-empirical because they are based on equations that embody physical understanding and calibrated to historical data. Semi-empirical models are a commonly used approach in the literature. The Kopp et al. (2016) model is based on a set of three differential equations: one to relate a change in sea level to a difference between projected atmospheric temperature and a theoretical equilibrium temperature, one to determine the change in the theoretical equilibrium temperature over time, and one to address the additional sea level rise from the climate response to long-term orbital changes. The parameters in these three equations are then calibrated against estimates of historical warming and sea level over the past millennia. The Kopp et al. model agreed well with process-based model and expert surveys available at the time. Semi-empirical models calibrated solely on historical data will not include processes that were not active over the historical calibration period, such as MICI processes (which are often not included in process-based models either).

Greenland and Antarctic melt that are consistent with the IPCC AR6 projections that include MICI. Inclusion of processes like MICI have the largest effects after 2100, and for the warmest scenarios, such that inclusion in the RCP8.5 scenario leads to an average increase of 15% in SLR by 2100 and 50% by 2150 (relative to 1850-1900, Table 9.10, IPCC 2021c). By 2300, inclusions of MICI processes for the RCP8.5 scenario results in SLR of 9.5 to 16.2 meters, which is substantially larger than the no ice-sheet acceleration assumption which yields a rise of 1.7 to 4.0 meters (Table 9.11, IPCC 2021c).

Figure 2.2.4 shows the projected global sea level change resulting from the FACTS- and BRICK-based SLR models, as implemented in the two damage modules discussed in Section 2.3. FACTS and BRICK have similar projections of SLR rise through the end of the century. BRICK, as expected, projects greater SLR in the out years because of its inclusion of accelerated melt processes for the Antarctic and Greenland ice sheet, consistent with the IPCC forecasts that include MICI processes. By 2300, BRICK estimates an average of 4 meters, while the implementation of FACTS used in this report generates SLR projections of 2 meters, on average. This difference in the out years is due to the choices of (a) relying only on IPCC's "medium confidence" SLR processes, and (b) taking an equal weighting rather than an outer envelope when combining multiple probability distributions. In the absence of a probabilistic assessment of the likelihood of these processes, this report retains use of both approaches.

In addition to surface temperatures and atmospheric concentrations, FaIR also calculates CO_2 uptake in the world's ocean as part of its carbon cycle calculation and generates projections of measures of ocean acidification (pH and ocean heat). The impacts of ocean acidification are not captured in the SC-GHG estimates presented in this report because functions that translate the pH and ocean heat outputs from FaIR into monetized global damages are not yet available in the damage module. However, given current understanding of the impacts of CO_2 emissions on the growth and survival of shellfish and coral reefs, coupled with the availability of market and nonmarket valuation studies on the ecosystem services they provide, it is likely feasible to develop damage functions that include ocean acidification impacts in future SC-GHG updates. See section 3.2 for more discussion of damages associated with ocean acidification and other impacts of climate change that are not captured in this report.

Figure 2.2.4: Global Sea Level Rise in FACTS and BRICK, 1950-2300
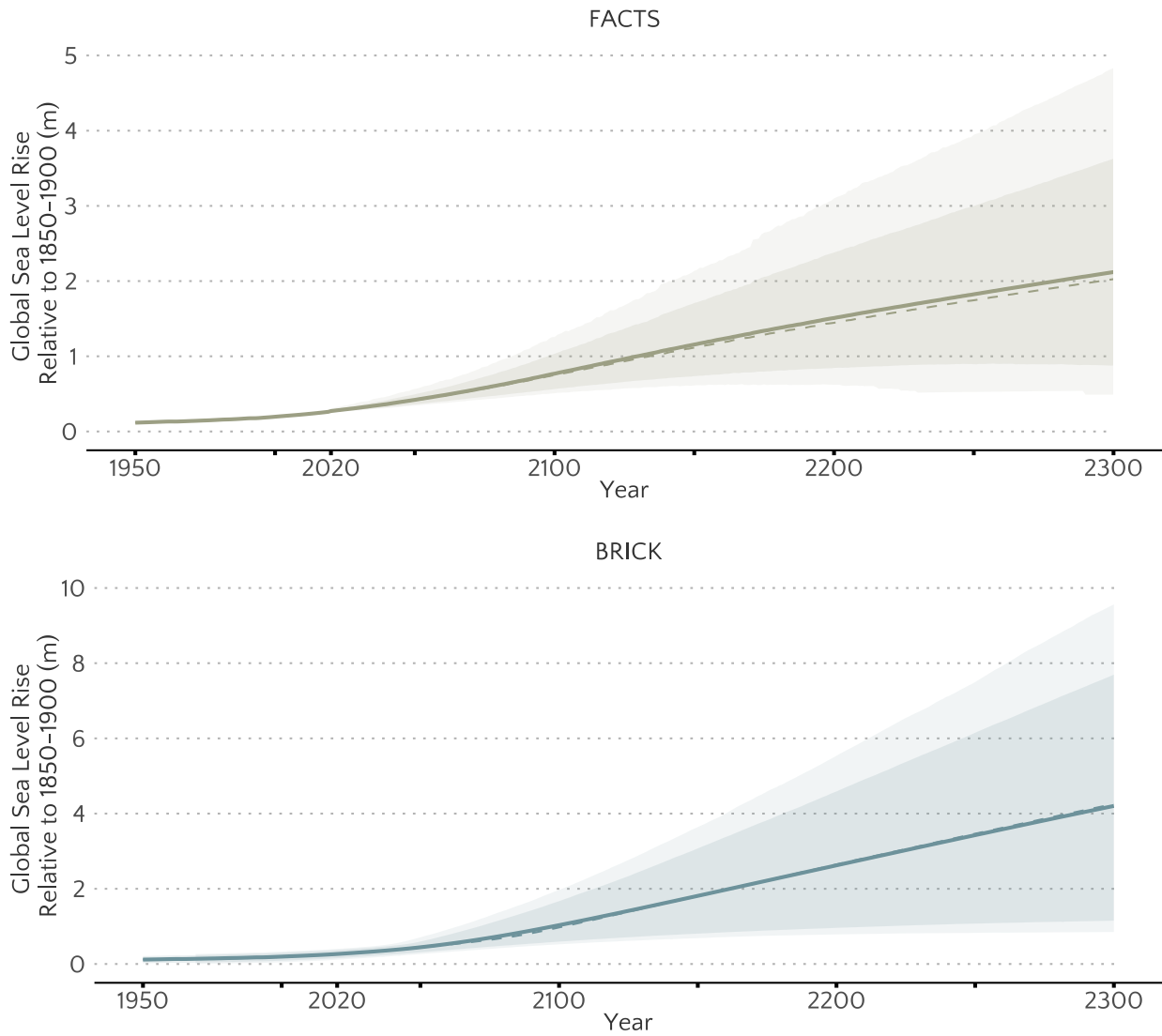
The range of global mean sea level rise relative to pre-industrial (1850-1900) as calculated by FACTS (top) and BRICK (bottom). Uncertainty comes from emissions uncertainty from the RFF-SP projections, physical climate uncertainty from FaIR, and parameter uncertainty underlying each SLR module. Mean (solid) and median (dashed) lines are shown along with the 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges.

2.3   Damage Module

The damage module contains the core "damage functions" in the SC-GHG estimation process. Damage functions translate changes in temperature and other physical impacts of climate change into monetized estimates of net economic damages. The damage functions capture multiple net damage pathways that can be broadly divided into market and non-market pathways. Some net economic damages are experienced through markets, such as changes in net agricultural productivity, net energy expenditures, and property damage from increased flood risk. Examples of net damages experienced through the nonmarket pathways include changes in net mortality rates and changes in ecosystem services, including those provided by biodiversity.

As discussed above, the SC-GHG estimates used in the EPA's analyses to date have maintained the damage functions contained in the default version of the DICE, FUND, and PAGE IAMs as used in the peer-reviewed literature. Specifically, the damages functions underlying the IWG SC-GHG estimates used since 2013 are taken from DICE 2010 (Nordhaus 2010); FUND 3.8 (Anthoff and Tol 2013a, 2013b); and PAGE 2009 (Hope 2013).[66] These models all take stylized, reduced-form approaches to estimating monetized damages as a function of temperature change and sea level rise. They use a suite of underlying studies to calibrate their damage functions. FUND 3.8 takes a regional bottom-up approach to specify the damage function by calibrating to or building up disaggregated pieces consisting of 14 separate damage categories or sectors using studies and assumptions relating to each sector. Damages in DICE 2010 are an aggregate based on a calibration of sectoral damages (Nordhaus and Boyer 2000) and scaled using aggregate damages. PAGE 2009 employs a regionalized hybrid approach with an estimate of four categories of damages: economic, sea-level rise, nonmarket, and discontinuities.

The National Academies' recommendations for the damage module, scientific literature on climate damages, updates to models that have been developed since 2010, as well as the public comments received on individual EPA rulemakings and the IWG's February 2021 TSD, have all helped to identify available sources of improved damage functions. The IWG (e.g., IWG 2010, 2016a, 2021), the National Academies (2017), comprehensive studies (e.g., Rose et al. 2014), and public comments have all recognized that DICE 2010, FUND 3.8, and PAGE 2009 do not include all the important physical, ecological, and economic impacts of climate change. The climate change literature and the science underlying the economic damage functions have evolved, and DICE 2010, FUND 3.8, and PAGE 2009 now lag behind the most recent research.

The challenges involved with updating damage functions have been widely recognized. Functional forms and calibrations are constrained by the available literature and need to extrapolate beyond warming

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[66] The damages functions underlying the IWG SC-GHG estimates used from 2010 to 2013 came from earlier versions of each model: DICE 2007 (Nordhaus 2008), FUND 3.5 (Narita et al. 2010), and PAGE 2002 (Hope 2006). The newer versions of each model that have been used by the IWG since 2013 included a number of updates related to their damage functions. For example, DICE 2010 included a re-calibrated damage function with an explicit representation of economic damages from sea level rise. Updates in FUND 3.8 included revised damage functions for space heating, SLR, and agricultural impacts. PAGE 2009 added an explicit representation of SLR damages, revisions to ensure damages do not exceed 100% of GDP, a change in regional scaling of damages, revised treatment of potential abrupt damages, and updated adaptation assumptions. See IWG (2013) for more discussion of each of these changes.

levels or locations studied in that literature. Research and public resources focused on understanding how these physical changes translate into economic impacts have been significantly less than the resources focused on modeling and improving our understanding of climate system dynamics and the physical impacts from climate change (Auffhammer 2018). Even so, as illustrated in Figure 2.3.1, there has been a large increase in research on climate impacts and damages in the time since DICE 2010, FUND 3.8, and PAGE 2009 were published. Along with this growth, there continues to be wide variation in methodologies and scope of studies. Comparability issues across both methods and studies create challenges for synthesizing the current understanding of impacts or damages.

Figure 2.3.1: Research on Climate Impacts, 1990-2021[67]
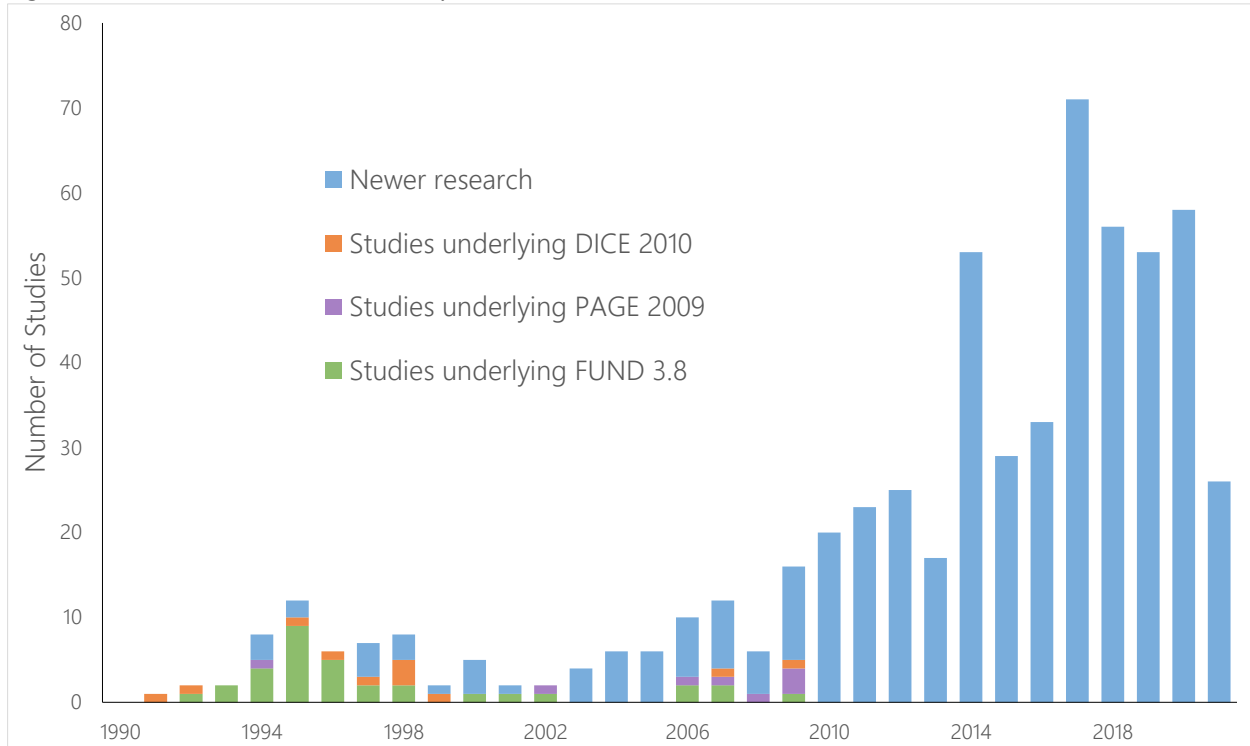
Source: Greenstone (2016), updated in 2021.

Approaches to developing a damage module for SC-GHG estimation can be generally grouped into two broad categories: those that estimate a damage function by calibrating to or building up disaggregated pieces, and studies that estimate an aggregate global damage function directly. The more disaggregated approach typically involves spatially explicit and sector-specific modeling of relevant processes and then

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[67] In many cases, the three IAMs used different studies for calibration. This is particularly true of FUND, which used studies relating to different subsectors of the model, whereas DICE and PAGE did not have as detailed a sectoral breakdown. That means that summing across these different models is likely valid in all but a few isolated cases. The blue bars include studies uncovered from a comprehensive literature review in the economics literature (and a few others in public health or relevant disciplines) by the Climate Impact Lab through early 2016. Each of the studies counted in blue was determined by CIL to have employed a research design that allowed for the causal interpretation of results (Greenstone 2016).

aggregates regional or sectoral damages.[68] Alternatively, the aggregate global damage function estimation approach often relies on meta-analysis techniques (e.g., as in recent versions of DICE (DICE 2013R and DICE 2016)) or total-economy empirical studies that econometrically estimate the relationship between GDP and a climate variable, usually temperature (e.g., used in part in the most recent version of the PAGE model (PAGE 2020 (Kikstra et al. 2021)). There are also more complex ways to estimate damage functions directly (e.g., that have been used in extensions of DICE) and through expert elicitation (e.g., Pindyck 2019, Howard and Sylvan 2021). Based on a review of available studies using these approaches, the SC-GHG estimates presented in this report rely on three damage functions. They are:

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

Each is discussed in turn.

2.3.1 Damage Module based on the Data-driven Spatial Climate Impact Model (DSCIM)

DSCIM was developed by the Climate Impact Lab (CIL). CIL is a multidisciplinary consortium of climate scientists, economists, computational experts, researchers, and analysts building empirically derived, local-level estimates of the net damages from climate change and empirically based SC-GHG estimates.[69] The DSCIM modeling runs performed for the estimates presented in this report are described in the September 2022 DSCIM User Manual (CIL 2022). DSCIM monetizes climate damages for nearly 25,000 global impact regions using econometric methods that account for local conditions, including adaptation investments, when estimating the effect of climate change on sector specific outcomes. These local damages are aggregated to develop an estimate of global damages as a function of global temperature changes. The damage functions for DSCIM are constructed through a five-step process. First, researchers collect and harmonize historic climate and socioeconomic data for each sector. Second, using variation in short-run weather and cross-sectional variation in the long-run average climate and socioeconomic conditions, they econometrically estimate the effect of changes in local climatic conditions on sector-specific outcomes, accounting for the adaptive effects of climate and socioeconomics, which can alter the sensitivity of outcomes to local climate. Third, they use a revealed preference approach to infer the adaptation costs incurred by populations as they adapt to warming, drawing on research by Guo and

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[68] There are also multisectoral, multiregional economic computable general equilibrium (CGE) models. CGE models calibrate to region-sector impact estimates but account for more interactions among regions, impacts, supply, and demand factors.

[69] The Climate Impact Lab team combines experts from the University of California, Berkeley, the Energy Policy Institute at the University of Chicago (EPIC), Rhodium Group, Rutgers University, University of California, Santa Barbara, and University of Delaware. More information on the individual researchers and institutions involved in the Climate Impact Lab can be found at: http://www.impactlab.org/.

Costello (2013) and Deryugina and Hsiang (2017).[70] Fourth, they project sector-specific outcomes and associated monetized damages into the future by combining the econometric results with a probabilistic ensemble of high-resolution downscaled climate projections from 33 global climate models[71] and aggregate the local damages to global damages. Finally, they use these projections to estimate global damages as a time-varying reduced-form function of global mean surface temperature. The advantage to this approach is that global damage estimates reflect the empirically derived local impact relationships, and account for the uncertainty in economic growth, temperature change, and adaptation. For the DSCIM model runs in this report, the outputs of the socioeconomic module (Section 2.1) and the GMST output from the climate module (Section 2.2) are used as inputs in DSCIM.[72]

At present, DSCIM includes the estimation of climate damages occurring in five sectors or impact categories: health, energy, labor productivity, agriculture, and coastal regions (CIL 2022).[73] Table 2.3.1 summarizes key elements of DSCIM's damage function estimation methods in each of these five sectors. The health component includes the value of net changes in hot- and cold-related mortality risk (Carleton et al. 2022). The building block of the global mortality damage function is the estimation of temperature's impact on mortality rates using historical data. The mortality data is assembled from various sources at the subnational spatial scale[74] for 40 countries covering 38 percent of the global population.[75] Temporal coverage for each country ranges from 13 years (1997-2010) to over 40 years (e.g., 1968-2010 for the U.S.) across the sample. The age-specific mortality-temperature response is estimated as a linear function of nonlinear daily grid-level temperature and precipitation data transformations. This specification, together with the inclusion of fixed effects to account for any time-varying trends or shocks to age-specific mortality rates unrelated to climate, allows them to isolate the impact of year-to-year, within-location variation in temperature and rainfall on mortality. Additionally, this model recovers the effect of climate-driven adaptation (e.g., more cooling systems) and income growth on the shape of the temperature mortality relationship, as observed in the historical record using cross-sectional variation in long-run average conditions. These econometric estimates are combined with high-resolution projections of climate, income, and demographics to compute age-specific projected impacts of climate change under

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[70] The method for estimating the costs of adaptation reflects that people invest in adaptive behaviors and technologies until the costs of doing so just equal the protective benefits. The protective benefits are observed through the changes in the estimated sensitivity of outcomes to temperature (or rainfall or sea level rise) as the climate gradually warms. The estimated measures of these benefits are used to back out the costs of the adaptation. See Carleton et al. (2022) for more discussion.

[71] See CIL (2022) for a detailed discussion of the ensemble of climate projections.

[72] To incorporate the RFF-SPs for model runs performed for this report, DSCIM uses an emulator approach that allows for the estimation of probabilistic socioeconomics in DSCIM's highly complex and disaggregated damage system. The emulator weights the outcome of annual global aggregate damage functions that are estimated using the suite of SSP-RCP combinations according to how closely the socioeconomics characteristics each year match those contained in the RFF-SPs. See CIL (2022) for more details.

[73] CIL plans to update DSCIM regularly with representation of additional sectors (CIL 2022).

[74] The mortality data is at the second administrative level (e.g., county), first administrative level (e.g., state), or somewhere in between.

[75] Carleton et al. (2022) also have data from India (which increases coverage to 55% of the global population) but are unable to include it in the main estimation of the mortality-temperature response function due to the absence of age-specific mortality statistics. Instead, the authors use the India data to assess external validity of their extrapolation methods and find the model generates conservative predictions of mortality impacts of climate change in India, a hot and poor region of the globe.

multiple emissions scenarios at the scale of ~25,000 global regions. While the main specification of DSCIM employs an age-adjusted valuation approach for monetizing net health damages (inclusive of adaptation costs), in the results presented in this report, the projected changes in premature mortality are monetized using country-level population-average measures of the willingness-to-pay for mortality risk reductions.[76]

The energy component includes energy expenditures from temperature-related changes in electricity and direct fuel consumption across residential, commercial, and industrial end-uses (Rode et al. 2021). Rode et al. provide the first estimate of the global impact of climate change on total energy consumption using globally comprehensive data, accounting for economic development and adaptive behavior. Energy consumption data for electricity and other fuels is compiled from the International Energy Agency and is available at the country-by-year level for 146 countries from 1971 to 2010. Daily historical climate data are aggregated to annual, country-level observations following the method in Carleton et al. (2022), which preserves local-level nonlinearities in the relationship between energy consumption and temperature. Modeled energy responses to temperature changes reflect income changes and climate adaptation (e.g., installation of air conditioning in areas that currently have little penetration and more frequent operation of existing air conditioning equipment). Similar to Carleton et al., the modeled energy-temperature relationship for a local impact region is a function of conditions at that location. This allows the authors to compute the additional impact of climate change on energy consumption, net of local factors (e.g., income) that will change in the future. Using the same income and climate projections as in Carleton et al. (2022), Rode et al. compute projected impacts of climate change on electricity and other fuels consumption under multiple emissions scenarios at the scale of ~25,000 global regions. To value these impacts, the results presented in this report use country-level energy prices from the International Energy Agency's (IEA) *World Energy Outlook* and *Energy Prices and Taxes* dataset. Prices are extrapolated into the future based on the growth rates projected in the U.S. Energy Information Administration's *Annual Energy Outlook 2021.* Specifically, based on the AEO projections, prices are assumed to grow at an annual rate of -0.27% and 0.82% for electricity and other fuels, respectively. See CIL (2022) for more discussion.

The labor productivity component of the model captures the value of labor losses, as measured in labor disutility, from responses in daily temperature (Rode et al. 2022). Evidence shows that workers in industries such as agriculture, construction, manufacturing, transport, and utilities reduce their hours worked when outdoor temperatures deviate from average temperatures.[77] Daily variation in weather for seven countries representing about 30 percent of the global population is used to econometrically

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[76] Specifically, projected changes in premature mortality in the U.S. are monetized using the same value of mortality risk reduction as in the EPA's regulatory analyses ($4.8 million in 1990 (1990USD)) and adjusted for income growth and inflation following current EPA guidelines and practice (EPA 2010) and consistent with EPA Science Advisory Board (SAB) advice (see e.g., EPA 2011, OMB 2003), resulting in a 2020 value of $10.05 million (2020USD). Valuation of mortality risk changes outside the U.S. is based on an extrapolation of the EPA value that equalizes willingness-to-pay as a percentage of per capita income across all countries (i.e., using an assumed income elasticity of 1). The use of a benefits transfer approach based on a positive income elasticity is consistent with the approach used in the default version of the models and published studies used in this report (e.g., Rennert et al. 2022b, Carleton et al. 2022, Diaz 2016), and other academic literature. See Appendix A.6 for more discussion.

[77] See Rode et al. (2021) for a listing of literature across many disciplines that have studied the effects of temperature on worker performance and labor, dating back to Huntington (1922).

estimate subnational labor supply responses to temperature changes. The labor response is estimated to be an inverted U-shaped relationship, with lost labor occurring at extreme hot and cold temperatures, for high-risk, weather-exposed sectors and low-risk sectors. The labor supply temperature response is projected globally and over time, following Carleton et al. (2022) and Rode et al (2021). It includes predicted shifts towards less weather-exposed industries as a function of average income per capita and long-run average temperature, analogous to other forms of adaptation accounted for in Carleton et al. (2022) and Rode et al (2021). The value of lost productivity is monetized as the compensating wage increase needed to offset the temperature change's disutility.

DSCIM captures the net production impact of climate change in the agriculture sector by computing projected impacts for six globally and regionally important staple crops that represent two thirds of global crop caloric production: maize, wheat, rice, soybean, sorghum, and cassava (Hultgren et al. 2022). The DSCIM reduced-form econometric approach simultaneously captures the combined impact of biophysical crop responses and producer decision-making to account for the costs, benefits, and adoption rates of producer adaptations as they are observed in practice around the world. This contrasts with prior analyses that rely on agronomic process-based models to explicitly characterize the biophysical processes to project yields. DSCIM accounts for several types of adaptation. First, the model allows for within-crop adaptations such as varietal switching and other changes in production methods, such as irrigation, fertilization, and planting dates. Second, in the monetization step, the results are multiplied by 0.45 to account for crop switching and trade protective effects, from frictionless trade within continents and global trade networks, based on an average of the estimates in prior research documenting these quantities (e.g., Rising and Devineni 2020; Costinot et al. 2016; Gouel and Laborde 2021; Stefanović et al. 2016). The DSCIM results presented in this report also account for the fertilization benefits of CO_2 emissions on crop yields based on established estimates in the literature (Moore et al. 2017).

Finally, the coastal component of DSCIM estimates damages resulting from sea level rise inundation in coastal regions. As described in Section 2.2, the GMSL projections are based on the probabilistic FACTS model that is being used in IPCC's AR6 report (Kopp et al. 2016, Garner et al. 2021). To generate a damage function relating GMSL to welfare loss, probabilistic local mean sea level (LMSL) projections are used as inputs to an updated version (Depsky et al. 2022) of the Coastal Impact and Adaptation Model (CIAM) (Diaz 2016). These projections come from LocalizeSL (Kopp et al. 2017), using AR5 emissions trajectories. The updated CIAM model (pyCIAM) estimates highly localized SLR related damages (Diaz 2016). CIAM is a deterministic optimization model that chooses the least-cost adaptation strategy for each of the 9,000 coastal segments defined in the Sea Level Impacts Input Dataset by Elevation, Region, and Scenario (SLIIDERS, Depsky et al. 2022)[78] after accounting for local physical and socioeconomic characteristics.[79]

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[78] The SLIIDERS dataset provides details on local physical and socioeconomic characteristics. The original CIAM uses 12,148 coastal segments in the Dynamic Interactive Vulnerability Assessment (DIVA) database. The use of 9,000 segments in DSCIM is just the result of Depsky et al. (2022)'s re-optimization of the coastal segment choices (e.g., in the original CIAM inputs, 10% of the 12,000 global segments were in French Polynesia).

[79] In CIAM the adaptation choice set includes: (1) retreating inland from the coastline, (2) protecting coastal communities and infrastructure, or (3) taking no adaptive measures. The decision maker first selects the lowest-cost combination of these and then chooses the degree of investment in coastal defense against several different return periods, under the assumption of perfect foresight about SLR conditions. Ongoing research is being developed by Diaz and collaborators to refine the foresight assumptions and the resulting coastal damages from SLR.

Damages are then estimated as the costs associated with the selected adaptation strategy plus the residual damages due to inundation, wetland loss, and flooding.

Table 2.3.1: Current Coverage of Climate Damages in DSCIM

Sector	Damage Categories Represented	Empirical Basis for Damage Function Estimation	Accounting for Adaptation	Documentation
Health	Heat- and cold-related mortality	Subnational annual mortality statistics for 40 countries covering 38% of global population; 1990-2010 or longer for most countries	Accounts for adaptive effects of income growth and estimates the costs of adaptive investments using a revealed preference approach	Carleton et al. (2022)
Energy	Expenditures for electricity and other direct fuel consumption	Annual country-level energy consumption data (residential, commercial, and industrial) by energy source for 146 countries, 1971-2010	Accounts for both climate- and socioeconomics-driven adaptive responses	Rode et al. (2021)
Labor Productivity	Labor disutility costs from labor supply responses to increased temperature	Daily worker-level labor supply data (minutes worked) from 7 countries representing nearly 30% of global population	Accounts for shifts in workforce composition to less weather-exposed industries	Rode et al. (2022)
Agriculture	Production impacts for six crops: maize, rice, wheat, soybeans, sorghum, and cassava	Subnational crop production data for over 12,658 sub-national administrative units from 55 countries	Accounts for CO_2 fertilization effects, varietal switching, changes in production methods (e.g., irrigation, fertilization, planting dates), crop switching, and trade effects	Hultgren et al. (2022)
Coastal regions	Impacts of SLR as realized through inundation, migration, protection, dry and wetland loss, and mortality and physical capital loss from SLR	Numerous empirical findings are used to parameterize the CIAM process model for 9,000 coastal segments. (Low levels of SLR in the historical record prohibit the use of a fully empirical model)	Reflects retreat or protective infrastructure and costs under an optimal adaptation scenario with perfect foresight of SLR	Kopp et al. (2016) and Garner et al. (2021) for SLR; Diaz (2016) and Depsky et al. (2022) for damages

2.3.2   Damage Module Based on the Greenhouse Gas Impact Value Estimator (GIVE)

The second damage module used in this report is taken from the GIVE integrated assessment model (IAM). GIVE is an open-source IAM developed under the Resources for the Future Social Cost of Carbon Initiative in collaboration with dozens of researchers from private and public institutions across the globe, spanning a wide range of disciplines (Rennert et al. 2022b). The model was developed in direct response to the National Academies (2017) recommendations surrounding needed improvements in the estimation of the SC-GHG. The damage function component of the model is structured in such a way that it can accommodate additional damage sectors underlying the estimation of the SC-GHG, making it particularly attractive for incorporating future research and findings.[80] Moreover, the model can accommodate components with differing temporal and spatial resolutions. The model can be estimated deterministically (fixed parameter) or in a Monte Carlo (random parameter) setting, sampling from socioeconomic, climate, and damage function distributions to allow for uncertainty within and across each of its components. In the model runs performed for this report, the outputs of the socioeconomic module and the GMST projections from the climate module described above serve as inputs to the damage function components of GIVE.

At present, GIVE includes estimation of climate damages occurring in four sectors or impact categories: health, energy, agriculture, and coastal regions.[81] The damage functions reflect recent scientific advancements in the peer-reviewed literature. Table 2.3.2 summarizes key elements of GIVE's damage function estimation methods in in each of these four sectors. The health damage function is based on a recent study authored by a collaboration of public health, epidemiology, climatology, and economics experts in response to the 2017 National Academies' recommendations (Cromar et al. 2022). The authors, along with an additional panel of convening experts, conducted a systematic review and meta-analysis of health impacts related to climate change. Then, regionally resolved all-cause mortality estimates from increases in temperature were generated through a random-effects pooling of studies that were identified in the systematic review.[82] Net changes in mortality risk associated with increased average annual temperatures were estimated for all global regions varying in their effect size and uncertainty across each of the 9 regions. The resulting changes in premature mortality are mapped to country-specific baseline mortality projections and rates such that premature mortality from global climate change is unique to all 184 countries. Uncertainty in the mortality damage function is parametric and sampled from the region-specific coefficient that relates GMST to changes in premature mortality. The GIVE model monetizes the projected changes in premature mortality using country-level population-average measures of the willingness-to-pay for mortality risk reduction (Rennert et al. 2022b), consistent with methodology used in the DSCIM model runs presented in this report and described above.

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[80] The GIVE model is built on the Mimi.jl platform, an open-source package for constructing modular integrated assessment models, www.mimiframework.org. GIVE is written using the Julia programming language which allows for extremely fast estimation times.

[81] The modular nature of GIVE offers a straightforward way to add other damage functions and sectors. For example, nonuse biodiversity losses are currently under development based on an approximation of Brooks and Newbold (2014).

[82] A total of 33 unique health studies, most of which were extensive multi-locational studies, were included in Cromar et al. (2022). Studies were predominately from North America, Europe, and East Asia and thus some of the more populous parts of the world were underrepresented (Cromar et al. 2022).

The energy damage function component of GIVE is based on a recent multidisciplinary study that estimates the relationship between changes in building energy expenditure (net heating and cooling expenses) and changes in local temperature and climate (Clarke et al. 2018). That study used the Global Change Analysis Model (GCAM) that models regional changes in heating and cooling expenditures as a proportion of regional gross domestic product resulting from changes in regional temperatures. That is, for each of the 12 GCAM regions, Clarke et al. (2018) find an approximately linear relationship between degrees of temperature change and net change in energy expenditures. Reflecting this, the climate-expenditure relationship from Clarke et al. (2018) is estimated within GIVE by a regional linear regression that yields region-specific damage functions to estimate changes in net energy expenditures within each of the 184 countries in the model.

The agriculture damage function component of GIVE follows Moore et al. (2017). It is derived using (1) a meta-analysis of over 1,000 published temperature-yield response estimates from 55 unique studies, and (2) an open-source computable general equilibrium (CGE) model that estimates the welfare consequences (as equivalent variation) of climate-induced productivity changes, accounting for adjustments in agricultural markets including trade patterns, consumption, and production. The productivity changes (for maize, rice, wheat, and soybeans) are based on biophysical crop impacts documented in the literature. Productivity impacts include both within-crop adaptations (e.g., varietal and planting date changes) as well as CO_2 fertilization using estimates of the size of these effects from the meta-analysis. Welfare changes at 1, 2 and 3 degrees of warming calculated from the CGE model give damage functions for 140 regions. GIVE maps the regions to all 184 countries for country-level effects on crop production. Within GIVE, the non-parametric uncertainty provided in Moore et al. (2017) is converted to parametric uncertainty and used in the Monte Carlo estimation.

The fourth damage sector in GIVE connects the BRICK sea level rise (SLR) model (Wong et al. 2017) and the CIAM model (Diaz 2016) to estimate SLR induced coastal damages from temperature change. As described in Section 2.2, GMST and ocean heat content from FaIR 1.6.2 are used as inputs to BRICK to generate projections of GMSL. As in the damage module described above based on DSCIM, the GMSL projections are downscaled to a 1-degree grid (Slangen et al. 2014) and used as inputs to CIAM to estimate local adaptation decisions and their associated costs.[83] Since CIAM is a deterministic model, uncertainty in coastal damages is the result of uncertainty in BRICK that arises due to the RFF-SP probabilistic emission scenarios and sampled climate and sea-level parametric uncertainty.

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[83] As noted in Section 2.3.1, CIAM includes 12,148 unique coastal segments. Of these 11,835 correspond to countries included in the GIVE model. See Rennert et al. (2022b) for a full description.

Table 2.3.2: Current Coverage of Climate Damages in GIVE

Sector	Damage Categories Represented	Empirical Basis/Methodology	Accounting for Adaptation	Documentation
Health	Heat- and cold-related mortality risk	Pooled effect estimates (36 studies across 9 regions) for changes in temperature on mortality risk, by region	Observed responses to changes in temperature are assumed to persist into the future	Cromar et al. (2022)
Energy	Expenditures for space heating and cooling in buildings	Regional costs of energy consumption, temperature, and climate	Implicit in the regional relationship between increases in energy expenditures and temperature	Clarke et al. (2018)
Agriculture	Welfare changes from temperature driven changes in production of four crops: maize, rice wheat, and soybeans	Meta-analysis of 1010 yield effect estimates from 55 studies and computable general equilibrium (CGE) model of trade	Explicit in the estimation of the damage function through assumed changes in on-farm, within-crop, management practices. Adaptive adjustments in agricultural markets through changes in crops, trade, consumption, and production patterns.	Moore et al. (2017)
Coastal regions	Impacts of SLR as realized through inundation, migration, protection, dry and wetland loss, and mortality and physical capital loss from SLR	Numerous empirical findings are used to parameterize the CIAM process model for 11,835 coastal segments	Reflects retreat or protective infrastructure and costs under an optimal adaptation scenario with perfect foresight of SLR	Wong et al. (2017) for SLR; Diaz (2016) for damages

The damage functions in DSCIM and GIVE represent substantial improvements relative to the damage functions underlying the SC-GHG estimates used by the EPA to date in reflecting the forefront of scientific understanding about how temperature change and SLR lead to monetized net (market and nonmarket) damages for several categories of climate impacts. The models' spatially explicit and sector-specific modeling of relevant processes allows for improved understanding and transparency about mechanisms through which climate impacts are occurring and how each sector contributes to the overall results, consistent with the National Academies' recommendations. DSCIM addresses common criticisms related to the damage functions underlying current SC-GHG estimates (e.g., Pindyck 2017) by developing multi-sector, empirically grounded damage functions.[84] The damage functions in the GIVE model offer a direct implementation of the National Academies' near-term recommendation to develop updated sectoral damage functions that are based on recently published work and reflective of the current state of knowledge about damages in each sector. Specifically, the National Academies noted that "[t]he literature on agriculture, mortality, coastal damages, and energy demand provide immediate opportunities to

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[84] Note that Pindyck has consistently noted that modeling and damage category considerations are not a reason to abandon the social cost of greenhouse gases; Pindyck has consistently supported updating the IWG's past estimates (Pindyck 2013, 2017, 2019, 2021).

update the [models]" (National Academies 2017, p. 199), which are the four damage categories currently in GIVE. A limitation of both models is that the sectoral coverage is still limited. Neither DSCIM nor GIVE yet accommodate estimation of other categories of temperature driven climate impacts (e.g., storm damage, morbidity, conflict, migration, biodiversity loss); damages that result from physical impacts other than temperature and SLR (e.g., changes in precipitation, ocean acidification, non-temperature-related mortality such as diarrheal disease and malaria); or many feedbacks and interactions across sectors and regions that can lead to additional damages.[85],[86] DSIM and GIVE do account for the most commonly cited benefits associated with CO_2 emissions and climate change – CO_2 crop fertilization and declines in cold related mortality.   As such, the GIVE- and DSCIM-based results presented in this report provide a partial estimate of future climate damages resulting from incremental changes in CO_2, CH_4, and N_2O. DSCIM and GIVE developers have work underway on other sectors that may be ready for consideration in future updates (e.g., morbidity and biodiversity). DSCIM and GIVE are structured so that future research can be reasonably incorporated into their damage modules.

2.3.3   Damage Module Based on a Meta-Analysis Approach

Given the still relatively narrow sectoral scope of the recently developed DSCIM and GIVE models, this report includes a third damage function that reflects a synthesis of the state of knowledge in other published climate damages literature. Studies that have employed meta-analytic techniques[87] offer a tractable and straightforward way to combine the results of multiple studies into a single damage function that represents the body of evidence on climate damages that pre-date CIL and RFF's research initiatives.

Meta-analysis is a common tool in empirical research. Within the climate change literature, meta-analyses have been used to analyze physical and sector impacts (e.g., Moore et al. 2017, Hoffmann et al. 2020, Cromar et al. 2022) and to directly estimate aggregate global damage functions. The first use of meta-analysis to combine multiple climate damage studies was done by Tol (2009) and included 14 studies. The studies in Tol (2009) served as the basis for the global damage function in DICE starting in version 2013R (Nordhaus 2014). The damage function in the most recent version of DICE, DICE 2016, is from an updated meta-analysis based on a rereview of existing damage studies and included 26 studies published over 1994-2013 (Nordhaus and Moffat 2017). Howard and Sterner (2017) provide a more recent peer-reviewed meta-analysis of existing damage studies (published through 2016) and account for additional features of the underlying studies. They address differences in measurement across studies by adjusting estimates such that the data are relative to the same base period. They also address issues related to double counting by removing duplicative estimates. Dependence across climate-damage estimates can arise over time due to the common practice of calibrating climate-model damage functions based on previous estimates in the climate damage literature. Howard and Sterner's review identified 35 studies that meet

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

[86] See Section 4.2 for more discussion of omitted categories of climate impacts and associated damages.

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

their *a priori* selection criteria, of which 15 were dropped because they duplicated studies already in the sample. Their final sample is drawn from 20 studies that were published through 2015.

Howard and Sterner (2017) present results under several specifications, and their analysis shows that their estimates are somewhat sensitive to defensible alternative modeling choices. Howard and Sterner's main specifications vary across two dimensions: (1) whether the sample includes estimates from studies that consider large temperature changes (i.e., above 4°C), and (2) whether the econometric specification explicitly accounts for different damage channels underlying the studies, such as studies that attempt to account for the effect of climate impacts on economic productivity, and whether or not the estimates of those damage channels should be additive to the primary damage estimate in the model.

Regarding the first dimension, this report focuses on a specification that includes estimates across the full range of temperature changes considered in the underlying studies. Howard and Sterner's reasoning for considering only estimates for temperature changes below 4°C is that, in their modeling, most present value damages occur before 2100 and at or below 4°C.[88] Applying the same logic would lead to the opposite conclusion in the current modeling framework. After incorporating major advancements in the socioeconomics, climate and discounting modules, as discussed in sections 2.1, 2.2, and 2.4, a significant share of the temperature anomaly distribution exceeds 4°C based on RFF-SPs and FAIR1.6.2 over the modeling horizon (2020 to 2300) and a significant amount of estimated discounted damages occur after 2100 (see Section 3). The coefficient estimate on the temperature variable in the specification in Howard and Sterner (2017) used in this report (i.e., the specification that includes estimates of damages at all temperatures, including those above 4°C) is smaller in magnitude than in the specification which limits the analysis to studies that estimate damages at temperatures less than 4°C. Thus, the specification used in this report reflects a more conservative estimate of the relationship between temperature and climate damages, and thereby leads to a lower estimate of the SC-GHG, all else equal.

Regarding the second dimension, this report focuses on Howard and Sterner's estimation of combined damage channels—the primary damage coefficient in their model. This choice, to exclude the coefficients on catastrophic and productivity effects, is consistent with the authors' recommendations in the published paper and follows the method Nordhaus (2019) uses to adjust the default damage function in DICE 2016 to reflect the findings of Howard and Sterner's meta-analysis. The authors' rationale for excluding the estimated coefficients on the control variables[89] for catastrophic damages and productivity impacts in the primary specification of the damage function was "because of their mixed [statistical] significance and volatility across the various specifications." The catastrophic damages coefficient is identified by five older studies which, while illustrative about the potential importance of such effects, are not grounded in empirical evidence or explicit modeling of tipping elements and other effects contemplated by the authors to lead to catastrophes.[90] There is a need for improved methods for

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[88] As noted in the published paper, "…the majority (approximately two-thirds) of the 2015 SCC estimate for DICE-2013R correspond to impacts occurring this century.…for which estimates for approximately 4°C or less are more germane" (Howard and Sterner 2017, p. 220).

[89] These control variables indicate Howard and Sterner's categorization of whether the underlying damage estimates account for potential for "catastrophic" impacts or account for the effects of climate change on economic growth.

[90] The 5 studies from which Howard and Sterner (2017) take damage estimates that were considered to include catastrophic damages were: Nordhaus (2014), Nordhaus (2008), Weitzman (2012) via Ackerman et al. (2012), Ackerman at al. (2012) adjusting Hanemann (2008), Meyer and Cooper (1995).

quantifying and incorporating these types of important elements of damages in future updates (e.g., through modeling specific tipping points and earth system feedback effects). See section 3.2 for further discussion of these considerations.

Productivity damages in Howard and Sterner (2017) are identified by four studies (2 statistical and 2 CGE) and the coefficient on the productivity indicator is estimated to be positive but not statistically different from zero in any of the specifications.[91] There is an ongoing investigation in the literature of whether temperature effects on the economy are only temporary or persistent—with empirical findings sensitive to model specification. Over the past decade, a host of empirical studies have found evidence of temperature changes having persistent effects on the economy (e.g., Dell et al. 2012; Burke et al. 2015; Deryugina and Hsiang 2017; Burke and Tanutama 2019; Colacito et al. 2019; Henseler and Schumacher 2019; Kahn et al. 2021; Kumar and Khanna 2019; Bastien-Olvera et al. 2022); this is an important finding because even small changes in economic growth rates accumulate into large economic impacts over time. However, other recent studies have failed to identify conclusive evidence of persistent effects of temperature changes (Newell et al. 2021, Kalkuhl and Wenz 2020). Given that the question of impact persistence remains largely unresolved in the empirical literature to date, and given the statistical insignificance of the estimated coefficient on the productivity indicator in the published Howard and Sterner meta-analysis, the SC-GHG estimates presented in this report do not rely on Howard and Sterner's specifications that include productivity effects. This is consistent with the authors' recommendations in the published paper, to only consider the inclusion of the productivity impact in sensitivity analysis.[92] However, this potentially important effect is worthy of additional study and the EPA will continue to follow advances in the literature on methodologies for identifying productivity effects of climate change. Finally, unlike Howard and Sterner (2017), the model runs performed for this report do not adopt a 25% adder (as used in the DICE model (e.g., Nordhaus 2017b)) to account for unknown or missing damages for the meta-analysis based damage module. Taken together, this report uses the most conservative damage function specification (that excludes duplicate studies) from Howard and Sterner (2017).[93]

2.3.4 Comparing the Three Damage Modules

Each of the three damage modules – based on DSCIM, GIVE, and the Howard and Sterner (2017) meta-analysis – is separately estimated in combination with the socioeconomics, climate, and discounting modules described elsewhere in this section. The sectoral damage modules in GIVE and DSCIM are based

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[91] The term "productivity" used in the Howard and Sterner (2017) damage function is distinct from the empirically grounded micro-economic labor productivity described in the DSCIM damages model. Instead, productivity in Howard and Sterner (2017) relates to the ongoing debate about persistence in damages as measured by changes in economic growth over time.

[92] Howard and Sterner (2017) conclude that "…given the debate over the impact of climate change on productivity and economic growth (Dell et al. 2012; Burke et al. 2015; Howard [and Sylvan] 2015), we recommend conducting an analysis of sensitivity to the inclusion of the productivity impact."

[93] This specification of Howard and Sterner's results (i.e., using the estimated temperature coefficient in specification 7 presented in Table 2 of their paper) is also provided as an alternative damage function option in the GIVE model (Rennert et al. 2022b). That is, when the Howard and Sterner (2017) damage function is used within the GIVE model, the other damage sectors (agriculture, mortality, energy, and coastal) are turned off and the Monte Carlo simulation samples from all relevant model parameter distributions including those underlying the Howard and Sterner (2017) meta-analysis damage parameters.

on different underlying information, data sources, and estimation methods.[94] GIVE and DSCIM are both independent lines of evidence from the meta-analysis-based damage module since the studies underlying each sectoral damage modules in GIVE and DSCIM are not included in Howard and Sterner's (2017) final sample of studies. Figure 2.3.2 illustrates the shape of the damage function across the three models. Specifically, the figure presents projections of total damages from climate change in 2100 as a function of GMST change. The points represent each trial of the Monte Carlo simulation where the socioeconomic and climate module parameters are consistent across damage modules (i.e., the first trial of DSCIM takes the same socioeconomic pathways and climate parameters as the first trial of GIVE and the meta-analysis-based damage function). The global damage functions shown here are generated using estimated damages in 2100 (the points) and regressing on temperature and temperature squared in 2100 at the mean (solid line), and quantile regressions at the median (dashed lines), 5th to 95th (dark shade) and 1st to 99th (light shade) percentiles.

As seen in Figure 2.3.2, there are notable differences between the damage functions. On average, DSCIM estimates lower damages but predicts a more rapidly increasing damage function beyond 4 degrees Celsius, compared to GIVE that has increasing but consistent damages throughout the temperature range. The meta-analysis-based damage function reflects the explicit quadratic nature of the published Howard and Sterner (2017) damage function. Section 3 presents the resulting SC-GHG estimates based on each damage module combined with the socioeconomic and climate modules and discusses the importance of omitted climate impacts and associated damages.

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[94] Only one component of the methodology for calculating coastal damages is common across the two models. Both DSCIM and GIVE rely on the CIAM model developed by Diaz (2016) to estimate the economic damages resulting from projections of SLR.

Figure 2.3.2: Annual Consumption Loss as a Fraction of Global GDP in 2100 Due to an Increase in Annual Global Mean Surface Temperature in the three Damage Modules
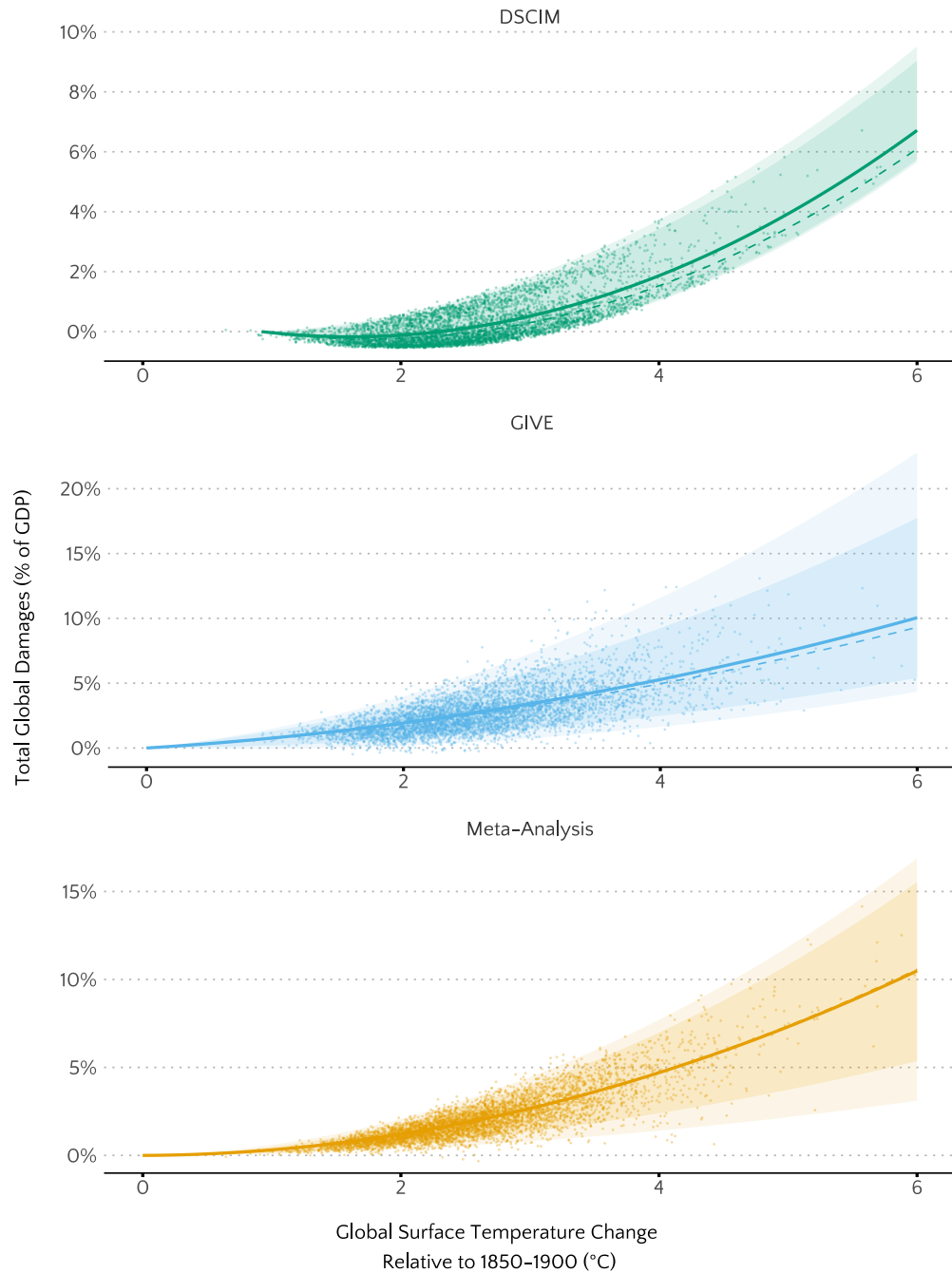
GDP loss functions are generated using estimated damages in 2100 (points) and regressing on temperature and temperature squared at the mean (solid line), and quantile regressions at the median (dashed lines), 5th to 95th (dark shade) and 1st to 99th (light shade). 5,000 of the 10,000 points for each module are randomly selected to simplify the presentation of damages. DSCIM estimates damages relative to global mean surface temparatures between 2000-2010 and was normalized here to 1850-1900 to be consistent with GIVE and the Meta-Analysis. GIVE and the Meta-Analysis presented here include the full uncertainty underlying each module in the Monte Carlo analysis, DSCIM observations present climate and socioeconomic uncertainty (no statistical uncertainty from the underlying damage functions). The IPCC (2021a) notes that present day global mean surface temperatures in the year 2020 are around 1.1 °C above preindustrial (1850-1900) levels.

2.4   Discounting Module

GHG emissions are stock pollutants, where damages result from the accumulation of the pollutants in the atmosphere over time. Because GHGs are long-lived, subsequent damages resulting from emissions today occur over many decades or centuries, depending on the specific GHG under consideration.[95] In calculating the SC-GHG, the stream of future marginal damages, as estimated by the damage modules discussed in Section 2.3, is calculated in terms of reduced consumption (or monetary consumption equivalents). Then that stream of future damages is discounted to its present value in the year when the additional unit of emissions was released. Given the long time horizon over which the damages are expected to occur, the approach to discounting greatly influences the present value of future damages.

Arrow et al. (1995) outlined two main approaches to determine the discount rate for climate change analysis, which they labeled "descriptive" and "prescriptive." The descriptive approach reflects a positive (non-normative) perspective based on observations of people's actual choices – e.g., savings versus consumption decisions over time, and allocations of savings among more and less risky investments. Advocates of this approach generally call for inferring the discount rate from market rates of return because "no justification exists for choosing [a social welfare function] different from what decisionmakers actually use" (Arrow et al. 1995).

In addition, the Kaldor-Hicks potential compensation test – one theoretical foundation for the benefit-cost analyses in which the SC-GHG will be used – suggests that market rates should be used to discount future benefits and costs. This is because the market interest rate would govern the returns potentially set aside today to compensate future individuals for the climate damages that they bear (e.g., Just et al. 2004). The word "potentially" indicates that there is no assurance that returns will be set aside to provide compensation, and the very idea of compensation is difficult to define in the intergenerational context. On the other hand, societies provide compensation to future generations through investments in human capital and the resulting increase in knowledge, infrastructure and other physical capital, and the maintenance and preservation of natural capital.

In contrast, the prescriptive (normative) approach specifies a social discount rate that formalizes the normative judgments that the decision-maker wants to incorporate into the policy evaluation. That is, it defines from the decision-maker's perspective how interpersonal comparisons of utility *should* be made and how the welfare of future generations *should* be weighed against that of the present generation. Ramsey (1928), for example, argued that it is "ethically indefensible" to apply a positive pure rate of time preference to discount values across generations.

Additional concerns motivate adjusting descriptive discount rates. Future generations' preferences regarding consumption versus environmental amenities may not be the same as those today, raising concerns about using the current market rate on consumption to discount future climate-related damages. Furthermore, markets for relatively riskless assets with a maturity similar to an intergenerational horizon, akin to the horizon over which climate change impacts are realized, do not exist (Gollier and Hammit 2014). Others argue that the discount rate should be below market rates to correct

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[95] "GHGs, for example, CO_2, methane, and nitrous oxide, are chemically stable and persist in the atmosphere over time scales of a decade to centuries or longer, so that their emission has a long-term influence on climate. Because these gases are long lived, they become well mixed throughout the atmosphere" (IPCC 2007b).

for market distortions and uncertainties or inefficiencies in intergenerational transfers of wealth (Schwartz and Howard 2022).

Further, a concern about discount rates developed using both the descriptive and prescriptive approaches is that they tend to obscure important heterogeneity in the population. For instance, many individuals smooth consumption by borrowing with credit cards that have relatively high rates. Some are unable to access traditional credit markets and rely on payday lending operations or other high-cost forms of smoothing consumption. This behavior may reflect rational intertemporal preferences, or it may reflect other factors such as present bias, lack of financial literacy, and other distortionary effects of poverty (Haushofer and Fehr 2014; Lusardi and Mitchell 2014). Nevertheless, whether one puts greater weight on the prescriptive or descriptive approach, the high interest rates that credit-constrained individuals accept suggest that some account should be given to the discount rates revealed by their behavior.

The EPA's analyses rely primarily on the descriptive approach to inform the choice of a discount rate for SC-GHG estimation, consistent with the rationale outlined in IWG TSDs (e.g., IWG 2010, 2021) and EPA's economic analysis guidelines (EPA 2010). With a recognition of its limitations, the IWG found this approach to be the most defensible and transparent given its consistency with both the standard contemporary theoretical foundations of benefit-cost analysis and the approach recommended by OMB's existing guidance.

In 2010, the IWG specifically elected to use three constant discount rates: 2.5, 3, and 5 percent per year. The 3 percent rate was included as consistent with the default recommendation provided in OMB's Circular A-4 (OMB 2003) guidance for the consumption rate of interest. The IWG found that the consumption rate of interest is the correct discounting concept to use when the future damages from climate change are estimated in consumption-equivalent units, as is done in the IAMs used to estimate the SC-GHG.[96] The 3 percent rate was roughly consistent with the average rate of return for long-term Treasury notes calculated at the time the OMB guidance was published. The upper rate of 5 percent was included to represent the possibility that climate-related damages are positively correlated with market returns, which would imply a certainty-equivalent[97] risk-adjusted rate higher than the consumption rate of interest. The low rate, 2.5 percent, was included to incorporate the concern that interest rates are highly uncertain over time, which would imply a risk-free certainty equivalent rate lower than the consumption rate of interest. Additionally, a rate below the consumption rate of interest would also be justified if the return to investments in climate mitigation is negatively (or weakly) correlated with the overall market rate of return. The use of this lower rate was also deemed responsive to certain judgments based on the prescriptive or normative approach for selecting a discount rate and related ethical objections about rates of 3 percent or higher. Further details about selecting these rates are presented in the 2010 TSD (IWG 2010).

Based on a review of the literature and data on consumption discount rates, the public comments received on individual EPA rulemakings, and the February 2021 TSD (IWG 2021), and the National Academies (2017)

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[96] Appendix A.2 provides additional detail on why the consumption discount rate is the appropriate rate to be used in estimating the SC-GHG.

[97] The certainty-equivalent discount rate is the certain discount rate that is equivalent to an uncertain discount rate in terms of the discount factor over a particular horizon. See National Academies (2017) for more explanation of this and other discounting terminology.

recommendations for updating the discounting module, this report uses a new set of discount rates that reflect more recent data on the consumption interest rate. The approach presented in this report continues to rely on a descriptive approach to discounting but more fully captures the role of uncertainty in the discount rate in a manner consistent with the other modules. Specifically, rather than using a constant discount rate, the evolution of the discount rate over time is defined following the latest empirical evidence on interest rate uncertainty and using a framework originally developed by Ramsey (1928) that connects economic growth and interest rates. The Ramsey approach explicitly reflects (1) preferences for utility in one period relative to utility in a later period and (2) the value of additional consumption as income changes. The resulting dynamic discount rate provide a notable improvement over the constant discount rate framework for SC-GHG estimation. Specifically, it provides internal consistency within the modeling and a more complete accounting of uncertainty[98], consistent with economic theory (Arrow et al. 2013, Cropper et al. 2014) and the National Academies (2017) recommendation to employ a more structural, Ramsey-like approach to discounting that explicitly recognizes the relationship between economic growth and discounting uncertainty. The following sections provide an overview of the Ramsey discounting formula and then describe the calibration of the new set of dynamic discount rates.

2.4.1   The Ramsey Formula

The Ramsey formula for discounting is derived from work by Frank Ramsey (1928) and others (Cass 1965, Koopmans 1963) on the optimal level of consumption and saving. The formula describes the optimal consumption discount rate as a function that explicitly reflects: (1) preferences for utility in one period relative to utility in a later period (called the "pure rate of time preference"); and (2) the value of additional consumption as income changes. These factors are combined in the equation

$$r_t = \rho + \eta g_t, \qquad\qquad (2.4.1)$$

where r_t is the consumption discount rate in year t, ρ is the pure rate of time preference, η is the elasticity of marginal utility with respect to consumption, and g_t is the representative agent's consumption growth rate in year t.[99]

The pure rate of time preference, ρ, is the rate at which the representative agent discounts utility in future periods due to a preference for utility sooner rather than later. The elasticity of marginal utility with respect to consumption, η, defines the rate at which the well-being from an additional dollar of consumption declines as the level of consumption increases. In this context, it is common to assume that

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[98] As noted in Circular A-4, "the longer the horizon for the analysis," the higher the "uncertainty about the appropriate value of the discount rate" (OMB 2003).

[99] The economic framework in this report implicitly assumes an exogenous fixed savings rate. With this assumption consumption growth and income (GDP) growth are equivalent. A more restrictive assumption that leads to the same result would be to assume that the savings rate is zero and consumption is equivalent to income. Relaxing the fixed savings rate assumption would require adding further complexity to calculate the optimal savings rate in each year.

well-being can be described by an isoelastic utility function, where utility, *u*, is a power function with respect to consumption, c_t, such that

$$u(c_t) = \frac{c_t^{1-\eta}}{1-\eta} .$$

(2.4.2)

This function implies that the elasticity of marginal utility with respect to consumption is a constant value (i.e., for a given percent increase in baseline consumption the benefit of an additional unit of consumption decreases proportionally). The per capita consumption growth rate, g_t, defines the projected change in consumption per capita over time. Under the common assumption of a constant savings rate, g_t would be expected to change with income over time.[100] When using the Ramsey formula to estimate the SC-GHG, the per capita consumption growth rate, g_t is calculated net of baseline climate change damages as estimated by the damage modules described in Section 2.3.

The use of the Ramsey formula provides internal consistency within the modeling between the socio-economic scenarios and the discount rate. With uncertainty in the per capita consumption growth rate, the Ramsey discount rate becomes a dynamic parameter within the modeling framework that reflects how uncertainty about future conditions has implications for how future impacts are valued. Gollier (2014) showed that when there is uncertainty in future consumption growth, the distribution of discount rates defined by the Ramsey formula will have a certainty-equivalent risk-free discount rate path that declines over time, under standard assumptions about individual preferences. This is particularly true when shocks to consumption growth are positively correlated over time, as they are in the probabilistic scenarios described in Section 2.1. The declining certainty-equivalent risk-free discount rate implied by the Ramsey formula reflects that additional climate change damages are a greater burden to society in future states of the world with relatively lower economic growth. Damages in low economic growth states of the world are given greater weight than if those same damages were realized in a future state of the world with relatively higher economic growth, all else equal (Gollier and Weitzman 2010). The declining certainty-equivalent discount rate implied by the Ramsey formula is also consistent with the empirical literature on discount rates under uncertainty (e.g., Newell and Pizer 2003, Bauer and Rudebusch 2021).[101]

The use of the Ramsey formula also provides internal consistency when accounting for the effect of correlations between climate change damages and economic growth. The correlation between climate change damages and future economic uncertainty is important in determining the appropriate discount rate. If climate change damages are positively correlated with economic growth (e.g., if the willingness to pay to avoid climate impacts increases with income or emissions), then the risk of climate change impacts being worse than expected is greater when the world is relatively wealthier than anticipated. In this case, less weight should be placed on those future impacts. Conversely, if climate change damages are negatively correlated with economic growth (e.g., if less adaptation is available at lower incomes or if climate damages slow economic growth), then the risk of climate change impacts being worse than

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[100] More information on the derivation of the Ramsey formula can be found in Dasgupta (2020).

[101] The approach employed in this report should not be confused with applying an exogenously specified declining discount rate. There are similarities, in that incorporating economic uncertainty in the Ramsey equation yields a declining certainty-equivalent discount rate. However, the application of an exogenously specified declining discount rate would fail to capture the way in which correlations between uncertain climate damages and uncertain economic growth affect estimates of the SC-GHG.

expected is greater when the world is relatively less wealthy than expected. In this converse case, more weight should be placed on those future impacts. Using the Ramsey formula for discounting in conjunction with probabilistic scenarios and modeling climate change damages under uncertainty ensures that the correlation between climate change damages and economic growth within the model is appropriately captured in the SC-GHG estimates. It allows for an internally consistent approach to capturing these effects, and exogenous adjustments to the discount rate are not required.

Incorporating dynamic discount rates through the application of the Ramsey formula remains widely used in the peer reviewed literature and is consistent with the National Academies' (2017) recommendations on discounting. It provides important improvements over the use of a static discount rate and incorporates connections between important components of the modeling. While offering an important improvement, the Ramsey formula is an approximation of complex economic processes and future research may provide methodological advancements that further improve the representation of those processes within dynamic discount rates.

2.4.2 Calibration of Discount Rate Distributions

The National Academies (2017) recommended that the IWG "choose parameters for the Ramsey formula that are consistent with theory and evidence and that produce certainty-equivalent discount rates consistent, over the next several decades, with consumption rates of interest." The SC-GHG estimates presented in this report adopt a descriptive approach to calibrating the Ramsey parameters, meaning that the parameters are calibrated based on observed interest rate data, consistent with the National Academies' recommendation. Specifically, the parameters are calibrated following the Newell et al. (2022) calibration approach, as applied in Rennert et al. (2022a, 2022b). Under this approach, the parameters are calibrated such that the decline in the certainty-equivalent discount rate path matches the latest empirical evidence on interest rate uncertainty estimated by Bauer and Rudebusch (2020, 2021). The parameters are also calibrated such that the average of the certainty-equivalent discount rate over the first decade matches a specified near-term consumption rate of interest. As described below, given the uncertainty about the appropriate starting rate, three near-term target rates (1.5, 2.0, and 2.5 percent) are used based on multiple lines of evidence on observed interest rate data. The calibration of the parameters is carried out using the same probabilistic socioeconomic scenarios presented in Section 2.1 to ensure internal consistency. This approach results in three discount rate paths and is consistent with the National Academies (2017) recommendation to use three sets of Ramsey parameters that reflect a range of near-term certainty-equivalent discount rates consistent with theory and empirical evidence on consumption rate uncertainty, and uncertainty surrounding long-run socioeconomic and emissions projections.

Specifying the near-term target rates. The near-term certainty-equivalent discount rate is calibrated based on observed interest rate data. Estimates of the risk-free consumption interest rate – used to represent temporal preferences in benefit-cost analysis – have generally focused on historical returns to long-term Treasury securities backed by the faith and credit of the U.S. Government. In particular, the estimates of the consumption interest rate published in OMB's Circular A-4 in 2003 are based on the real

rate of return on 10-year Treasury Securities[102] from the prior 30 years (1973 through 2002). However, there has been a substantial and persistent decline in real interest rates over the past four decades. Recent research has found that the decline in real interest rates reflects a reduction in the equilibrium real interest rate, suggesting that lower real interest rates are expected to persist (Bauer and Rudebusch 2020). These changes indicate the need for new estimates of the near-term consumption rate of interest that incorporate recent data.

From 2003 onwards, it is possible to use the 10-Year Treasury Inflation-Protected Securities (TIPS)[103] as a measure of the real rate of return on 10-Year Treasury Securities. Prior to the TIPS introduction, nominal returns on Treasury securities needed to be adjusted for inflation. To use the consumption interest rate as an estimate of social preferences for trading off consumption over time, the inflation adjustment should reflect investor expectations about inflation over the maturity period to produce an estimate of the tradeoff investors believe they are making. There are multiple approaches to adjusting the nominal rate for inflation expectations over the maturity of the security at the time of purchase. Three measures of inflation expectations are considered. The first is a ten-year moving average of the consumer price index (CPI)[104] prior to the year of the security issuance. This measure assumes that recent trends in inflation inform expectations over future inflation. The second is a ten-year moving average of inflation expectations as measured by the Livingston Survey, which is a survey of forecasters about key economic variables.[105] This approach has been used in the economics literature to measure inflation expectations when examining real rates of return (e.g., Newell and Pizer, 2003). The third is the perceived inflation target rate (PTR) from the Federal Reserve's FRB/US model. The PTR is an expectation of long-run inflation estimated from the Survey of Professional Forecasters (SPF). For years before the inception of the SPF, the PTR is estimated econometrically.[106] The PTR has also been used in the economics literature as a measure of inflation expectations when examining real rates of return (e.g., Fuhrer et al. 2012, Bauer and Rudebusch 2017, Bauer and Rudebusch 2020).

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[102] Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis, Series name: DGS10, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS10

[103] Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis, Inflation-Indexed, Series name: DFII10, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DFII10

[104] U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, Series name: CPIAUCSL, retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL

[105] Federal Reserve Bank Philadelphia, Consumer Price Index seasonally adjusted, rate of growth over the period from the last monthly or quarterly historical value to the month that is 12 months beyond the survey date or four quarters beyond the survey date, Series name: G_BP_To_12M; https://www.philadelphiafed.org/-/media/frbp/assets/surveys-and-data/livingston-survey/historical-data/meangrowthrate.xlsx. Additional information available at https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/livingston-survey

[106] Board of Governors of the Federal Reserve System (US), Trend price inflation measured using survey data on ten-year inflation expectations, Series name: PTR; https://www.federalreserve.gov/econres/files/data_only_package.zip. Additional information on the FRB/US model and the PTR are available from the U.S. Federal Reserve at https://www.federalreserve.gov/econres/us-models-about.htm

Table 2.4.1 presents the average real return on 10-Year Treasury securities for two time periods. The first is a 30-year period (1991-2020) following the approach taken by OMB (2003) in developing Circular A-4. The second is 48-years long (1973-2020) and includes all the years originally used by OMB (2003) in developing Circular A-4 as well as more recent data (2003-2020). The average real returns are lower under the shorter time period, reflecting the decline in real interest rates over recent decades.[107]

Table 2.4.1: Average Real Return on 10-Year Treasury Securities

	Time Period	
Inflation Measure	1991-2020	1973-2020
Consumer Price Index (CPI)	1.55%	2.12%
Livingston Survey	1.62%	2.48%
Perceived Inflation Target Rate (PTR)	1.98%	2.80%

The consideration of more recent versus older data depends on whether the downward trend in real interest rates is due to structural changes in the economy that are expected to persist. Bauer and Rudebusch (2021) estimate the current equilibrium real interest using three empirical models for the interest rate process that allows for an evolution in the equilibrium real interest rate over time. Using a time series of 10-Year Treasury securities they estimate current equilibrium real interest rates of 1.3, 1.9, and 2.4 percent.[108] When using a longer time series of long-term government securities, Bauer and Rudebusch (2021) estimate current equilibrium real interest rates of 1.5, 2.3, and 3.0 percent.[109]

Other government assessments of consumption interest rates suggest a focus on a similar range. The U.S. Congressional Budget Office's Long-Term Economic Projections forecast real rates on 10-Year Treasury securities returning to levels of 2.0% and higher over the next couple of decades (CBO 2021a, 2021b). The most recent Social Security Administrations Trustees report (SSA 2021) uses three estimates of the long-run real interest rate of 1.8%, 2.3%, and 2.8% based on their assessment of interest rates over the next couple of decades.

The empirical evidence on central tendencies for the consumption interest rate is also consistent with recent surveys of economists and technical experts on the appropriate discount rate. Drupp et al. (2018) surveyed economists who have published at least one paper on discounting in a leading economics journal

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[107] The average real return on 10-Year Treasury securities has, in general, trended downwards since the 1990s. The average real return on 10-Year Treasury securities in the period 2001-2020 was 1.1 percent and in the period 2011-2020 it was 0.2 percent. Based on empirical evidence, Bauer and Rudebusch (2021) utilize the year 1991 as a breakpoint when considering potential shifts in long-run mean of the interest rate process, which coincide with the start of the 30-year period considered in Table 2.4.1. The focus on a 30-year period is also consistent with the approach used by OMB (2003) used in developing guidance on consumption discount rates in Circular A-4. In addition, under the Ramsey approach used in this report, the certainty-equivalent discount rate for the first 30 years remains close to the near-term target, suggesting shorter time periods may not be adequately capturing the interest rate characteristics over the relevant time period.

[108] Time series of 10-Year Treasury securities from 1968-2019 with a PTR based inflation adjustment. When using 1-Year Treasury securities Bauer and Rudebusch (2021) find lower estimates of the equilibrium real interest rate ranging from 0.7 to 1.3 percent.

[109] Bauer and Rudebusch (2021) use a time series of long-term government securities from Newell and Pizer (2003), updated to include more recent data, that spans 1798-2019 and uses a ten-year moving average of the Livingston Survey CPI expectation as inflation adjustment after 1954.

about the appropriate social discount rate, finding a mean of 2.3% and a median of 2%. Howard and Sylvan (2020) surveyed experts who have published at least one article related to climate change in a leading economics or environmental economics journal about the appropriate discount rate for calculating the SC-GHG, also finding a mean of 2.3% and a median of 2%. Pindyck (2019) also surveyed economists on discounting and other topics related to the SC-GHG and found a mean discount rate of 2.7% and a median of 2.0%.

The National Academies (2017) recommended the use of "three sets of Ramsey parameters, generating a low, central, and high certainty-equivalent near-term discount rate, and three means and ranges of SC-CO_2 estimates." Recent studies have found empirical evidence suggestive of a structural break in the interest rate process sometime during the 1990s that has been associated with declining equilibrium interest rates in recent decades (e.g., Del Negro et al. 2017, Christensen and Rudebusch 2019, and Bauer and Rudebusch 2020). Based on empirical evidence, Bauer and Rudebusch (2021) utilize the year 1991 as a breakpoint when considering potential shifts in long-run mean of the interest rate process. Given the evidence of structural shifts in the interest process beginning in the 1990s, and the precedent for using 1991 as a reasonable and empirically formed breakpoint, this report places greater focus on the range of mean interest rate estimates from 1991-2020 presented in Table 2.4.1. To cover that range, this report includes a half a point spread in certainty-equivalent near-term target rates of 1.5 to 2.0 percent. Given the potential value in considering a longer time series, this report also considers a third near-term target rate of 2.5 percent reflective of the average of the Table 2.4.1 estimates using the longer time series[110], which is also consistent with the lines of evidence above suggesting a consumption interest rate of slightly above 2 percent. Therefore, considering the multiple lines of evidence on the appropriate certainty-equivalent near-term rate, the modeling results presented in this report consider a range of near-term target rates of 1.5, 2.0, and 2.5 percent. This range of rates allows for a symmetric one point spread around 2.0 percent.

Calibration of Ramsey parameters. Calibration of the Ramsey parameters follows Rennert et al. (2022a, 2022b) using the specified set of near-term discount rates to generate a certainty-equivalent discount rate path. Rennert et al. (2022a, 2022b) apply the Newell et al. (2022) calibration approach to the same set of probabilistic socioeconomic scenarios presented in Section 2.1 and adopted in this report. The Ramsey parameters, ρ and η, were calibrated to meet two conditions. First, the average certainty-equivalent rate over the first 10 years is equal to the near-term target rate. Second, the shape of the certainty-equivalent discount rate path over the time horizon fits the empirical estimates of Bauer and Rudebusch (2021).[111] The resulting calibrated values of the Ramsey formula parameters are presented in Table 2.4.2.

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[110] The average across the estimate in Table 2.4.1 form the window 1973-2020 using different approaches to adjust for inflation is 2.47 percent, which rounded to one significant digit is 2.5 percent.
[111] Additional details of the calibration methodology are available in Newell et al. (2022).

Table 2.4.2: Calibrated Ramsey Formula Parameters

Near-Term Target Certainty-Equivalent Rate	ρ	η
1.5%	0.01%	1.02
2.0%	0.20%	1.24
2.5%	0.46%	1.42

Source: Rennert et al. (2022b)

Figure 2.4.1 presents the resulting distribution of time-averaged discount rates using the calibrated ρ and η associated with each of the three near-term target rates. The mean and 95th percentile range of the discount rate used to discount climate damages back to 2020 for the RFF-SPs probabilistic growth scenarios are presented using dashed and dotted lines. The solid lines illustrate the certainty-equivalent risk-free discount rate that would lead to the same average discount factor over a specific time horizon as using the full distribution of dynamic discount rates to calculate a distribution of discount factors. This path is the same as the calibrated certainty-equivalent risk-free term structures presented in Rennert et al. (2021a).

Figure 2.4.1: Distribution of the Dynamic Discount Rates
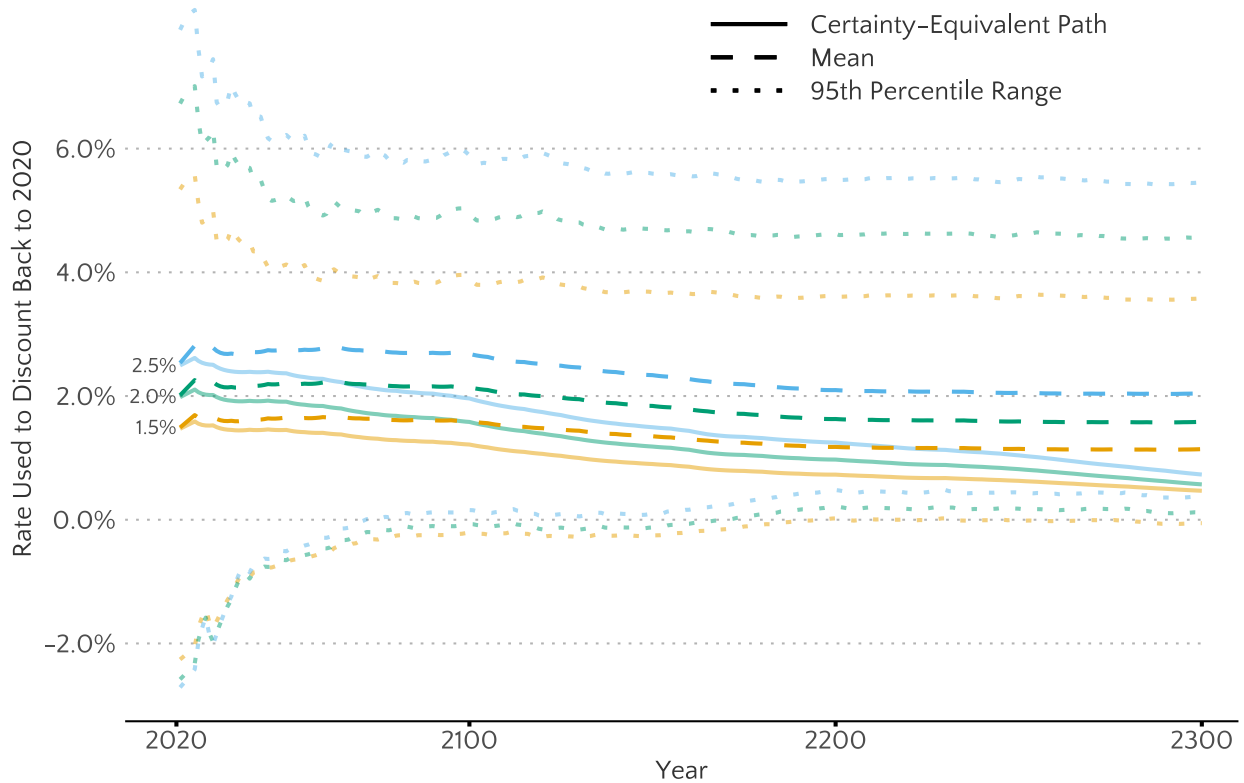
The range of the dynamic discount rates used to discount climate damages back to 2020 in any one year for the three near-term target rates is summarized by the mean (dashed lines) and 5th to 95th percentiles (dotted lines). Also shown here is an illustration of the corresponding certainty-equivalent risk-free path (solid lines) implied by the calibration procedure described in Section 2.4.2. During the calibration, Newell et al.(2022) place additional constraints on the rates in each trial such that rates are allowed to go negative but cannot remain negative for the duration of the time period (2020-2300).

While the certainty-equivalent path illustrates the declining certainty-equivalent risk-free discount rate implied by the Ramsey formula, it is important to emphasize that this does not illustrate the discount rate used to estimate the SC-GHG values. First, an exogenous, certainty-equivalent declining discount rate is not used to discount climate damages; each scenario is discounted using the calibrated ρ and η values presented here and the specific consumption growth rate for that scenario. Second, the consumption growth rate used for discounting is net of baseline climate damages for each model (Kelleher and Wagner 2019).

The calibration approach and resulting Ramsey parameters presented above are consistent with the National Academies' (2017) recommendation to use a descriptive calibration based on empirical interest rate data. The resulting parameters presented in Table 2.4.2 are also within the ranges of values of ρ and η used in the peer-reviewed literature, including many studies that state their parameter choices are based on prescriptive reasoning. For example, the IWG (2010) noted that most papers in the climate change literature adopt values for η in the range of 0.5 to 3, although not all authors articulate whether their choice is based on prescriptive or descriptive reasoning (IWG 2010). The IPCC AR5 report found values of η in the literature in the range of 1 to 4 (IPCC 2014b). Values between 1 and 1.45, consistent with the calibrated range in Table 2.4.2, have been commonly used in recent peer-reviewed studies (Lemoine 2021, Hänsel et al. 2020, Glanemann et al. 2020, Tol 2019, Dietz and Venmans 2019, Nordhaus 2018, Burke et al. 2018, Adler et al. 2017). The Drupp et al. (2018) survey asked economists about the most appropriate values for η, and found a median (mean) value of 1 (1.35), and a mode value (i.e., the most frequently provided response) of 1.

With respect to the pure rate of time preference, the calibrated values presented in Table 2.4.2 are also within the ranges of ρ used in the peer-reviewed literature. The vast majority of papers in the climate change literature adopt values for ρ in the range of 0 to 2 percent per year, with most studies in the lower end of the range (IPCC 2014a). The selection of rates on the lower end of that range tend to emerge from ethical concerns. Some have argued that to use any value other than ρ = 0 would unjustly discriminate against future generations (e.g., Arrow et al. 1995, Stern 2006). When Drupp et al. (2018) surveyed economists about the most appropriate values for ρ, the experts' responses had a median (mean) value of 0.5 (1.1) percent, and a mode value of 0. However, even under the case of intergenerational neutrality, a small positive pure rate of time preference may be appropriate to account for the probability of unforeseen cataclysmic events (Stern 2006).[112] Furthermore, it has been argued that very small values of ρ can lead to an unreasonable rate of optimal savings (Arrow et al. 1995), particularly with η around 1 (Dasgupta 2008, Weitzman 2007).

Regardless of the theoretical approach used to derive the discount rate(s), there remain inherent conceptual and practical difficulties of adequately capturing consumption trade-offs over many decades or even centuries. While this report relies on the descriptive approach for selecting specific discount rates based on observed preferences for temporal tradeoffs of consumption, the EPA is aware of the normative dimensions of both the debate over discounting in the intergenerational context and the consequences of selecting one discount rate over another.

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[112] Stern (2006) assumes a pure rate of time preference of 0.1%. This reflects a 91% probability of the human race surviving 100 years.

2.5   Risk Aversion

The impacts associated with GHG emissions present substantial new risks and exacerbate existing risks to human health and welfare (USGCRP 2018b, NIC 2021). This raises the question of how to account for individuals' preferences over these risks in the valuation of climate damages. Individuals are typically not indifferent between a situation with a certain outcome and a situation with a risky outcome whose expected value is the same as the certain outcome. That is, in most decision-making processes individuals tend to be risk averse. This is evident by the existence of voluntary insurance markets where individuals demonstrate a positive willingness to pay to reduce risk exposure.

U.S. regulatory benefit-cost analyses to date commonly assume risk neutrality (i.e., zero risk aversion). This assumption is justified in cases where idiosyncratic risks can be pooled across regulations, are uncorrelated with baseline economic uncertainty, or are shared across large populations (OECD 2018). However, the largest climate change risks are collective in nature, affecting large shares of the population, and, therefore, may not be diversifiable (Heal & Kriström 2002). The marginal damages are also expected to be correlated with baseline consumption (inclusive of baseline climate change damages) and may add to society's overall risk (National Academies 2017, Dietz et al. 2018). Therefore, in the case of climate change risk reductions, individuals are expected to have a positive willingness to pay for that reduced risk exposure beyond the value of the mean damages. The peer reviewed climate economics literature has demonstrated the importance of accounting for risk aversion in estimates of the SC-GHG (e.g., Anthoff et al. 2009, Cai et al. 2016, Lemoine 2021, van den Bremar and van der Ploeg 2021).

In the EPA's analyses relying on the IWG SC-GHG estimates to date risk aversion was incorporated through adjustments to the discount rate and through consideration of the fourth estimate reflecting the 95th percentile for a 3% discount rate. However, in the IWG's 2010 TSD, the IWG acknowledged the limitations of these approaches to provide a unified framework for valuing risk changes. For the SC-GHG estimates presented in this report, the value of risk associated with marginal GHG emissions is explicitly incorporated into the modeling following the economic literature and consistent with the National Academies' (2017) recommendations.

Assuming a time separable welfare function for a population of size L_t with representative agent utility $u(\cdot)$ and per capita consumption c_t, the SC-GHG is defined as

$$SC\text{-}GHG = \frac{E\left[\int_0^T e^{-\rho t} u'(c_t)\Delta_t dt\right]}{u'(c_0)}, \tag{2.5.1}$$

where Δ_t are the marginal damages associated with emissions in a given year. That is, the SC-GHG is the expected marginal changes in utility normalized by the marginal utility of consumption to convert to a

willingness to pay in monetary units. Setting aside uncertainty in future populations for ease of exposition, a second order Taylor expansion of u' around $E[c_t]$ allows the SC-GHG to be decomposed as

$$SC\text{-}GHG \approx \int_0^T \frac{e^{-\rho t}}{u'(c_0)} \left\{ u'(E[c_t])E[\Delta_t] + \frac{1}{2}u'''(E[c_t])E[\Delta_t]Var(c_t) + Cov\big(u'(c_t), \Delta_t\big) \right\} dt. \qquad (2.5.2)$$

| Expected Damages | Precautionary | Insurance |

The first term in the braces on the right-hand side of equation (2) is the change in utility from the expected marginal damages, which drives the willingness to pay for the expected marginal damages. The second two terms incorporate the way in which risk impacts the SC-GHG estimates and have been referred to as the precautionary and insurance channels, respectively (Kimball 1990).[113] The precautionary term captures the result that climate damages are more impactful when consumption is lower, all else equal, leading the returns to mitigation to increase with uncertainty in future consumption. The insurance term, also referred to as the risk premium, captures the covariance between marginal utility along the baseline and marginal damages. This term incorporates the degree to which mitigation provides a hedge against future economic uncertainty, sometimes referred to as the "climate beta" (e.g., Dietz et al. 2021). In other words, the precautionary channel represents the willingness to pay to avoid the additional climate change risk itself and the insurance channel represents the willingness to pay to avoid the broader change in society's risk based on how climate change damages intersect with economic growth.

The IWG SC-GHG estimates used by EPA to date have focused on explicitly quantifying the first component in equation (2). Incorporating the precautionary and insurance channels into the estimation requires probabilistic socioeconomic scenarios, which were not available at the time those estimates were developed. Instead, the IWG partially incorporated the impact of risk into the estimates through adjustments to the discount rates. The motivation for using a lower 2.5 percent discount rate to capture risk in future economic conditions was premised on the precautionary channel. The motivation for using a higher 5.0 percent discount rate was premised on the insurance channel if there is a positive covariance between economic conditions and climate change damages.[114] The fourth value (the 95th percentile at a 3 percent discount rate) was included to represent the extensive evidence in the scientific and economic literature of the potential for lower-probability, higher-impact outcomes from climate change, which would be particularly harmful to society. Absent formal inclusion of risk aversion in the modeling, considering values above the mean in a right skewed distribution with long tails acknowledges society's preference for avoiding risk.

Accounting for risk aversion more explicitly in the analysis allows valuation of the precautionary and insurance channels based on the specific evidence of future economic uncertainty and the correlation with marginal climate change damages presented in Sections 2.1 and 2.3. That is, the value of risk aversion is incorporated into the SC-GHG estimates based on the marginal climate change risk reductions identified by the modeling as opposed to through exogenous adjustments. Explicitly incorporating risk aversion into

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[113] The second and third components on the right-hand side of equation (2) are sometimes also referred to as the diversifiable and non-diversifiable components of risk valuation (OECD 2018).

[114] If there is a negative covariance between economic growth and climate change damages a downward adjustment in the discount rate would be warranted.

the analysis requires a functional form for the representative agent's utility function. The most commonly used utility function in the climate economics literature and one consistent with the approach to discounting identified in Section 2.4, is the isoelastic utility function, $u(c_t) = c_t^{1-\eta}/(1-\eta)$, where utility is a power function with respect to consumption. If the utility function is assumed to follow an isoelastic function, the definition of the SC-GHG in equation (2.5.1) reduces to the expected value of the marginal damages discounted using the Ramsey formula,

$$SC - GHG = E\left[\int_0^T e^{-(\rho+\eta g_t)t}\Delta_t dt\right], \qquad\qquad (2.5.3)$$

where g_t is the time averaged per capita consumption continuous growth rate through time t. Therefore, by discounting via the Ramsey formula as detailed in Section 2.4 and incorporating uncertainty throughout the modeling process as detailed in Sections 2.1-2.3, the SC-GHG estimates incorporate the climate risk through the precautionary and insurance channels.

Within the isoelastic utility function, the single parameter, η, has a role in reflecting both intertemporal and risk preferences which can present challenges in calibrating the utility function. As noted in Section 2.4, the calibrated values for η presented in Table 2.4.2 are consistent with the calibrated range (1 to 1.45) that has been commonly used in recent peer reviewed studies employing an isoelastic utility function (Lemoine 2021, Hänsel et al. 2020, Glanemann et al. 2020, Tol 2019, Dietz and Venmans 2019, Nordhaus 2018, Burke et al. 2018, Adler et al. 2017). However, while that range of values may be appropriate for η in its role representing intertemporal preferences, they may be too conservative for η in its role representing risk preferences. Some have suggested that values of η between 2 and 10 would be required to match empirical and experimental evidence on rates of risk aversion (Crost and Traeger 2014, Jensen and Traeger 2014, Cai et al. 2016, Cai and Lontzek 2019, Daniel et al. 2019, Okullo 2020, Lemoine 2021, Jensen and Traeger 2021, Van den Bremer and Van der Ploeg 2021). To address this calibration challenge, some recent SC-GHG studies have used alternative utility function specifications (e.g., Epstein-Zin specifications) that allow for the separation of intertemporal and risk preferences (Cai et al. 2016, Daniel et al. 2019, Cai and Lontzek 2019, Okullo 2020, Lemoine 2021, Van den Bremer and Van der Ploeg 2021). These studies can incorporate a higher rate of relative risk aversion without affecting the calibration of the intertemporal preferences. While these approaches have promise for improving the calibration of risk preferences, they are relatively new in the climate economics literature, computationally complex, and require additional assumptions (e.g., timing of uncertainty resolution) for which there is no consensus in the literature. For these reasons, these alternative utility functions are not used in this report, but they are worthy of additional investigation, consistent with recommendations of the National Academies (2017). Furthermore, the use of an isoelastic utility function via equation (2.5.3) remains widely used in the peer reviewed literature and is consistent with the National Academies' (2017) recommendations on robustly capturing the value uncertainty through probabilistic scenario, climate, and damage function models in conjunction with a Ramsey-like approach to discounting. However, because the calibrated values of η using the isoelastic utility function may be low from a risk aversion perspective, the value of reducing climate change risk included in the SC-GHG estimates will likely be an underestimate, holding all else equal.

When using the damage module based on GIVE and Howard and Sterner (2017), the SC-GHG is calculated using equation (2.5.3) for a global representative agent. Implicit in the use of a global representative agent is that all risks can be pooled at the global level. This is the model developers' default approach in GIVE, and the global nature of the Howard and Sterner (2017) damage module precludes other assumptions. However, when using the DSCIM damage module, a conceptually similar approach is applied but, following the model developers' default approach, a different assumption on risk pooling is applied. Specifically, when the DSCIM damage module is used, it is assumed that risks associated with uncertainty in the climate response and future socioeconomic conditions can be pooled globally, but damage function risks (conditional on a given level of climate change and RFF-SP socioeconomic realization) are pooled at the damage function's impact region level. All else equal, assuming that risk can be pooled across broader geographic areas reduces the value of risk reductions within the SC-GHG estimates.

3   Modeling Results

3.1   Social Cost of Carbon (SC-CO₂), Methane (SC-CH₄), and Nitrous Oxide (SC-N₂O) Estimates by Damage Module

This section presents the SC-GHG values estimated using the methodological updates described in Section 2. The combination of using three specifications of the damage module over the modeling time horizon[115] and three near-term target discount rates produces nine separate distributions of SC-GHG estimates for each emissions year and GHG. Each distribution consists of 10,000 estimates based on draws from the distributions of uncertain parameters in each module.[116] Given the consideration of multiple lines of evidence in the damage module and multiple near-term discount rates, the results are first presented separately for each of the three damage modules by discount rate.[117] Table 3.1.1, Table 3.1.2, and Table 3.1.3 show the certainty-equivalent SC-CO₂, SC-CH₄, and SC-N₂O estimates, respectively, in ten-year increments for emissions years 2020-2080 by damage module and near-term discount rate.[118] As expected, estimates based on a higher near-term discount rate are consistently lower, while lower near-term discount rates result in higher SC-GHG estimates independent of the damage module. There is some variation in the SC-GHG estimates across the three damage modules. This is expected given that the damage modules are, at least to some extent, measuring different categories of damages and with different approaches. The SC-GHG estimates based on the meta-analysis damage module tend to be higher than those based on damage modules from the DSCIM or GIVE models for CO₂ and N₂O. For CH₄, which has a notably shorter atmospheric lifetime than the other two gases, the SC-GHG estimates based on the GIVE damage module tends to have higher estimates. This suggests differences across the models as to the damage from climate change in the near-term.

The near-term SC-CO₂ estimates reported in Table 3.1.1 are comparable in magnitude to recent published SC-CO₂ estimates that were developed using non-IAM based approaches. For example, Pindyck's (2019) recent survey of several hundred experts in climate science and climate economics yielded mean SC-CO₂ estimates around or above $200 per metric ton CO₂ for various subsets of his sample of respondents.[119]

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[115] As mentioned in Section 1.2, the National Academies recommended that the modeling time horizon "extend far enough in the future to provide inputs for estimation of the vast majority of discounted climate damages." In the case of models presented here, the discounted streams of marginal damages in all models and discount rates peak by the end of the century (2100) and begin to steadily decline through the end of the modeling time horizon (2300)—capturing the majority of the quantified discounted damages associated with the emissions of a metric ton of CO₂, CH₄, and N₂O.

[116] Monte Carlo methods are used to run the combined suite of modules 10,000 times. In each simulation the uncertain parameters are represented by random draws from their defined probability distributions.

[117] Estimates in this report are discounted back to the year of emissions and presented as certainty-equivalent values that account for uncertainty in the socioeconomic scenarios. See Appendix A.3 for more information on how those transformations were made and Section 4 for how they can be used in analyses.

[118] Values in Table 3.1.1, Table 3.1.2, and Table 3.1.3 are rounded to two significant figures.

[119] Pindyck's (2019) full sample of respondents yielded mean SC-CO₂ estimates above $200/mtCO₂, after dropping responses where values fell outside the 5th or 95th percentiles. Responses from economists were lower (on average $174) while the mean SC-CO₂ for other groups was close to $300. To further illustrate the heterogeneity in responses, Pindyck (2019) also reported results based on further trimming of responses, e.g., to 10th through 90th percentile

Studies using other types of survey techniques have found similar ranges of SC-CO$_2$ estimates. For example, based on the results of a vehicle choice experiment, Hulshof and Mulder (2020) derived a mean willingness-to-pay estimate for CO$_2$ emission reduction of \$236 per metric ton CO$_2$.[120] An earlier vehicle choice survey by Achtnicht (2012), using a different population and a somewhat different method to translate the WTP for clean cars into WTP for emission reductions, found car buyers to be willing to pay between \$130 and \$372 per metric ton of CO$_2$ reduced.[121]

For all damage modules, the SC-GHG estimates increase over time – i.e., the societal harm in 2030 from one metric ton emitted in 2030 is greater than the harm in 2020 caused by one metric ton emitted in 2020. Emissions further in the future produce larger incremental damages as physical and economic systems become more stressed in response to greater climatic change and because income is growing over time. As income grows so does the willingness to pay to avoid economic damages. The growth rate of the SC-GHG is generally larger in the case of the DSCIM climate module than the other damage modules. In the case of longer-lived CO$_2$ and N$_2$O emissions, this can lead the SC-GHG estimates based on the DSCIM damage module to eventually exceed those based on one or both of the other damage modules. This is reflective of the marginal damages in the DSCIM damage module being more sensitive to baseline climate change than in the other damage modules (see Figure 2.3.2).

Table 3.1.1: Social Cost of Carbon (SC-CO$_2$) by Damage Module, 2020-2080 (in 2020 dollars per metric ton of CO$_2$)

	Near-Term Ramsey Discount Rate and Damage Module								
	2.5%			2.0%			1.5%		
Emission Year	DSCIM	GIVE	Meta-Analysis	DSCIM	GIVE	Meta-Analysis	DSCIM	GIVE	Meta-Analysis
2020	110	120	120	190	190	200	330	310	370
2030	140	150	150	230	220	240	390	350	420
2040	170	170	170	280	250	270	440	390	460
2050	210	200	200	330	290	310	500	430	520
2060	250	220	230	370	310	350	550	470	570
2070	280	240	250	410	340	380	600	490	610
2080	320	260	280	450	360	410	640	510	650

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values (which reduces mean SC-CO$_2$ estimates to \$147-243/mtCO$_2$), or to the experts who reported high confidence in their impact probabilities (which reduced mean SC-CO$_2$ estimates to \$108-138/mtCO$_2$).

[120] We convert the results reported in Hulshof and Mulder (2020) to U.S. dollars using December 2017 exchange rates (1.1836 USD/Euro (https://www.federalreserve.gov/datadownload/Choose.aspx?rel=H10)), the month the survey was administered.

[121] We convert the results reported in Achtnicht (2012) to U.S. dollars using the average exchange rate during the time period when the survey was administered, August 2007 through March 2008 (1.4502 USD/Euro (https://www.federalreserve.gov/datadownload/Choose.aspx?rel=H10)).

Table 3.1.2: Social Cost of Methane (SC-CH₄) by Damage Module, 2020-2080 (in 2020 dollars per metric ton of CH₄)

Emission Year	Near-Term Ramsey Discount Rate and Damage Module								
	2.5%			2.0%			1.5%		
	DSCIM	GIVE	Meta-Analysis	DSCIM	GIVE	Meta-Analysis	DSCIM	GIVE	Meta-Analysis
2020	470	1,600	1,700	850	1,900	2,200	1,500	2,500	2,900
2030	1,100	2,300	2,300	1,600	2,800	2,800	2,400	3,500	3,700
2040	1,900	3,300	2,900	2,500	3,800	3,500	3,300	4,700	4,500
2050	2,700	4,200	3,700	3,400	4,900	4,400	4,300	5,900	5,600
2060	3,500	5,000	4,400	4,200	5,800	5,300	5,200	7,000	6,700
2070	4,200	5,700	5,100	5,100	6,600	6,200	6,100	7,900	7,800
2080	5,100	6,300	5,900	6,000	7,300	7,100	7,100	8,800	8,900

Table 3.1.3: Social Cost of Nitrous Oxide (SC-N₂O) by Damage Module, 2020-2080 (in 2020 dollars per metric ton of N₂O)

Emission Year	Near-Term Ramsey Discount Rate and Damage Module								
	2.5%			2.0%			1.5%		
	DSCIM	GIVE	Meta-Analysis	DSCIM	GIVE	Meta-Analysis	DSCIM	GIVE	Meta-Analysis
2020	30,000	38,000	38,000	49,000	55,000	58,000	81,000	85,000	96,000
2030	40,000	47,000	46,000	63,000	67,000	69,000	98,000	100,000	110,000
2040	52,000	57,000	55,000	77,000	78,000	81,000	120,000	110,000	130,000
2050	64,000	67,000	66,000	93,000	91,000	95,000	140,000	130,000	150,000
2060	77,000	75,000	76,000	110,000	100,000	110,000	150,000	140,000	160,000
2070	89,000	82,000	84,000	120,000	110,000	120,000	170,000	150,000	180,000
2080	100,000	89,000	94,000	140,000	120,000	130,000	190,000	160,000	200,000

For a given near-term target discount rate, the certainty-equivalent SC-GHG estimate is the value applied to GHG emission changes in benefit-cost analysis (see Section 2.5 for a definition of the SC-GHG). These certainty-equivalents are calculated over a distribution of SC-GHG estimates reflecting the full range of quantified uncertainties incorporated into the modeling (see Section 2 for a description of the quantified uncertainty in each module). Figure 3.1.1 shows the full distribution of SC-GHG estimates for emissions in 2030, where the boxes span the inner quartile range (25th to 75th quantile), whiskers extend to the 5th (left) and the 95th (right) quantiles. The vertical lines inside of the boxes mark the median of each distribution, and the points inside of the boxes and dollar estimates on top of the boxes mark the simple mean (average). In these distributions, the uncertainty that is explicitly characterized includes the socioeconomics and emissions projections from the RFF-SPs and the GHG concentrations and temperature changes generated from the FaIR model. Explicit characterization in these distributions of uncertain parameters in the modeling of SLR and the parametric uncertainty captured in the estimation of each damage function varies across the three damage modules.

It is important to note that the distributions presented here do not fully characterize uncertainty about the SC-GHG due to impact categories omitted from the models and sources of uncertainty that have not been fully characterized due to data limitations. These limitations are discussed in Section 3.2 below.

Uncertainty grows over the modeled time horizon. Therefore, under cases with a lower near-term target discount rate – that give relatively more weight to impacts in the future – the distribution of the SC-GHG is wider (see Figure 3.1.1). Across damage modules, the DSCIM based runs generate the widest distribution of results. The DSCIM damage module has a greater degree of curvature in the damage function mapping temperature to economic damages than the GIVE and H&S specifications (see *Figure 2.3.2*). The interquartile ranges overlap across the three damage modules.

Figure 3.1.1: Distribution of Social Cost of Carbon Dioxide (SC-CO$_2$) Estimates for 2030, by Near-term Ramsey Discount Rate and Damage Module
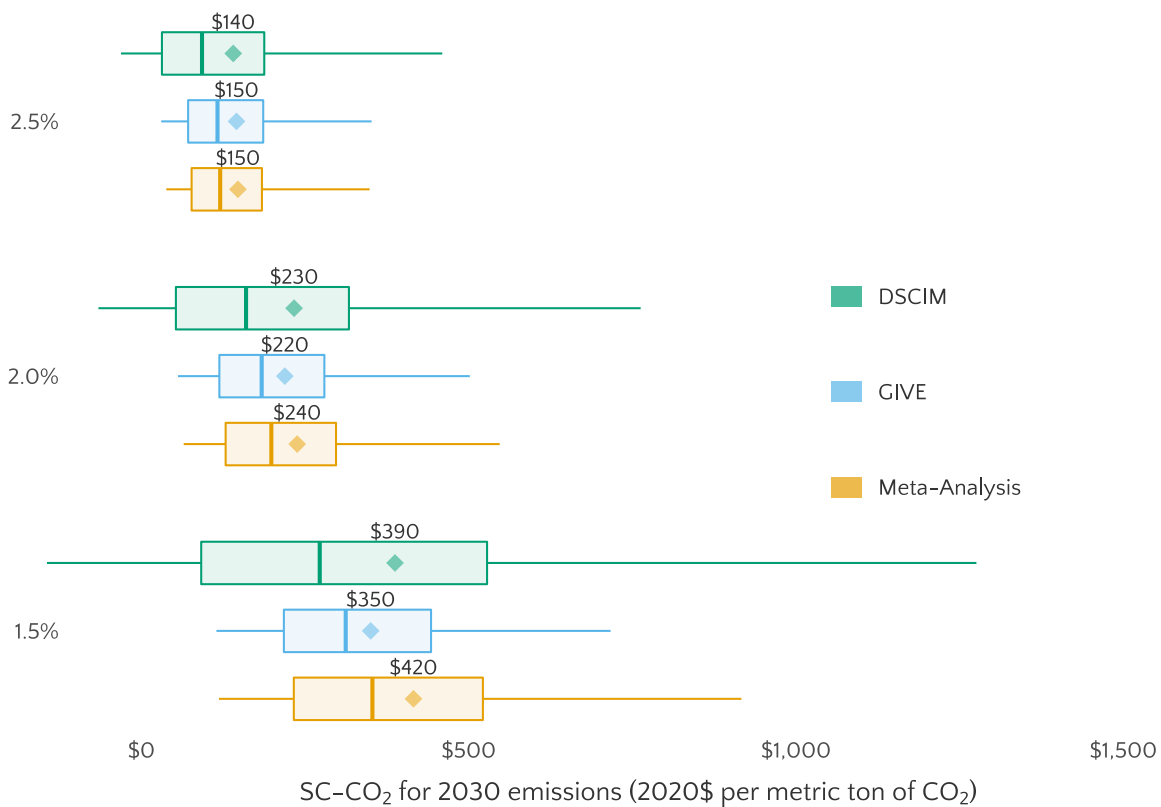
Boxes span the inner quartile range (25th to 75th percentiles), whiskers extend to the 5th (left) and the 95th (right) percentiles. The vertical lines inside of the boxes mark the median of each distribution, and the points inside of the boxes and dollar estimates on top of the boxes mark the simple mean (average).

Table 3.1.4 provides a disaggregation of the SC-CO$_2$ results by sector or impact category for emissions in 2030 under the GIVE and DSCIM based damage modules – alongside the meta-analysis-based damage module that does not permit a sectoral disaggregation. The GIVE and DSCIM damage modules are consistent in that net mortality risk increases are the largest share of marginal damages across the sectors considered in each damage module. However, the share of marginal damages due to net mortality risk

increases is larger for the DSCIM damage module compared to the GIVE damage module. Variation across the two damage modules for the other sectors reflects uncertainty in the underlying scientific literature and differences in the sectors included in the models (e.g., labor productivity). See Section 2 for detailed descriptions of the methodological differences across models. The differences in results are the aggregate effect of these different methodologies.

Table 3.1.4: Sectoral Disaggregation of Social Cost of Carbon (SC-CO$_2$) for 2030 under a 2.0% Near-Term Ramsey Discount Rate (in 2020 dollars per metric ton of CO$_2$)

Damage sector or category	Damage Module		
	DSCIM	GIVE	Meta-Analysis
Health	$179	$104	-
Energy	-$4	$10	-
Labor productivity	$47	-	-
Agriculture	$4	$103	-
Coastal	$3	$2	-
Total	$233	$219	$238

3.2   Omitted Damages and Other Modeling Limitations

The research community's considerable progress in developing new data and methods have helped to bring the SC-GHG estimates presented in Section 3.1 closer to the frontier of climate science and economics and address many of the National Academies' (2017) near-term recommendations. However, the SC-GHG estimates presented in this report still have several limitations, as would be expected for any modeling exercise that covers such a broad scope of scientific and economic issues across a complex global landscape. There are still many important categories of climate impacts and associated damages that are not yet reflected in these estimates due to data and modeling limitations. There is also incomplete coverage of some categories that are represented, including important sectoral and regional interactions.

Table 3.2.1 below highlights some of these limitations. For important categories within climate science, impacts and associated damages, and methodology, the table denotes those that the SC-GHG estimates in this report have been able to incorporate, those only partially incorporated, and those that are not yet included. For example, the damage modules currently focus on climate change damages driven by changes in annual average temperatures or sea level rise. The damage modules have not yet explicitly incorporated damages associated with other changes in the temperature distribution such as variability and changes in the probability of extreme temperatures throughout the year. Nor have the damage modules explicitly considered damages associated with changes in precipitation or humidity due to climate change.

The climate module considered in this report omits some potentially large-scale Earth system changes (e.g., from tipping elements) or non-climate mediated effects of GHG emissions (e.g., ocean acidification, tropospheric ozone formation due to CH$_4$ emissions). Climate change impacts described as resulting from tipping elements are often associated with crossing a threshold in an Earth system, or 'tipping point', after which a relatively small perturbation in radiative forcing results in a large, often irreversible change in the climate or other Earth systems (see, e.g., Kopits et al. (2014) for a review of this literature). A few of these

processes (e.g., Arctic Sea ice loss and surface albedo feedback, slowdown of the Atlantic Meridional Overturning Circulation (AMOC)) are captured in the underlying CMIP6 models in which FaIR v1.6.2 was calibrated to and are thus implicitly reflected in the climate module used in this report (Weijer et al. 2020). For other processes – such as Amazon Forest dieback, melting of permafrost, changes in the Indian summer monsoon (ISM) – it is less certain how well their behavior is captured in CMIP6 models or whether they are implicitly included in FaIR1.6.2 (see, e.g., Arora et al. 2020, IPCC 2021d). Lastly, methane hydrates, Greenland (GIS) and Antarctic icesheet (AIS) collapse are not included at all within FaIR. However, GIS and AIS are simulated within the sea-level models used in this report.

Recent studies have started to make progress on incorporating more of the tipping elements discussed above in the estimation of SC-GHG. In particular, Dietz et al. (2021) developed a response function that maps increases in global mean surface temperature (GMST) to additional warming that is realized through feedbacks in the underlying biophysical systems such as permafrost thaw, ocean methane hydrates, Amazon rainforest dieback, GIS and AIS collapse, the AMOC slowdown, and ISM variability. This allows for an improved, more explicit accounting of the temperature-driven damages resulting from these types of large-scale feedback effects within SC-GHG estimation. The EPA will continue to follow progress in this line of research and look for opportunities to better reflect tipping elements and other Earth system changes and to account for non-climate mediated GHG effects in future updates of the SC-GHG estimates. Additional discussion of these is provided in Section 3.2.1 below.

The bottom-up damage modules from the DSCIM and GIVE models provide a transparent accounting of which climate change damages are incorporated into the modules, as discussed in Section 2.3.[122] While the advancements in these newer damage modules is laudable, it is clear that many categories of climate change damages are not yet represented. Examples include changes in the demand for water resources, the costs and feasibility of providing safe drinking water, changes in ecosystem services, and the productivity of the livestock, aquaculture, and forestry industries just to name few.

For those damage categories that are represented, they may only be a partial accounting. For example, the estimated health damages in GIVE and DSCIM only include temperature- and SLR-related mortality, and exclude other sources of mortality impacts (e.g., climate mediated changes in storms, wildfire, flooding, air pollution), and morbidity impacts (e.g., infectious diseases, malnutrition, allergies). Studies are available on how climate-relate changes impact infectious diseases (Levy et al. 2016, Trinanes et al. 2021, Colón-González et al. 2021, Ryan et al. 2019, Ryan et al. 2015, Mordecai et al. 2020) but additional work in needed to both model metrological conditions (e.g., humidity, precipitation patterns, length of transmission seasons, and daily temperature ranges) under climate change and link these to infectious disease damage functions (Cromar et al. 2022). Importantly, none of the damage modules incorporate cross-country or regional spillovers that occur through migration, national security concerns, tourism, or supply chain disruptions. The physical and economic pathways that drive many of these omitted or partially included categories are well documented in key scientific assessments, such as those developed

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[122] For the GIVE model, Rennert et al. (2022b) illustrate the impact that the updated damage functions have on the SC-CO_2 estimates relative to damages functions used in earlier studies. The authors find the SC-CO_2 estimate is notably larger when using GIVE's updated four-sector damage function ($185/mtCO2 in 2020 under 2% Ramsey discounting compared to using the aggregate top-down damage function approach used in the latest version of the DICE model (DICE 2016) ($152/mtCO2 in 2020), which was stated to be more comprehensive in scope and included a 25% adder for omitted impacts (holding all else equal in the modeling).

by the IPCC (e.g., IPCC 2008, 2014a, 2018, 2019a, 2019b, 2021a) and the U.S. Global Change Research Program (e.g., USGCRP 2016, 2018a). However, key data and research gaps currently prevent incorporating these damage categories into global damage modules for the purpose of estimating the SC-GHG.

While the SC-GHG estimates presented in this report provide numerous methodological improvements over the previous estimates, as detailed in Section 2, there are opportunities for future improvements. For example, none of the damage modules explicitly consider potential interactions among damage categories. For example, the modules do not account for how climate change-mediated impacts to water supply will interact with climate-mediated changes in the demand for water resources by the agricultural and electric power sectors that may be in competition in similar water markets.

Equally important to note among the methodological limitations is the valuation of risk aversion in the updated SC-GHG estimates. As noted in Section 2.5, the SC-GHG estimates provide an improved accounting of risk aversion over the estimates used in the EPA's analyses to date. However, the approach relies on an isoelastic utility function in which a single parameter has a role in reflecting both intertemporal and risk preferences. In this report, the utility function parameter is calibrated based on its role representing intertemporal preferences leading to lower values than would be expected if it was calibrated based on its role representing risk preferences. As a result, the SC-GHG estimates likely underestimate the damages associated with increased climate risk resulting from a marginal ton of emissions, all else equal. As noted in Section 2.5, to address this calibration challenge, some recent SC-GHG studies have used alternative utility function specifications (e.g., Epstein-Zin specifications) that allow for the separation of intertemporal and risk preferences (Cai et al. 2016, Daniel et al. 2019, Cai and Lontzek 2019, Okullo 2020, Lemoine 2021, Van den Bremer and Van der Ploeg 2021).

Although not all omitted climate change impacts work in the same direction in terms of their influence on the SC-GHG estimates, taken together, the numerous omitted damage categories, modeling assumptions that go in the direction of being conservative, and other limitations discussed above and throughout Section 2, make it likely that the SC-GHG estimates presented in this report underestimate the damages from GHG emissions. For example, first, as discussed above, many categories of damages are only partially modeled or omitted altogether in the DSCIM- and GIVE-based damage modules. Second, many interactions and feedback effects are not yet represented, both in modeling physical earth system changes (e.g., feedback effects of tipping elements) and economic damages. For the GIVE model-based results, Rennert et al. (2022b) "expect that, in total, the future inclusion of additional damage sectors and tipping elements is likely to raise the estimates of the SC-CO_2, and that therefore the estimates from the present study are likely best viewed as conservative." Third, as noted in Section 2.3, data limitations have been pointed out as a likely cause of the estimated response function in DSCIM to be generating conservative predictions of mortality risk increases in some low income regions. Fourth, under the meta-analysis-based damage module, the results are based on a Howard and Sterner (2017) specification to which those authors and other researchers (e.g., Nordhaus and Sztorc 2013, Nordhaus 2017b) have routinely added a generic 25% increase in recognition of omitted damages that are likely significant. Fifth, coastal damages in both GIVE and DSCIM are estimated based on an optimistic assumption that optimal, lowest cost adaptation opportunities will be realized globally under perfect foresight about SLR. Finally, the method employed to account for risk aversion likely underestimates the damages associated with increased climate risk resulting from a marginal ton of emissions.

EXTERNAL REVIEW DRAFT

Table 3.2.1: Scope of Climate Science, Impacts, and Damages Included in the Updated SC-GHG Estimates[123]

Climate Science		Impacts and Associated Damages	
Temperature change	◐	**Human Health and Well-being**	◐
Averages	●	Heat and cold related mortality	●
Extremes	○	Mortality and morbidity from extreme weather events (e.g., storms, wildfire, flooding), and sea level rise	◐
Variability	○	Mortality and morbidity from climate mediated changes in the formation of criteria air pollutants (e.g., ozone, PM2.5)	○
Sea level rise	◐	Infectious diseases	○
From average temperature change	●	Other morbidity (e.g., malnutrition, allergies)	○
Non-linear effects (e.g., ice-sheet collapse)	◐	Displacement and migration	○
Precipitation	○	**Labor**	◐
Averages	○	Labor supply (i.e., hours worked)	●
Extremes	○	Labor productivity (i.e., output per hour worked)	○
Variability	○	**Energy**	◐
Humidity – wet-bulb temperature	○	Energy consumption (e.g., heating, cooling)	●
Large scale Earth system changes (tipping elements, etc.)	◐	Energy production and provision (e.g., hydroelectric, thermal power generation)	◐
Additional changes in temperature	◐	**Water**	○
Sea level rise	◐	Water consumption (residential, industrial, commercial)	○
Precipitation	○	Provision of safe drinking water	○
Extreme weather events	○	Water storage and distribution	○
Ecosystems	○	**Land**	◐
Other impacts	○	Coastal land loss from sea level rise	◐
Non-climate mediated effects (e.g.)	◐	**Buildings, transportation, and infrastructure**	◐
Carbon fertilization (CO2)	●	Sea level rise	◐
Ocean acidification (CO2)	○	Intensity or frequency of coastal storms	○
Tropospheric ozone formation (CH4)	○	Extreme weather inland (e.g., storms, wildfire, flooding)	○
Stratospheric ozone destruction (N2O)	○	Environmental conditions (e.g., melting permafrost, air temperature and moisture)	○
		Food production	◐
Methodology	◐	Agriculture/Crop production	◐
Explicit treatment of uncertainty	●	Animal and livestock health and productivity	○
Accounting for adaptation and costs of adaptation	◐	Fisheries and aquaculture production	○
Interactions/feedbacks across sectors	○	**Forestry**	○
Feedbacks from damages to socioeconomics and emissions	○	Timber, pulp, and paper production	○
Valuation of risk	◐	**Tourism, recreation, aesthetics**	○
		Visitation, locations, and opportunities (e.g., recreational fishing, skiing, scuba diving, scenic views)	○
		Ecosystem services	○
		Availability and quality of natural capital used in the production of marketable goods	○
		Biodiversity and wildlife habitat (e.g., aquatic environments, breeding grounds)	○
		Other provisioning and regulating services (e.g., water filtration, wildfire and flood mitigation, medicinal resources, pest control, pollination)	○
		Cultural services	○
		Crime (property, violent)	○
		National Security	○
		Military base impacts	○
		Military mission impacts from international civil conflict	○
		International development, humanitarian assistance	○
		Trade and logistics	○

Legend
- ● Incorporated
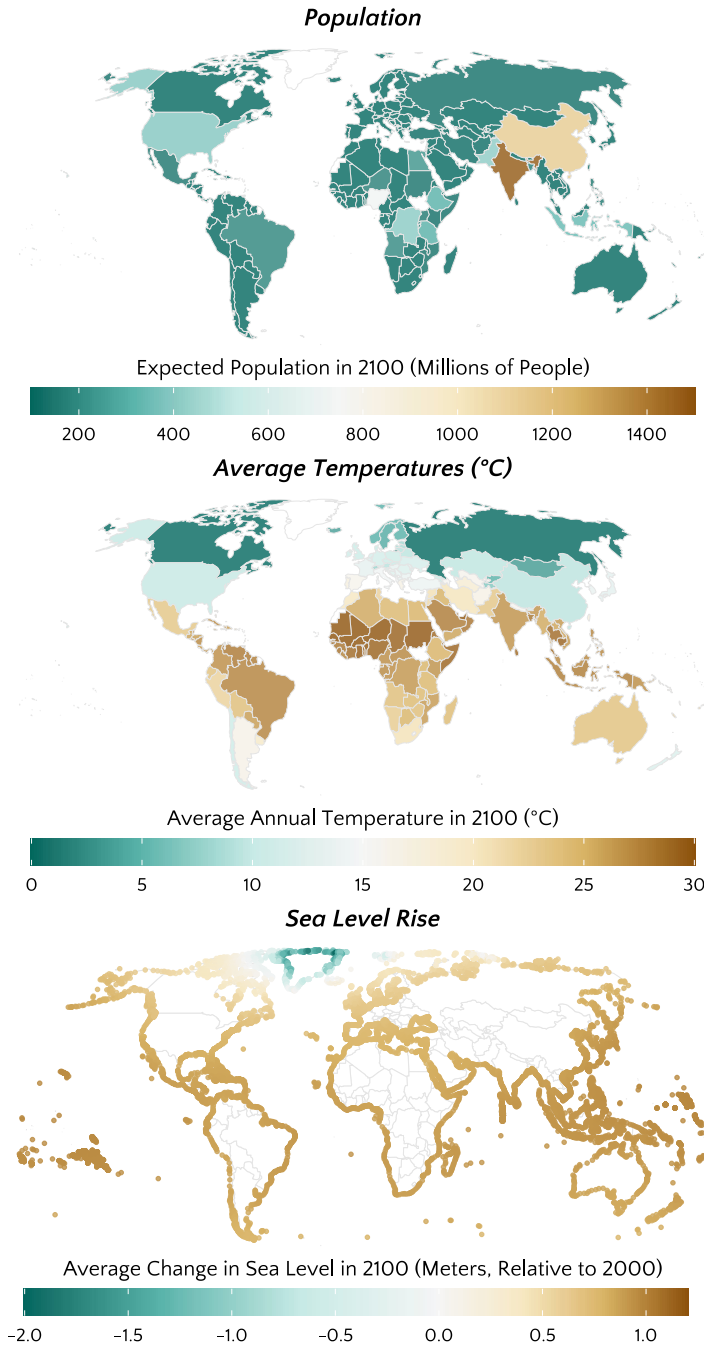- ◐ Partially Incorporated
- ○ Not Yet Incorporated

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[123] Table 3.2.1 presents a general indication of the climate science, impacts, and damages included across the three damage modules used in this analysis and may not be reflective of any one specific damage module.

| | Supply chain disruption (e.g., from extreme weather) | ○ |
| | Supply chain transitions (e.g., altering trade routes) | ○ |

One way to illuminate the potential magnitude of some omitted damage categories is to consider the current spatial distribution of global population and climate indicators. Figure 3.2.1 shows that a substantial portion of the world's population lives in latitudes that are projected to experience some of the highest temperatures. And although not explicitly captured in the figure, within each country most

Figure 3.2.1: Population, Temperature, and Sea Level Rise in 2100

Population

Expected Population in 2100 (Millions of People)

200   400   600   800   1000   1200   1400

Average Temperatures (°C)

Average Annual Temperature in 2100 (°C)

0   5   10   15   20   25   30

Sea Level Rise

Average Change in Sea Level in 2100 (Meters, Relative to 2000)

−2.0   −1.5   −1.0   −0.5   0.0   0.5   1.0

these populations are located near the coasts in areas expected to experience significant sea level rise. The spatial correlations that exist between population centers and known damage pathways highlight how temperature- and SLR-related damages will impact a significant share of the world's population. This further underlines the significance of impacts not currently reflected in the estimates, such as geopolitical and regional tensions, conflict, scarcity, displacement, and migration, all of which are issues that affect an interconnected global economy.

3.2.1 Further Discussion of Ocean Acidification and Other Non-Climate Mediated Impacts of GHG Emissions

SC-GHG estimation to date has primarily focused on the climate-mediated effects: e.g., the pathway from emissions, to concentration, to radiative forcing, to temperature, to climate change, and to economic damages. However, there are other impacts of GHG emissions. The only non-climate-mediated effect included in SC-GHG estimates to date and those in this report is the crop fertilization effects resulting from elevated CO_2 concentrations.

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However, there are several other potentially important non-climate mediated GHG effects. These include, for example, the ecosystem effects of ocean acidification and aragonite undersaturation resulting from elevated concentrations of CO_2, the health and agricultural impacts of tropospheric ozone generated through chemical conversion of methane in the atmosphere, and the health effects of stratospheric ozone destruction resulting from elevated concentrations of N_2O. Several studies have investigated these effects and are discussed here.

Ocean acidification from carbon dioxide (CO_2) concentrations. In addition to its effects on temperature and other climate endpoints, CO_2 emissions contribute to ocean acidification, which will likely result in substantial changes to marine ecosystems. The ocean absorbs about 30 percent of the CO_2 released into the atmosphere. Higher atmospheric levels of CO_2 cause the ocean to absorb more, which affects the carbonate chemistry of seawater. Water and carbon dioxide combine to form carbonic acid, contributing to ocean acidification (i.e., the pH decreases and the ocean becomes more acidic). As noted in Section 2.2, the FaIR reduced complexity climate model calculates carbon dioxide uptake in the world's ocean as part of its carbon cycle calculation and provides projections of pH and ocean heat uptake. Specifically, the model estimates the changes in pH with a simple function to approximate globally averaged surface ocean pH from atmospheric CO_2 concentrations (National Academies 2017) and accounts for uncertainty in the atmospheric CO_2 concentrations. Figure 3.2.2 depicts the range of ocean pH and ocean heat that is predicted by the coupling of the RFF-SPs with FaIR1.6.2. Under these projections, mean ocean pH is expected to decrease by 0.11 pH units by 2100 relative to 2020.

Figure 3.2.2: Global Ocean pH and Ocean Heat, 2020-2300
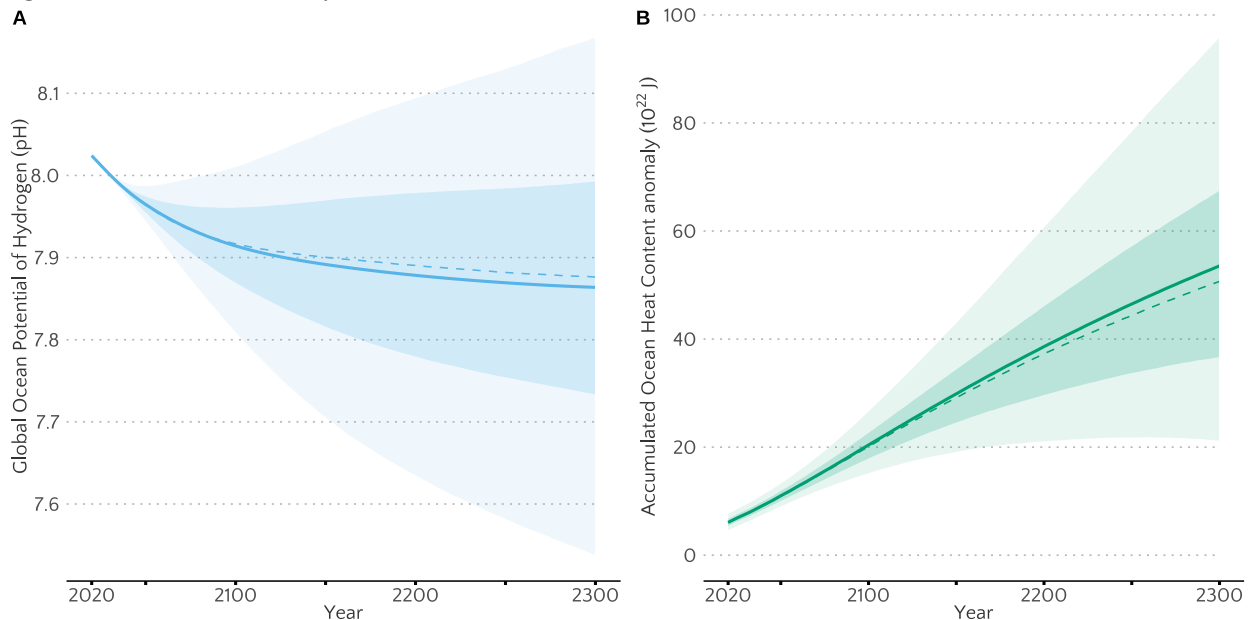
Uncertainty is represented by the emissions uncertainty from the RFF-SP projections and physical climate uncertainty from FaIR1.6.2. Mean (solid) and median (dashed) lines along with 5th to 95th (dark shade) and 1st to 99th *(light shade) percentile ranges.*

One of the impacts of ocean acidification is a reduction in the concentration of carbonate ions available to calcifying marine organisms to build and maintain skeletons, shells, and other carbonate structures. Among the affected organisms are mollusks, bivalves, reef building corals, and microorganisms at the base

of the marine food web. Commercially valuable shellfish including oysters, clams, and abalone exhibit reduced growth and survival rates under conditions expected by mid-century (Ries et al. 2009). The synergistic effects of marine heatwaves and acidification on coral reefs will inhibit corals' ability to recover from increasingly frequent bleaching events (Klein et al. 2022). The scale of follow-on effects of ocean acidification on marine ecosystems (including fisheries) resulting from a reduced availability of habitat and prey is much more uncertain and difficult to quantify.

Studies estimating the economic impacts of ocean acidification necessarily focus on those for which the biophysical outcomes are best understood. Several studies forecast producer and consumer welfare losses in commercial shellfish markets in the US (Cooley and Doney 2009, Cooley et al. 2015, Moore 2015), in Europe (Fernandes et al. 2017, Narita and Rehdanz 2017), and globally (Narita et al. 2012). Some of the largest forecasted welfare impacts of ocean acidification arise from the recreational and existence value of coral reefs (Brander et al. 2012, Lane et al. 2013) while other studies include the impacts of lost coral reef habitat on finfish (Colt and Knapp 2016, Kite-Powell 2009, Speers et al. 2016).The impacts of ocean acidification are not included in the damage modules used in this report because work remains to upscale existing regional studies to capture global economic impacts. Among the challenges is accounting for synergistic effects between temperature and seawater chemistry and how the ecological impacts differ across economically important species. With the current understanding of pH and temperature effects on growth and survival of shellfish and corals, and existing market and nonmarket valuation data for the ecosystem services they provide, we expect that it will be feasible to develop damage functions for some ocean acidification impacts in future SC-GHG updates.

Tropospheric ozone formation from methane (CH$_4$) emissions. In addition to its climate effects, methane oxidation in the atmosphere leads to the production of tropospheric ozone, which has harmful effects for human health and plant growth (USGCRP 2018c). Due to methane's atmospheric perturbation lifetime of about 12 years (IPCC 2021e), methane is well-mixed globally and therefore the effects on ozone are also global (in contrast to regional ozone effects from NO$_x$ and VOC emissions). Studies have estimated that half of the increase in global annual mean ozone concentrations since preindustrial times is due to anthropogenic methane emissions (IPCC 2013).

One study estimated the monetized increase in human mortality risk from the ozone produced due to methane emissions to be \$800 to \$1800 per ton of methane emissions (Sarofim et al. 2017), using a methodology similar to that of the IWG SC-GHG estimates at the time the paper was written. A more recent study estimated that sustained reductions of a million tons of methane emissions per year could prevent about 1,430 premature deaths annually, along with preventing the loss of 145,000 tons of wheat, soybeans, maize and rice (UNEP 2021). The UNEP results are larger than the Sarofim et al. (2017) estimate of 239 to 591 premature deaths avoided due to the mitigation of a million tons of methane. UNEP used an improved methodology to estimate the ozone changes resulting from methane mitigation, but also used an estimate of the cardiovascular mortality risk due to elevated ozone concentrations that may be larger than estimates used by the EPA (EPA 2020).

Stratospheric ozone destruction from nitrous oxide (N$_2$O) emissions. In addition to its climate effects, N$_2$O has impacts on stratospheric ozone. When N$_2$O is in the stratosphere, high-energy photons break it apart resulting in the production of nitric oxide (NO). Like the chlorine atoms from CFCs, NO can catalytically destroy ozone. Because of this reaction, it has become clear that as CFC emissions are eliminated, N$_2$O

emissions have become the largest anthropogenic contributor to the destruction of stratospheric ozone (Ravishankara et al. 2009, Portmann et al. 2012, WMO 2018). A recent article (Kanter et al. 2021) estimated the monetized impacts of the stratospheric ozone loss due to N_2O emissions on human health and crop damages as $2,000 per ton N_2O (2020 dollars)[124], or over 11% of the value of the SC-N_2O estimate for 2020 emissions in the IWG February 2021 TSD.

Other effects. As discussed in Section 2, the SC-GHG estimates presented in this report include the monetized value of carbon dioxide fertilization effects on agriculture. There may be additional benefits of carbon dioxide fertilization for ecosystems. However, elevated CO_2 concentrations can also lead to reductions in the nutrient content (such as protein, iron, and zinc) of some crops, with potential negative effects on diets (Beach et al. 2019). Elevated CO_2 concentrations can also change the production and allergenicity of aeroallergens (Ziska, 2020). These additional impacts have not been monetized.

One approach for accounting for non-climate mediated GHG effects in SC-GHG estimates would be to use the estimates of the dollar impacts of a ton of emissions of a given gas from existing studies and add those impacts to the appropriate social cost. Another approach would be to estimate the monetized damages within the existing SC-GHG modeling framework. For example, as recommended in Kanter et al. (2021), this might involve estimating the change in stratospheric ozone concentrations over time resulting from an additional ton of N_2O emissions, and then calculating the increase in the risk of health effects resulting from the increased ozone concentration (e.g., skin cancer morbidity and mortality). The health effects can then be valued within the framework in the same way that mortality resulting from extreme heat events or other climate effects is valued.

3.3 Distribution of Modeled Climate Impacts

As discussed in detail in Section 1, benefit-cost analysis of Federal regulations and other actions include the global net damages from expected changes in GHG emissions. The distinctive global nature of GHG emissions combined with an increasingly interconnected world means that climate change impacts occurring on one side of the world can directly and indirectly affect the welfare of citizens and residents of a country located on the other side of the world through a multitude of pathways. As the prominent 2014 CNA study concluded, the increasing political complexity and economic integration across the world makes it "no longer adequate to think of the projected climate impacts to any one region of the world in isolation. Climate change impacts transcend international borders and geographic areas of responsibility" (CNA 2014).

However, there is heterogeneity in the distribution of climate change damages across the globe and within the U.S. The SC-GHG by design, and consistent with the economic theory and methods for benefit-cost analysis, is an aggregation across individuals of their willingness to pay to avoid the marginal damages of climate change. As such the SC-GHG is not designed to assess the important distributional considerations

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[124] Kanter et al. (2021) estimate a median value of US$2.66 per kg N_2O–N (in 2008 dollars) for the ozone impacts of N_2O emissions. We convert this estimate to $/ton N_2O using the N_2O-N to N_2O factor of 1.57 and adjust for inflation to 2020 dollars using the annual GDP Implicit Price Deflator values in the U.S. Bureau of Economic Analysis (BEA) NIPA Table 1.1.9 (specifically, using 2020USD = 2008USD x (113.648 / 94.419, accessed February 7th, 2022). See https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=3&isuri=1&select_all_years=0&nipa_table_list=13&series =a&first_year=2005&last_year=2020&scale=-99&categories=survey&thetable= .

of climate change damages.[125] Therefore, it is important for the results of analyses using the SC-GHG to be placed in context with respect to how the impacts of climate change are expected to be distributed across populations. This section presents the available evidence on the distribution of climate change impacts based on the results from the SC-GHG modeling above.

The spatial distribution of climate impacts is the result of complex physical and economic dynamics interacting with the existing heterogeneity in physical and socioeconomic conditions. As discussed at length in Section 2.3 and emphasized in Section 3.2, the damage modules used in this report do not capture all of the pathways through which climate change impacts public health and welfare and hence only cover a subset of potential climate change impacts. Furthermore, the damage modules do not capture spillover or indirect effects whereby climate impacts in one country or region can impact the welfare of residents in other countries or regions, as detailed in Section 1.3. Only two modules, the DSCIM and GIVE damage modules, have spatial resolution that allows for any geographic disaggregation of future climate impacts across the world. Hence, the results from the SC-GHG modeling in this report are only able to provide partial evidence of the global distribution of climate change impacts. Conditional on these critical caveats, the spatial resolution in both models does allow for the calculation of a partial SC-GHG measure of damages resulting from climate impacts physically occurring within a particular country. For example, the DSCIM damage module, which includes net impacts on temperature-related mortality, agriculture, energy expenditures, labor productivity, and sea level rise, estimates damages from climate change impacts physically occurring within the U.S. of $11/mtCO_2$ for a 2020 emissions year, rising to $27/mtCO_2$ for a 2080 emissions year (under a near-term target discount rate of 2%).[126] The GIVE damage module, which includes net impacts on temperature related mortality, agriculture, energy expenditures, and sea level rise, estimates damages from climate change impacts physically occurring within the U.S. of $14/mtCO_2$ for 2020 CO_2 emissions, rising to $24/mtCO_2$ for 2080 CO_2 emissions (under a near-term target discount rate of 2%).[127] These estimates are not equivalent to an estimate of the benefits of GHG mitigation accruing to U.S. citizens and residents even for the 4-5 damage categories included in GIVE and DSCIM. First, due to technical modeling limitations these estimates do not include damages from physical impacts occurring in all U.S. territories. For example, damages occurring in Guam, a U.S. territory which is already being affected by climate change, are not captured in these estimates. As highlighted in a recent DoD report, "[a]t Naval Base Guam, recurrent flooding limits capacity for a number of operations and activities including Navy Expeditionary Forces Command Pacific, submarine squadrons, telecommunications, and a number of other specific tasks supporting mission execution" (DoD 2019). Second, for the reasons discussed in Section 1, these estimates exclude the myriad of pathways through which global climate impacts directly and indirectly impact the interests of U.S. citizens and residents. For example, climate change is likely to worsen public health, change migration patterns, and disrupt aspects of the global supply chain. Changing economic and health conditions across countries will impact U.S.

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[125] Some analysts (e.g., Azar and Sterner 1996, Anthoff et al. 2009, Anthoff and Emmerling 2019) employ "equity weighting" to incorporate distributional equity objectives into estimates of the SC-GHG. As noted by Anthoff and Emmerling (2019), "[e]xisting equity weighting studies assume a social welfare function (SWF) that exhibits inequality aversion over per capita consumption levels."

[126] The analogous DSCIM results for 2020 emissions of CH_4 and N_2O (under a near-term Ramsey discount rate of 2%) are $22/mtCH_4$ and $2,900/mtN_2O$, rising to $382/mtCH_4$ and $8,500/mtN_2O$ by 2080.

[127] The analogous GIVE results for 2020 emissions of CH_4 and N_2O (under a near-term Ramsey discount rate of 2%) are $223/mtCH_4$ and $4,400/mtN_2O$, rising to $534/mtCH_4$ and $7,900/mtN_2O$ by 2080.

business, investments, and travel abroad. In addition to the economic consequences, unrest and political instability in foreign countries are expected to have national security ramifications for the U.S. (DoD 2021). Empirical estimates of some international spillover impacts have started to appear in the academic literature. For example, as noted in IPCC (2022), "Schenker (2013) estimated that the climate impacts on trade from developing to developed countries could be responsible for 16.4% of the total expected cost of climate change in the US in 2100."For these reasons, and those discussed in Section 1, such estimates of damages from climate change impacts physically occurring within the U.S. do not provide a robust estimate of damages to U.S. populations.

These GIVE and DSCIM estimates of damages physically occurring within the U.S. are subject to the broader set of limitations discussed in Section 3.2, including the omission of important damage categories. Additional modeling efforts can shed further light on some of these categories. For example, the Framework for Evaluating Damages and Impacts (FrEDI) is a modeling framework developed by the EPA to facilitate the characterization of net climate change impacts in numerous sectors within the contiguous U.S. and monetize the associated net damages (EPA 2021d, Sarofim et al. 2021b). FrEDI includes 20 sectoral impact categories, many with multiple adaptation scenarios and sub-impacts, across seven U.S. regions.[128] FrEDI was originally developed to calculate impacts through the end of the 21st Century. Developments are underway to extend the estimates from within FrEDI out to 2300. Results from the most recent version of FrEDI that show that damages resulting from climate change impacts within U.S. borders and in sectors not represented in GIVE and DSCIM are expected to be substantial. For example, under the RFF-SPs and FaIR model outputs used within this report, FrEDI estimates total net damages (undiscounted) across 20 sectors in 2060 to be over $300 billion annually, growing to over $600 billion per year by 2090 (2020$).[129] Some of the sectors not appearing in DSCIM or GIVE but having large economic damages estimated in FrEDI for 2090 include: transportation related damages from hightide flooding

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[128] The FrEDI model uses estimates of physical and economic impacts of climate change by degree of warming developed using existing sectoral impacts models to project impacts and damages resulting from any emission scenario. It is designed to synthesize the results of a broad range of peer-reviewed climate change impact and damage projections, including those derived from econometric approaches and detailed, processed-based simulation models. These include various impacts to human health, coastal and inland property (e.g., from SLR, flooding and storms), transportation and other infrastructure, energy demand and supply, water resources, labor, and winter recreation. Currently, all impacts in FrEDI are based on changes in temperature or SLR, although the relationship between climate and impacts in the underlying models often includes other factors, such as precipitation; the framework employ a variety of assumptions regarding adaptive responses to climate impacts. EPA (2021d) provides a complete list of endpoints and details regarding the scope and assumptions for each sector. For additional description of FrEDI please see www.epa.gov/cira/fredi and www.github.com/USEPA/FrEDI.

[129] Inputs to FrEDI include a time series of global mean temperature from the baseline scenario calculated the mean over an ensemble of 10,000 FaIR v1.6.2, U.S. population in each of the 7 National Climate Assessment regions (i.e., Northeast, Southeast, Midwest, Northern Great Plains, Southern Great Plains, Southwest, Northwest) and U.S. GDP in 2015$ from the RFF-SPs. Regional population was calculated as a percentage of total national population from FrEDI. FrEDI provides damage estimates in 2015USD. These were brought to 2020USD for this report using U.S. Bureau of Economic Analysis (BEA) Table 1.1.9 (specifically, using 2020USD = 2015USD x (113.648 / 104.691), accessed February 7th, 2022). See https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=3&isuri=1&select_all_years=0&nipa_table_list=13&series=a&first_year=2005&last_year=2020&scale=-99&categories=survey&thetable= .

($142 billion annually in 2090), premature mortality from climate-driven changes in ozone and PM2.5 ($90 billion annually in 2090), and property damage from hurricane winds ($28 billion annually in 2090).

Due to the limitations associated with the DSCIM and GIVE damage modules these models significantly underestimate the benefits of GHG mitigation to U.S. citizens and residents. The EPA will continue to review developments in the literature, including robust methodologies for estimating the magnitude of the various direct and indirect damages to U.S. populations from climate impacts occurring abroad and reciprocal international mitigation activities.

Just as there is heterogeneity in the distribution of climate change damages across the globe, the scope and magnitude of climate change impacts is not uniform across the U.S. Although subnational detail on the distribution of impacts and associated monetized damages is not available from the SC-GHG modeling presented in Section 3.1,[130] scientific assessment reports and additional modeling efforts can shed further light on the distribution of damages expected to occur within the U.S. For example, scientific assessment reports on climate change produced over the past decade by the U.S. Global Change Research Program provide detailed findings as to the distribution of climate changes impacts across the U.S. (e.g., USGCRP 2016, 2018a). Modeling efforts using a predecessor of DSCIM (e.g., Hsiang et al. 2017) and using the FrEDI model provide additional information about how damages are expected to be substantial and distributed unevenly across U.S. regions. For example, of the sectors examined in FrEDI in 2021, the largest source of modeled damages differed from region to region, with wildfire impacts the largest for the Northwest, air quality impacts on the East Coast and the Southwest, temperature-related mortality in the Midwest, wind damage in the Southern Plains, and damages to rail infrastructure in the Northern Plains. In addition, a growing body of literature is focusing on the disproportionate and unequal risks that climate change is projected to have on communities that are least able to anticipate, cope with, and recover from adverse impacts. National Academies of Science, Engineering, and Medicine reports provide evidence of how the impacts of climate change create potential environmental justice concerns (NRC 2011, National Academies 2017). For a recent detailed discussion of climate change impacts in the U.S. and their intersection with environmental justice concerns, see the 2021 Climate Change and Social Vulnerability report (EPA 2021e).

4   Using SC-GHG Estimates in Policy Analysis

This section discusses how the SC-GHG results presented in Section 3.1 can be used in the EPA analysis of policies that affect GHG emissions. Section 4.1 presents a combination of the multiple lines of evidence on damages into a manageable number of values for policy analysis. Section 4.2 describes how the SC-GHG values are applied to a stream of estimated emissions changes in an analysis.

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[130] The GIVE damage module is only resolved at the country level, such that subnational detail on the distribution of impacts is not available. The DSCIM damage module is resolved at a spatial resolution resembling counties, though that level of detail is unavailable for the model results based on the probabilistic socioeconomic scenarios used in this report.

4.1   Combining Lines of Evidence on Damages

The SC-GHG estimation process in this report produces nine separate estimates of the SC-CO$_2$, SC-CH$_4$, and SC-N$_2$O for a given year, the product of three damage modules and three discount rates. To produce a range of estimates that reflects the uncertainty in the estimation exercise while providing a manageable number of estimates to incorporate into policy analysis, the multiple lines of evidence on damage modules can be combined by averaging the results presented in Table 3.1.1, Table 3.1.2, and Table 3.1.3 across the three damage module specifications. In assigning equal weight to each damage module specification no underlying line of evidence is given greater weight than another. As discussed in Section 2.3, the sectoral damage modules in GIVE and DSCIM are based on different underlying information, data sources, and estimation methods.[131] GIVE and DSCIM are both independent lines of evidence from the meta-analysis-based damage module since the studies underlying each sectoral damage modules in GIVE and DSCIM are not included in Howard and Sterner's (2017) final sample of studies.

Table 4.1.1 presents the resulting SC-GHG estimates for each emissions year, gas, and near-term target discount rate after averaging across three damage module specifications. This table displays the rounded values; the annual unrounded values for use in calculations are available for all emissions years over 2020-2080 in Table A.4.1 in the Appendix.

Table 4.1.1: Estimates of the Social Cost of Greenhouse Gases (SC-GHG), 2020-2080 (in 2020 dollars per metric ton)

| | SC-GHG and Near-term Ramsey Discount Rate | | | | | | | | |
| | SC-CO$_2$ *(2020 dollars per metric ton of CO$_2$)* | | | SC-CH$_4$ *(2020 dollars per metric ton of CH$_4$)* | | | SC-N$_2$O *(2020 dollars per metric ton of N$_2$O)* | | |
Emission Year	2.5%	2.0%	1.5%	2.5%	2.0%	1.5%	2.5%	2.0%	1.5%
2020	120	190	340	1,300	1,600	2,300	35,000	54,000	87,000
2030	140	230	380	1,900	2,400	3,200	45,000	66,000	100,000
2040	170	270	430	2,700	3,300	4,200	55,000	79,000	120,000
2050	200	310	480	3,500	4,200	5,300	66,000	93,000	140,000
2060	230	350	530	4,300	5,100	6,300	76,000	110,000	150,000
2070	260	380	570	5,000	5,900	7,200	85,000	120,000	170,000
2080	280	410	600	5,800	6,800	8,200	95,000	130,000	180,000

Note, given the relatively modest variation in the SC-GHG estimates across the three damage modules in Tables 3.1.1-3.1.3, the values presented in Table 4.1.1 are similar to what would be obtained under alternative approaches for drawing on the multiple lines of evidence represented by the three damage modules. For example, if the estimates for each model were weighted in such in way that the weighted

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[131] Only one component of the methodology for calculating coastal damages is common across the two models. Both DSCIM and GIVE rely on the CIAM model developed by Diaz (2016) to estimate the economic damages resulting from projections of SLR. This small degree of overlap across the two modules is unlikely to affect the representation of structural uncertainty when pooling estimates across the two damage modules.

average is the certainty-equivalent across the models,[132] the average (unrounded) SC-CO$_2$ in emissions year 2020 would change by less than 1% for all three near-term discount rates. The SC-GHG estimates resulting from averaging across the models (as presented in Table 4.1.1) are also similar to the central estimates presented in Tables 3.1.1-3.1.3. That is, the unrounded estimates based on the DSCIM damage module for the 2.5% discount rate, and the GIVE damage module for the 2.0% and 1.5% discount rates, in emissions year 2020 differ from the three-model average estimates by only 2% (2.5% discount rate), -1% (2.0% discount rate), and -1% (1.5% discount rate).

4.2 Application of SC-GHG Estimates in Benefit-Cost Analysis

The SC-GHG reflects the future stream of damages associated with an additional ton of emissions discounted back to the year of the emissions. Several steps are necessary when using the SC-GHG estimates in an analysis that includes GHG emissions changes in multiple future years in addition to other benefits and costs. First, the gas-specific SC-GHG estimates corresponding to the year of estimated emissions change need to be applied and discounted to the year of analysis to monetize the emissions. Second, the monetized GHG emissions impacts need to be incorporated with other costs and benefits considered in the analysis.

The SC-GHG estimates presented in Table 4.1.1 represents the damages associated with each additional ton of emissions released discounted back to the year of emissions. To calculate the monetized value of damages from emissions in year τ discounted back to the year of analysis, denoted as year 0, two steps are required. First, the emissions changes in the future year, x_τ, are multiplied times the SC-GHG in that future year, $scghg_\tau$, to the obtain the future monetized net damages associated with those emissions. Second, that value needs to be discounted back to the year of analysis to obtain the present value of the damages, pv_0, using the discount factor $\widetilde{\delta}_\tau$. Mathematically, these two steps can be written as

$$pv_0 = x_\tau \cdot scghg_\tau \cdot \widetilde{\delta}_\tau .$$ (4.2.1)

The correct discount factor to use when discounting the SC-GHG estimates presented in this report is the certainty-equivalent discount factor, $\widetilde{\delta}_\tau$. This is because the SC-GHG estimates are certainty-equivalent values that account for the uncertainty in future consumption per capita. As described more fully in Appendix A.3, the certainty-equivalent discount factor incorporates the uncertainty in future consumption using the RFF-SP probabilistic growth scenarios. Discounting the SC-GHG estimates using a constant discount rate equal to the near-term target rate would not capture the uncertainty in consumption per capita for that year. This means that precise discounting of a stream of future emissions

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[132] Specifically, the weight is estimated for each module, near-term discount rate and emission year using: $w_{\tau,m,\eta} = \frac{E\left[(C_{\tau,m})^{-\eta}\right]}{\sum_m^M E[(C_{\tau,m})^{-\eta}]}$, where c is consumption net climate change, τ is emission year, m is damage module, and η is the elasticity of marginal utility with respect to consumption. The resulting weights given to the damage module based on DSCIM, GIVE, and Howard and Sterner (2017) are: 0.331, 0.334, 0.334, respectively, under Ramsey discounting with a 2.0% near-term target rate. These weights are close to an equal weight (0.333) on modules. These three modules share the same distributions of GDP and have estimates of damage under climate change that are comparable. Therefore, the distributions of net consumption across the three modules are similar, leading to similar weights.

requires the SC-GHG for each year (provided in Table A.4.1) together with the certainty-equivalent discount factor for that year.

While applying the certainty-equivalent discount factor would ensure a full accounting of scenario uncertainty, this process introduces substantial complexity in the calculations, which may not be warranted in all situations. If the stream of future emissions being evaluated is moderate (e.g., 30 years or less), the difference between discounting from the year of emissions to the year of analysis using a constant discount rate equal to the near-term target rate, and discounting using the certainty-equivalent discount factor, $\widetilde{\delta}_\tau$ will be small. For example, if the year of analysis is 2022 using the near-term target rate to discount back from the year of emissions instead of the certainty-equivalent discount factor will underestimate the present value emission reductions by less than 1% for the first ten years of future emissions. The present value of emission reductions 30 years in the future will be underestimated by slightly over 2% yielding a conservative approximation to the more complete calculation.[133] (The differences from using a constant discount rate rather than the certainty-equivalent discount factor for each year in the future are provided in Figure A.3.1.) Therefore, discounting the monetized value of emission reductions over the first 30 years of the analysis using the near-term target rate provides a close approximation.

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[133] This example is based on the SC-GHG estimates using a 2 percent near-term Ramsey discount rate. The quantitative results will vary slightly across the near-term target rates considered in this report, but the difference between the two approaches remains relatively small over the first 30 years.

5   Summary

This report presents new estimates of the SC-GHG that reflect recent advances in the scientific literature on climate change and its economic impacts and recommendations made by the National Academies of Science, Engineering, and Medicine in 2017.

Since 2008, the EPA has used estimates of the SC-GHG in analyses of actions that affect GHG emissions. The values used by the EPA from 2009 to 2016, and since 2021, have been consistent with those developed and recommended by the Interagency Working Group on the SC-GHG (IWG), and the values used from 2017-2020 were consistent with those required by E.O. 13783. During that time, the National Academies conducted a comprehensive review of the social cost of carbon and issued a final report in 2017 that recommended specific criteria for future updates to the SC-CO$_2$ estimates, a modeling framework to satisfy the specified criteria, and both near-term updates and longer-term research needs pertaining to various components of the estimation process. The IWG was reconstituted in 2021 and E.O. 13990 directed it to develop a comprehensive update of its SC-GHG estimates, recommendations regarding areas of decision-making to which SC-GHG should be applied, and a standardized review and updating process to ensure that the recommended estimates continue to be based on the best available economics and science going forward.

The EPA is a member of the IWG and is participating in the IWG's work under E.O. 13990. While that process continues, this report presents a set of SC-GHG estimates that incorporates recent research addressing the near-term recommendations of the National Academies. The report takes a modular approach in which the methodology underlying each of the four components, or modules, of the SC-GHG estimation process – socioeconomics and emissions, climate, damages, and discounting – is developed by drawing on the latest research and expertise from the scientific disciplines relevant to that component. Table 5.1 summarizes the key elements of the National Academies' near-term recommendations for each module and how the methodological updates employed in this report addressed those recommendations.

The modeling implemented in this report reflects conservative methodological choices, and, given both those choices and the numerous categories of damages that are not currently quantified and other model limitations, the resulting SC-GHG estimates likely underestimate the marginal damages from greenhouse gas pollution. The EPA will continue to review developments in the literature, including more robust methodologies for estimating the magnitude of the various direct and indirect damages from GHG emissions, and look for opportunities to further improve SC-GHG estimation going forward.

Table 5.1: Implementation of National Academies Recommendations in this Report

Near-term National Academies' recommendations	Methodological updates employed in this report
Overarching	
☐ Framework: Adopt a modular approach to allow relevant disciplinary expertise to shape each part of the analysis.	☐ Adopted a modular modeling framework that unbundled the socioeconomic-emissions scenarios, climate modeling, damage function modeling, and discounting to allow each component to be informed by high-quality science from the relevant disciplines.
☐ Scientific basis: Modules should be consistent with scientific knowledge in the current, peer-reviewed literature.	☐ Selected modeling frameworks and parameters for each module based on recent peer-reviewed scientific literature and scientific consensus reports.
☐ Uncertainty characterization: Key uncertainties, including functional forms, parameter assumptions, and data inputs, should be adequately represented and uncertainties not quantified should be identified.	☐ Expanded upon past estimates used by the EPA by incorporating a quantitative consideration of uncertainty into all modules and using a Monte Carlo approach to develop SC-GHG distributions that captures interactions across modules' uncertainties.
☐ Transparency: Documentation should allow readers to understand and assess the modules, including which features are evidence-based or judgment-based. Model code should be available to researchers.	☐ Documented modeling features in detail, including within replication instructions and computer code that has been made publicly available.
Socioeconomic module	
☐ Use statistical methods and expert elicitation for projecting probability distributions of GDP, population growth and emissions into the future.	☐ Adopted the probabilistic RFF-SPs, which provide multi-century projections of population, GDP per capita, and GHG emissions based on statistical and structured expert judgment methods that account for future policies and connections between variables.
Climate module	
☐ Employ a reduced complexity Earth system model that satisfies well-defined diagnostic tests, such as the FaIR model, to represent temperature change over time, and include sea-level rise and ocean pH components.	☐ Adopted FaIR 1.6.2 to serve as the basis for an updated climate module, which provides an accurate representation of the latest scientific consensus on the relationship between global emissions and global mean surface temperature under a wide range of socioeconomic emissions scenarios, complemented by the BRICK and FACTS models of sea-level rise.
Damages module	
☐ Improve and update existing damage functions to reflect recent scientific literature.	☐ Adopted a suite of three updated damage functions (GIVE, DSCIM, and the meta-analysis), which together represent the major scientific lines of evidence on the economic impacts of climate change that are available, capture uncertainty, and, in the cases of GIVE and DSCIM, provide transparent bottom-up modeling that map Earth system changes to damages.
Discounting module	
☐ Incorporate the relationship between discount rates and economic growth using a Ramsey-like framework and parameters chosen consistent with theory and empirical evidence on consumption interest rates.	☐ Adopted a Ramsey discounting approach that endogenously connects the discount rate and the socioeconomic scenarios and where the parameters are empirically calibrated based on observed behavior of interest rates and economic growth.

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A. Appendix

A.1. Additional Discussion of Scientific Updates in IPCC's Sixth Assessment Report

Several updates to the science of greenhouse gas radiative efficiency[134], atmospheric lifetimes, and chemistry have been made since the IWG published its first set of recommended SC-GHG estimates in 2010. In this report projections of temperature change from a pulse of GHG emissions are based on the FaIR climate model, version 1.6.2, rather than using the simplified lifetime and forcing equations from the IPCC AR4 assessment that were embedded in the IAMs underlying the SC-GHG estimates used to date. While FaIR is a more complex model that includes internal feedbacks and chemistry such that gas lifetimes and interactions are not constant, it can be instructive to examine how the more simplistic equations have been updated between AR4 (IPCC 2007b) and AR6 (IPCC 2021b) as FaIR 1.6.2 reflects many of the same scientific advances in understanding.

The radiative efficiency of all gases has been updated, in part because of updates to the science and in part because radiative efficiency is a function of background concentrations. The radiative efficiency of CO_2 has decreased by 5% relative to AR4, while the radiative efficiencies of CH_4 and N_2O have both increased by about 5%. AR6 also updated the indirect effects of CH_4 and N_2O that occur through atmospheric chemistry. The indirect radiative effects of CH_4 that occur through increases in ozone and stratospheric water vapor decreased by about 6%. Meanwhile, the radiative effects of N_2O now include the impact of N_2O on CH_4 and stratospheric ozone, leading to a decrease in N_2O radiative efficiency of almost 13%. When accounting for all radiative changes, the effective radiative efficiency of CH_4 has increased by about 10%, while that of N_2O has decreased by almost 8%, relative to AR4.

Separately, the AR6 estimate of lifetime of CH_4 decreased by about 2%, and that of N_2O by about 4%, relative to AR4. The changes in the CO_2 lifetime are more complex, but over 100 years, the effective lifetime of CO_2 increased by about 13%. AR6 also included the possibility of accounting for the CO_2 produced through the oxidation of CH_4 of fossil origins in the atmosphere, using an oxidation factor of 0.75 to account for CH_4 that does not oxidize to CO_2 but rather leaves the atmosphere through a deposition process.[135,136] AR6 also accounts for the climate-carbon feedbacks that result from non-CO_2 greenhouse gases warming the atmosphere and impacting the carbon cycle; in AR4, this effect was only included for CO_2.

Including all these scientific updates to lifetimes, atmospheric chemistry interactions, and radiative efficiency, the AR6 assessment estimates that the 100-year global warming potential (GWP) of CH_4 has increased by almost 9% relative to the estimates from AR4 (from 25 to 27.2), whereas the 100-year GWP of N_2O has decreased by about 8% (from 298 to 273). Between AR4 and AR6 there was also a discussion

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[134] Radiative efficiency is a measure of a gas' greenhouse gas strength, defined as the change in radiative forcing for a unit change in the atmospheric concentration of a gas (in $W/m^2/ppb$).

[135] While FaIR 1.6.2 reflects the advances in understanding presented in AR6, the CH_4 oxidization factor in FaIR 1.6.2 was still set to 0.60 (based on AR5) in the model runs conducted for this report. In corresponding with the FaIR model developers, they have stated that it will be updated to the AR6 value in the next version of FaIR 2.0.

[136] Note that inventories based on using GWPs often use the non-fossil value for all CH_4 emissions because in some cases there is a potential for CO_2 double counting: for example, if complete combustion is assumed when calculating CO2 emissions from a natural gas turbine, then the carbon from any methane leakage has already been accounted for.

of climate-carbon feedbacks. Including the climate-carbon feedback means taking into account the effect that a changing climate has on the carbon cycle. AR4 GWPs were calculated with climate-carbon feedbacks included for CO_2, but not for non-CO_2 greenhouse gases. This inconsistent treatment of climate-carbon feedbacks can lead to underweighting the non-CO_2 greenhouse gases relative to their actual impacts. The publication of more studies using climate-carbon feedbacks for all gases, and the determination that a consistent approach was superior, led AR6 to include the climate-carbon feedbacks for all gases in the only GWP that was presented.

Another way of considering the impact of different greenhouse gases is to attribute the temperature changes of the last decade (2010-2019) to historical emissions of each gas. According to the AR6 assessment, historical emissions of carbon dioxide have contributed almost 0.8 degrees of warming to those temperatures, compared to about half a degree for historical emissions of CH_4, and almost one tenth of a degree for historical emissions of N_2O. These attributed temperature increases sum to more than the observed temperature change of almost 1.1 degrees because some of the warming is masked by various cooling influences, the most important of which is about half a degree of cooling resulting from historical emissions of sulfur dioxide.

A.2. Consumption Rate of Interest and Integration into Benefit-Cost Analysis

When analyzing policies and programs that result in GHG emission reductions, it is important to account for the difference between the social and private rate of return on any capital investment affected by the action. Market distortions, such as taxes on capital income, cause private returns on capital investments to be different from the social returns. In well-functioning capital markets, arbitrage opportunities will be dissipated, and the cost of investments will equal the present value of future private returns on those investments. Therefore, an individual forgoing consumption or investment of equal amounts as the result of a regulation will face an equal private burden. However, because the social rate of return on the investment is greater than the private rate of return, the overall social burden will be greater in the case where investment is displaced. Thus, society is not indifferent between a regulation that displaces consumption versus investment in equal amounts.

OMB's Circular A-4 points out that "the analytically preferred method of handling temporal differences between benefits and costs is to adjust all the benefits and costs to reflect their value in equivalent units of consumption and to discount them at the rate consumers and savers would normally use in discounting future consumption benefits" (OMB 2003). The damage estimates developed for use in the SC-GHG are already estimated in consumption-equivalent terms. Therefore, an application of this OMB guidance would use the consumption discount rate to calculate the SC-GHG, while also developing a more complete estimate of social costs to account for the difference in private and social rates of return on capital for any investment displaced as a result of the action being analyzed. This more complete estimate of social costs could be developed using either the shadow price of capital approach or by estimating costs in a general equilibrium framework, for example by using a computable general equilibrium model. In both cases, displaced investment would be converted into a flow of consumption equivalents that could be discounted at the consumption rate.

In cases where the costs are not adjusted to be in consumption-equivalent terms, OMB's Circular A-4 recommends that analysts provide a range of estimates for net benefits based on two approaches. The first approach is based on using the consumption rate of interest to discount all costs and benefits. This approach is consistent with the case where costs are primarily borne as reduced consumption. The second approach, the opportunity cost of capital approach, focuses on the case where the main effect of an action is to displace or alter the use of capital in the private sector (OMB 2003). When interpreting the opportunity cost of capital approach from the point of view of whether to invest in a single government project, it is asking whether the benefits from the project would at least match the returns from investing the same resources in the private sector. Interpreting the approach from the standpoint of a benefit-cost analysis of a regulation, the approach focuses on adjusting estimates of benefits downward by discounting at a higher rate to offset additional social costs not reflected in the private value of displaced investment used to develop the cost estimate (assuming the costs of the regulation are borne upfront).

Harberger (1972) derived a general version of the opportunity cost of capital approach, recognizing that policies will most likely displace a mix of consumption and investment and therefore, a blended discount rate would be needed to adjust the benefits to account for the omitted costs. In his partial equilibrium approach, the blended discount rate is a weighted average of the consumption interest rate and rate of return on capital, where the weights are the share of a policy's costs borne by consumption versus investment. This general result has been applied to the general equilibrium context by Sandmo and Drèze (1971) and Drèze (1974) and can be extended to account for changes in foreign direct investment (CEA 2017). This highlights that using the opportunity cost of capital to discount benefits and costs is, at best, creating a lower bound on the estimate of net benefits that would only be met in an extreme case where regulatory costs fully displace investment. If the beneficial impacts of the regulation induce private investment whose returns have not been quantified and fully converted to consumption equivalents, then this approach would not even be a lower bound, as the net benefits calculated using the opportunity cost of capital would be even lower than the theoretically correct lower bound.

An important limitation of the opportunity cost of capital approach is that its correct application depends heavily on the temporal patterns of the displaced capital returns and future benefits, including the lifetime of the displaced capital investment versus the lifetime of the benefit stream being valued (Li and Pizer 2021). In fact, using the opportunity cost of capital approach is only an accurate approximation of the correct shadow price of capital approach if these patterns are exactly the same. Li and Pizer (2021) show that a rate lower than the rate of return to capital is appropriate when displaced investment is relatively short-lived compared to the benefits stream and a higher rate is appropriate when displaced investment is relatively long-lived compared to benefits.

In benefit-cost analysis of policy actions whose benefits and costs occur over a relatively short time frame, the range of net benefits computed using the two discounting approaches may be relatively narrow. In this case, there may not be much error in presenting the opportunity cost of capital discounting approach side-by-side with consumption discounting as an effort to represent an uninformed prior over the share of regulatory costs that will displace investment and using the potential bounding cases for net benefits. However, for cases where the costs are borne early in the time horizon and benefits occur for decades or even centuries, such as with GHG mitigation, the two estimates of net benefits will differ significantly. Importantly, in this circumstance, the opportunity cost of capital approach will substantially underestimate net benefits even for the case where the policy fully displaces investment. In this case,

there is high risk of uninformative results from an analysis when using this two-discount-rate approach to provide an uninformed prior over the share of regulatory costs borne by investment. The preferred approach (OMB 2003, Li and Pizer 2021) is to develop more complete consumption-equivalent measure of costs and benefits, accounting for any effects on investment either by using a shadow price of capital approach or a general equilibrium framework, and then discounting those streams at the consumption rate of interest alone.

The "shadow price of capital" approach, described below, provides a method of ensuring that any additional social costs of displaced capital are accounted for in an analysis, as has been widely recognized in the academic literature (Lind 1990; Lyon 1990; Moore et al. 2013; Li and Pizer 2021) and in domestic and foreign government guidance documents (OMB 1972, 2003; EPA 2010; OECD 2018) as more appropriate than using the opportunity cost of capital approach. The most straightforward, although extreme, illustration of this approach is to consider the consumption value of a marginal dollar of displaced investment that persists forever. A permanent loss of investment is a very strong assumption because we would expect the displaced investment to be replaced eventually, but it is an instructive example of the approach. If this dollar had been invested, it would have earned a return on capital, r_i, every period into the future. If that yield was returned as consumption (or taxes that ultimately benefit households), the infinite stream of r_i should be discounted at the consumption rate of interest r_c. The present value of this infinite stream is r_i/r_c.[137] Under this strong assumption of a permanent displacement of capital, the shadow price of capital (SPC) would be calculated as the opportunity cost of capital divided by the consumption rate of interest. Because $r_i > r_c$, the SPC is greater than one, reflecting the additional cost of the displaced capital. Multiplying any portion of costs (and/or benefits) that affect investment in this way, and then discounting using the consumption rate of interest would appropriately account for the displaced investment.

However, r_i/r_c would only be the correct SPC to use in the extreme case where changes in the productive capital stock persist in perpetuity. A more realistic version of the SPC accounts for how savings and depreciation cause the impact of displaced capital to dissipate in the future. In particular, with a savings (or reinvestment) rate of s from gross income and a depreciation rate of μ, an invested dollar returns $(1 - s)(r_i + \mu)$ in consumption in the first period. Each period after that, the amount of investment that continues to be displaced is determined by the savings rate, assuming a closed economy. However, the invested capital also declines according to the depreciation rate. This creates a stream of consumption benefits equal to

$$C_t = \sum_{t=0}^{\infty} (1 - s)(r_i + \mu)[1 + s(r_i + \mu) - \mu]^t, \qquad (A.2.1)$$

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[137] An infinite stream of return is a type of annuity called a perpetuity. The present value of a perpetuity, r_i, that begins in year 1 and is discounted at a rate of r_c is $PV = \frac{r_i}{(1+r_c)} + \frac{r_i}{(1+r_c)^2} + \frac{r_i}{(1+r_c)^3} + \cdots = \frac{r_i}{r_c}$. That is, the present value of a perpetuity is the annual return, r_i, divided by the rate of discount, r_c.

which is discounted at the consumption discount rate r_c. Including constant savings and depreciation rates yields a shadow price of capital[138] equal to

$$SPC = \frac{(1-s)(r_i+\mu)}{r_c+\mu-s(r_i+\mu)}. \qquad (A.2.2)$$

Equation A.2.2 can be updated to include a capital tax rate that explicitly defines a difference between r_i and r_c, but the result of the analysis would not change if the tax revenue was used to benefit society.[139] In the analysis, the portion of costs (and/or benefits) that displace investment would be multiplied by the SPC to adjust for any missing social impacts and then all costs and benefits would be discounted at the consumption rate of interest.

Estimates of the closed economy SPC in the academic literature are in the range of 1.1 to 2.2 (Groom et al. 2005, Boardman et al. 2010, Moore et al. 2013, Li and Pizer 2021). In an open economy model the SPC may be closer to 1.0 (Lind 1990). Implementing this approach in practice can be challenging because it requires an assessment of the portion of costs (and/or benefits) that displace investment. However, even in the absence of information as to the share of costs that displace consumption, multiplying the full cost estimate by the SPC and discounting all costs and benefits at the consumption rate of interest likely provides a more informative lower-end bounding case for net benefits than using the opportunity cost of capital approach under the premise of full displacement.

A.3. Derivations of the SC-GHG Values for use in Analyses

This report presents SC-GHG estimates as certainty-equivalent values that account for the uncertainty (a range of possible outcomes) in future consumption underlying the RFF-SP probabilistic growth scenarios. To recover a discounted present value of climate damages from future emissions, analysts consider the SC-GHG associated with future emissions and then discount that value to the year of their analysis. For example, an analyst interested in the present value in the year 2022 of changes in future emissions in the year 2030 would use the 2030 SC-GHG and discount back to recover a present value in the year 2022. However, there is uncertainty in future consumption such that analysts should account for the range of

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[138] When including depreciation, μ, the gross return on a capital stock k_0 will be $(r_i+\mu)k_0$, where μ is the depreciation rate. With a savings or reinvestment rate of s, a capital stock of k_0 in period 0 will return $(1-s)(r_i+\mu)k_0$ as consumption and $s(r_i+\mu)k_0$ will be saved for reinvestment. In period 1, the capital stock will be the original capital less depreciation, plus the amount reinvested, $k_1 = \{(1-\mu)k_0\}+\{s(r_i+\mu)k_0\} = [1+s(r_i+\mu)-\mu]k_0$. This will return $(1-s)(r_i+\mu)[1+s(r_i+\mu)-\mu]k_0$ as consumption in period 1 and $s(r_i+\mu)[1+s(r_i+\mu)-\mu]k_0$ will be reinvested. The capital stock in period 2 will be $k_2 = \{(1-\mu)[1+s(r_i+\mu)-\mu]k_0\}+\{s(r_i+\mu)[1+s(r_i+\mu)-\mu]k_0\} = [1+s(r_i+\mu)-\mu]^2k_0$, which will return $(1-s)(r_i+\mu)[1+s(r_i+\mu)-\mu]^2k_0$ as consumption. This creates an infinite consumption stream of $C = (1-s)(r_i+\mu)k_0 + (1-s)(r_i+\mu)[1+s(r_i+\mu)-\mu]k_0 + (1-s)(r_i+\mu)[1+s(r_i+\mu)-\mu]^2k_0 + \dots$ This is a perpetuity of $[(1-s)(r_i+\mu)k_0]$ with a growth rate of $[s(r_i+\mu)-\mu]$, and should be discounted at the consumption rate of discount r_c. The present value of perpetuity A, growing at a rate of g, and discounted at rate r is $PV = \frac{A}{(1+r)} + \frac{A(1+g)}{(1+r)^2} + \frac{A(1+g)^2}{(1+r)^3} + \dots = \frac{A}{(r-g)}$. So, the present value of the perpetuity described above would be $PV = \frac{(1-s)(r_i+\mu)k_0}{(r_c-[s(r_i+\mu)-\mu])} = \frac{(1-s)(r_i+\mu)}{r_c+\mu-s(r_i+\mu)}k_0$.

[139] If a portion of the tax revenues affect investments, then it requires an analogous adjustment to account for the fact that it creates a current period consumption value greater than one according to the "marginal value of public funds," v_G. In this case, the numerator in the SPC equation would be equal to $(1-s)(r_i+\mu) + (v_G-1)\tau r_i$, where τ is the tax rate on capital (Li and Pizer 2021).

possible outcomes. This is because risk-averse agents value the costs of future emissions differently than risk-neutral agents by accounting for the range of uncertain outcomes. There are several ways to account for this uncertainty. The approach taken in this report provides certainty-equivalent SC-GHG values that can be easily used by analysts with a conventional discounting approach, as described in Section 4.2. This section describes the equations used to recover those certainty-equivalent SC-GHG estimates for an emissions year τ, denoted as $scghg_\tau$.

To begin with a motivating example, imagine a hypothetical regulation that reduces x tons of greenhouse gas emissions in year τ, and the regulation will be in place for the years 2040 through 2050. An analyst wants to calculate the present value pv of the regulation's benefits from future reductions in greenhouse gas emissions in the year of analysis j, where j is some year between now and 2040. The analyst would use the SC-GHG estimates found in this report for each of the years from 2040 through 2050, each denoted as $scghg_\tau$. In addition, the analyst would need the certainty-equivalent discount rate path specific to the year of analysis, $\tilde{r}_t$, from year j to year τ (see Figure 2.4.1 for one example path). The analyst then calculates the present value of the regulation's benefits as

$$pv_j = \sum_{\tau=2040}^{2050} x_{\tau.} \cdot scghg_\tau \cdot e^{-\tilde{r}_t(\tau-j)} \qquad (A.3.1)$$

The $scghg_\tau$ values presented in this report yield the present value when discounted using the certainty-equivalent discount factor $e^{-\tilde{r}_t(\tau-j)}$. This discount factor was written as $\tilde{\delta}_\tau$ in Section 4.2 but is defined in more detail below.

The remainder of this section describes the derivation of the certainty-equivalent SC-GHG $scghg_\tau$. The certainty-equivalent discount factor for the Ramsey framework is

$$e^{-t \cdot \tilde{r}_t} = E[e^{-\Sigma_{s=0}^t (\rho + \eta g_s)}], \qquad (A.3.2)$$

where $\tilde{r}_t$ is the certainty-equivalent discount rate. This is the single, time-averaged discount rate that produces the same discount factor over a specific time horizon as the distribution of uncertain discount rates. This certainty-equivalent discount rate is defined as

$$\tilde{r}_t = \rho - \left(\frac{1}{t}\right)\left(\ln E\left[e^{-\Sigma_{s=0}^t(\eta g_s)}\right]\right) = \rho + \left(\frac{1}{t}\right)E\left[\ln\left(\frac{c_t}{c_0}\right)^\eta\right] \qquad (A.3.3)$$

and

$$e^{-t \cdot \tilde{r}_t} = e^{-t \cdot \left[\rho + \left(\frac{1}{t}\right)E\left[\ln\left(\frac{c_t}{c_0}\right)^\eta\right]\right]} = e^{-t\rho} \cdot E\left[\left(\frac{c_t}{c_0}\right)^{-\eta}\right] = E\left[\left(\frac{1}{1+\tilde{\rho}}\right)^t \cdot \left(\frac{c_t}{c_0}\right)^{-\eta}\right]. \qquad (A.3.4)$$

Here, as described in Section 3.4, r_t is the consumption discount rate in year t, ρ is the pure rate of time preference and η is the elasticity of marginal utility with respect to consumption. c_t and g_t are the representative agent's year t consumption and consumption growth rate, respectively. Importantly, c_t is consumption *net of climate change damages*. Also, $\tilde{\rho} = e^\rho - 1$ is the discrete annual pure rate of time preference.

Consider a stream of marginal damages md_t from a single emissions year τ. The $scghg_0$ is the present value of the social cost of GHG emissions for year $t = 0$ and is given by

$$scghg_0 = \sum_{t=0}^{T} E\left[\frac{1}{(1+\tilde{\rho})^t}\left(\frac{c_t}{c_0}\right)^{-\eta} md_t\right], \qquad (A.3.5)$$

where md_t is the marginal damage in year t from a pulse of emissions in year τ. Because md_t is the marginal damage from a single emissions year τ, $md_t = 0$ for t=0 to τ-1. The $scghg_0$ is the SC-GHG in the present year $t = 0$. This is not equal to $scghg_\tau$, which is the SC-GHG in year τ.

The present value $scghg_0$ for any emission year τ should also be equal to the $scghg_\tau$ discounted back to current period $t = 0$ using the certainty-equivalent discount rate

$$scghg_0 = scghg_\tau \cdot E\left[\frac{1}{(1+\tilde{\rho})^\tau}\left(\frac{c_\tau}{c_0}\right)^{-\eta}\right]. \qquad (A.3.6)$$

So

$$scghg_\tau = \frac{scghg_0}{E\left[\frac{1}{(1+\tilde{\rho})^\tau}\left(\frac{c_\tau}{c_0}\right)^{-\eta}\right]} = \sum_{t=0}^{T} \frac{E\left[\frac{1}{(1+\tilde{\rho})^t}\left(\frac{c_t}{c_0}\right)^{-\eta} md_t\right]}{E\left[\frac{1}{(1+\tilde{\rho})^\tau}\left(\frac{c_\tau}{c_0}\right)^{-\eta}\right]}. \qquad (A.3.7)$$

Assuming that consumption is certain in the present year (t=0), c_0 can be canceled

$$scghg_\tau = \sum_{t=0}^{T} \frac{E\left[\frac{1}{(1+\tilde{\rho})^t}(c_t)^{-\eta} md_t\right]}{E\left[\frac{1}{(1+\tilde{\rho})^\tau}(c_\tau)^{-\eta}\right]}. \qquad (A.3.8)$$

Simplifying this expression yields

$$scghg_\tau = \frac{1}{E[(c_\tau)^{-\eta}]} \sum_{t=0}^{T} E\left[\frac{1}{(1+\tilde{\rho})^{t-\tau}}(c_t)^{-\eta} md_t\right]. \qquad (A.3.9)$$

Note that equation (A.3.9) is not the same as simply discounting the marginal damages back to the year of emissions, which would be the expected value

$$scghg_\tau' = \sum_{t=\tau}^{T} E\left[\frac{1}{(1+\tilde{\rho})^{t-\tau}}\left(\frac{c_t}{c_\tau}\right)^{-\eta} md_t\right]. \qquad (A.3.10)$$

The $scghg_\tau$ estimates based on the GIVE model (Rennert et al. 2022b) and the Meta-Analysis (Howard and Sterner 2017) are directly estimated using equation (A.3.9). The $scghg_\tau$ estimates under the DSCIM damage module, however, are adjusted post-estimation to exactly equal equation (A.3.9). The remainder

of this section describes this adjustment alongside its analogue for GIVE. Consider trial i, year t, emissions year τ, net consumption per capita c_{it}, and marginal damages md_{it}. A trial i is a unique socioeconomic pathway and FaIR1.6.2 climate scenario pairing. For each trial GIVE estimates

$$scghg_{i\tau} = \frac{\sum_{t=\tau}^{2300} \left(\frac{1}{c_{it}}\right)^{\eta} \frac{1}{(1+\tilde{\rho})^{t-\tau}} md_{it}}{E[c_{\tau}^{-\eta}]}, \qquad (A.3.11)$$

and the $scghg_{\tau}$ from equation (A.3.9) results from applying the expectation operator to equation (A.3.11).

In contrast to equation (A.3.11), DSCIM estimates

$$scghg_{i\tau}' = \sum_{t=\tau}^{2300} \left(\frac{c_{i\tau}}{c_{it}}\right)^{\eta} \frac{1}{(1+\tilde{\rho})^{t-\tau}} md_{it}. \qquad (A.3.12)$$

Equations (A.3.11) and (A.3.12) can be equated by

$$scghg_{i\tau} = \frac{1}{c_{i\tau}^{\eta} E[c_{\tau}^{-\eta}]} scghg_{i\tau}' \qquad (A.3.13)$$

The first expression on the right-hand side of Equation (A.3.13) is the adjustment factor that is used to convert the values provided by DSCIM for use in the report. This adjustment equation is trial-specific, so the values presented in this report are the means across trials (i.e., applying expectation operator to equation (A.3.11)).

The full derivation of a certainty-equivalent discount rate path involves damage-module-specific net consumption paths, damage-module-specific SC-GHG estimates, and a unique certainty-equivalent rate path for each analysis year. However, as noted in Section 4.2, the error associated with using a constant discount rate rather than the certainty-equivalent rate path (i.e., $E\left[\frac{1}{(1+\tilde{\rho})^{\tau}} \left(\frac{c_{\tau}}{c_0}\right)^{-\eta}\right]$ in equation A.3.6) to calculate the present value of a future stream of monetized climate benefits is small for analyses with moderate time frames (e.g., 30 years or less). In other words, for analyses with a moderate time frame, the present value of the regulation's benefits can be calculated as

$$pv_j = \sum_{\tau=2040}^{2050} x_{\tau.} \cdot scghg_{\tau} \cdot e^{-\bar{r}(\tau-j)}, \qquad (A.3.14)$$

where $\bar{r}$ is simply the near-term (2.5%, 2%, and 1.5%) corresponding to the SC-GHG value used. Figure A.3.1 provides an illustration of the amount that climate benefits from reductions in future emissions will be underestimated by using a constant discount rate relative to the more complicated certainty-equivalent rate path.

Figure A.3.1 The Difference Between using a Certainty-Equivalent Rate and Constant Discount Rate to Discount Climate Benefits from Future Reductions in GHG Emissions Back to the Year of the Analysis
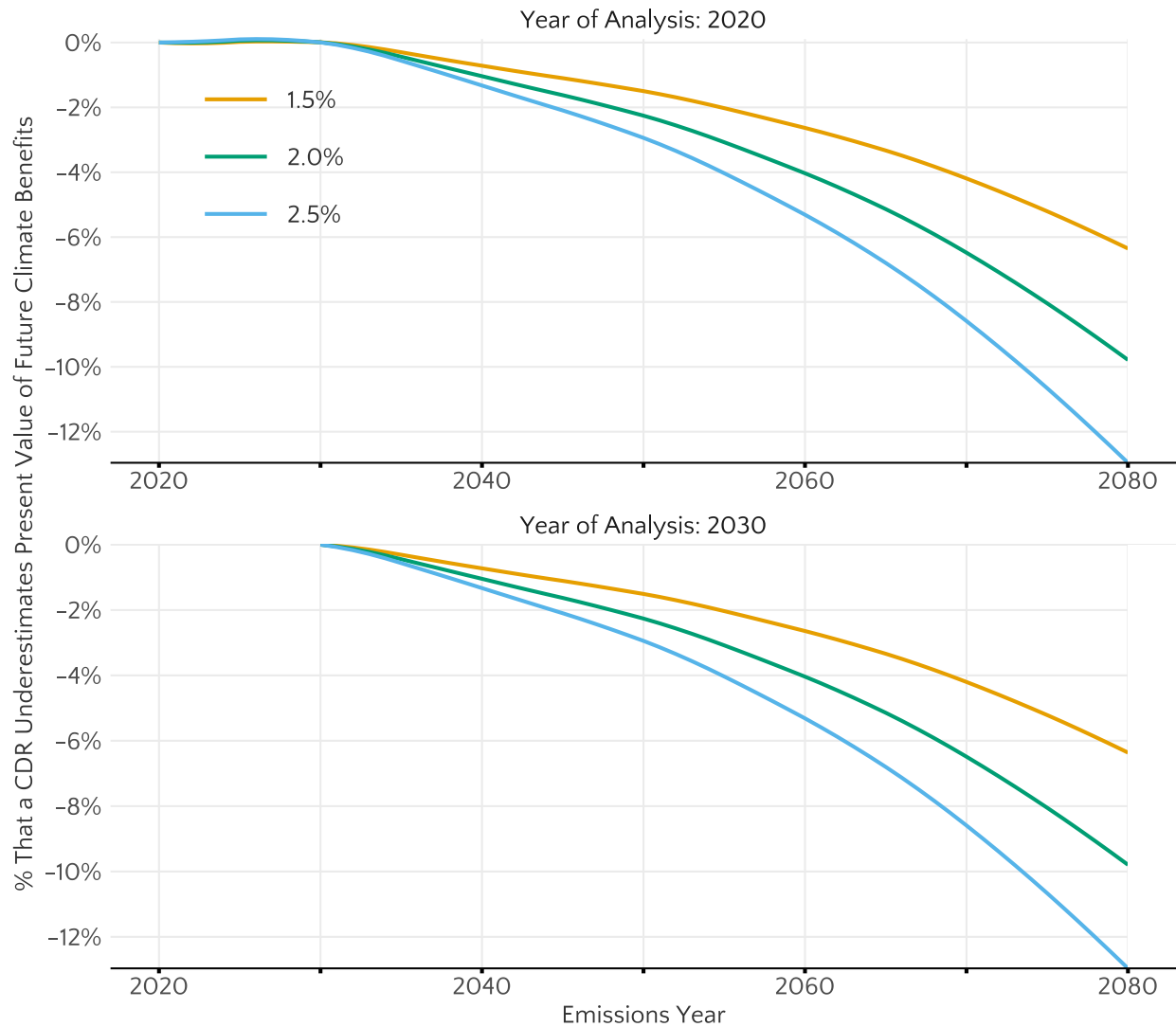
When using a constant discount rate (CDR) to discount climate benefits from future GHG emissions reductions back to the year of the analysis, the resulting present value of climate benefits will be underestimated (i.e., future emissions reductions will be valued using a lower SC-GHG than they would be if the analyst used a certainty-equivalent rate (CER) to discount those same future emission reductions. The lines represent the average percent that these future values would be undervalued at three near-term Ramsey discount rates. For example, if the analyst discounts the monetized value of a 2080 emissions reduction back to the year 2030 using a constant discount rate (i.e., 2.5%, 2.0%, or 1.5%) as shown in the middle panel, that present value would be approximately 13% lower than when using the 2.5% CER, 10% lower than when using the 2.0% CER, and 6% lower than when using the 1.5% CER.

A.4. Annual Unrounded SC-CO₂, SC-CH₄, and SC-N₂O Values, 2020-2080

Table 4.2.1: Unrounded SC-CO₂, SC-CH₄, and SC-N₂O Values, 2020-2080

	SC-GHG and Near-term Ramsey Discount Rate								
	SC-CO₂ (2020 dollars per metric ton of CO₂)			SC-CH₄ (2020 dollars per metric ton of CH₄)			SC-N₂O (2020 dollars per metric ton of N₂O)		
Emission Year	2.5%	2.0%	1.5%	2.5%	2.0%	1.5%	2.5%	2.0%	1.5%
2020	117	193	337	1,257	1,648	2,305	35,232	54,139	87,284
2021	119	197	341	1,324	1,723	2,391	36,180	55,364	88,869
2022	122	200	346	1,390	1,799	2,478	37,128	56,590	90,454
2023	125	204	351	1,457	1,874	2,564	38,076	57,816	92,040
2024	128	208	356	1,524	1,950	2,650	39,024	59,041	93,625
2025	130	212	360	1,590	2,025	2,737	39,972	60,267	95,210
2026	133	215	365	1,657	2,101	2,823	40,920	61,492	96,796
2027	136	219	370	1,724	2,176	2,910	41,868	62,718	98,381
2028	139	223	375	1,791	2,252	2,996	42,816	63,944	99,966
2029	141	226	380	1,857	2,327	3,083	43,764	65,169	101,552
2030	144	230	384	1,924	2,403	3,169	44,712	66,395	103,137
2031	147	234	389	2,002	2,490	3,270	45,693	67,645	104,727
2032	150	237	394	2,080	2,578	3,371	46,674	68,895	106,316
2033	153	241	398	2,157	2,666	3,471	47,655	70,145	107,906
2034	155	245	403	2,235	2,754	3,572	48,636	71,394	109,495
2035	158	248	408	2,313	2,842	3,673	49,617	72,644	111,085
2036	161	252	412	2,391	2,929	3,774	50,598	73,894	112,674
2037	164	256	417	2,468	3,017	3,875	51,578	75,144	114,264
2038	167	259	422	2,546	3,105	3,975	52,559	76,394	115,853
2039	170	263	426	2,624	3,193	4,076	53,540	77,644	117,443
2040	173	267	431	2,702	3,280	4,177	54,521	78,894	119,032
2041	176	271	436	2,786	3,375	4,285	55,632	80,304	120,809
2042	179	275	441	2,871	3,471	4,394	56,744	81,714	122,586
2043	182	279	446	2,955	3,566	4,502	57,855	83,124	124,362
2044	186	283	451	3,040	3,661	4,610	58,966	84,535	126,139
2045	189	287	456	3,124	3,756	4,718	60,078	85,945	127,916
2046	192	291	462	3,209	3,851	4,827	61,189	87,355	129,693
2047	195	296	467	3,293	3,946	4,935	62,301	88,765	131,469
2048	199	300	472	3,378	4,041	5,043	63,412	90,176	133,246
2049	202	304	477	3,462	4,136	5,151	64,523	91,586	135,023
2050	205	308	482	3,547	4,231	5,260	65,635	92,996	136,799

Table 4.2.2: Unrounded SC-CO$_2$, SC-CH$_4$, and SC-N$_2$O Values, 2020-2080 (continued...)

Emission Year	SC-CO$_2$ (2020 dollars per metric ton of CO$_2$)			SC-CH$_4$ (2020 dollars per metric ton of CH$_4$)			SC-N$_2$O (2020 dollars per metric ton of N$_2$O)		
	2.5%	2.0%	1.5%	2.5%	2.0%	1.5%	2.5%	2.0%	1.5%
2050	205	308	482	3,547	4,231	5,260	65,635	92,996	136,799
2051	208	312	487	3,624	4,320	5,363	66,673	94,319	138,479
2052	211	315	491	3,701	4,409	5,466	67,712	95,642	140,158
2053	214	319	496	3,779	4,497	5,569	68,750	96,965	141,838
2054	217	323	500	3,856	4,586	5,672	69,789	98,288	143,517
2055	220	326	505	3,933	4,675	5,774	70,827	99,612	145,196
2056	222	330	510	4,011	4,763	5,877	71,866	100,935	146,876
2057	225	334	514	4,088	4,852	5,980	72,904	102,258	148,555
2058	228	338	519	4,165	4,941	6,083	73,943	103,581	150,235
2059	231	341	523	4,243	5,029	6,186	74,981	104,904	151,914
2060	234	345	528	4,320	5,118	6,289	76,020	106,227	153,594
2061	236	348	532	4,389	5,199	6,385	76,920	107,385	155,085
2062	239	351	535	4,458	5,280	6,480	77,820	108,542	156,576
2063	241	354	539	4,527	5,361	6,576	78,720	109,700	158,066
2064	244	357	543	4,596	5,442	6,671	79,620	110,857	159,557
2065	246	360	547	4,666	5,523	6,767	80,520	112,015	161,048
2066	248	363	550	4,735	5,604	6,862	81,419	113,172	162,539
2067	251	366	554	4,804	5,685	6,958	82,319	114,330	164,030
2068	253	369	558	4,873	5,765	7,053	83,219	115,487	165,521
2069	256	372	562	4,942	5,846	7,149	84,119	116,645	167,012
2070	258	375	565	5,011	5,927	7,244	85,019	117,802	168,503
2071	261	378	569	5,085	6,013	7,344	86,012	119,027	170,013
2072	263	382	573	5,160	6,099	7,444	87,006	120,252	171,523
2073	266	385	576	5,234	6,184	7,545	87,999	121,477	173,033
2074	269	388	580	5,309	6,270	7,645	88,992	122,702	174,543
2075	271	391	583	5,383	6,355	7,745	89,985	123,926	176,053
2076	274	394	587	5,458	6,441	7,845	90,978	125,151	177,563
2077	276	398	591	5,532	6,527	7,946	91,971	126,376	179,073
2078	279	401	594	5,607	6,612	8,046	92,964	127,601	180,582
2079	282	404	598	5,681	6,698	8,146	93,958	128,826	182,092
2080	284	407	601	5,756	6,783	8,246	94,951	130,050	183,602

A.5. Additional Figures, Tables, and Results

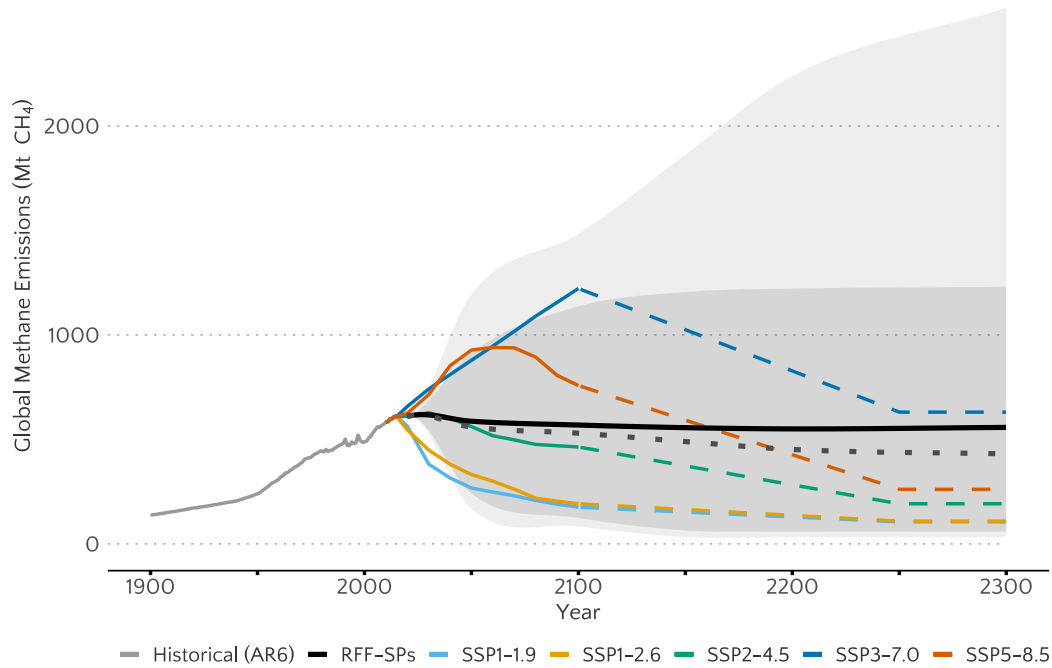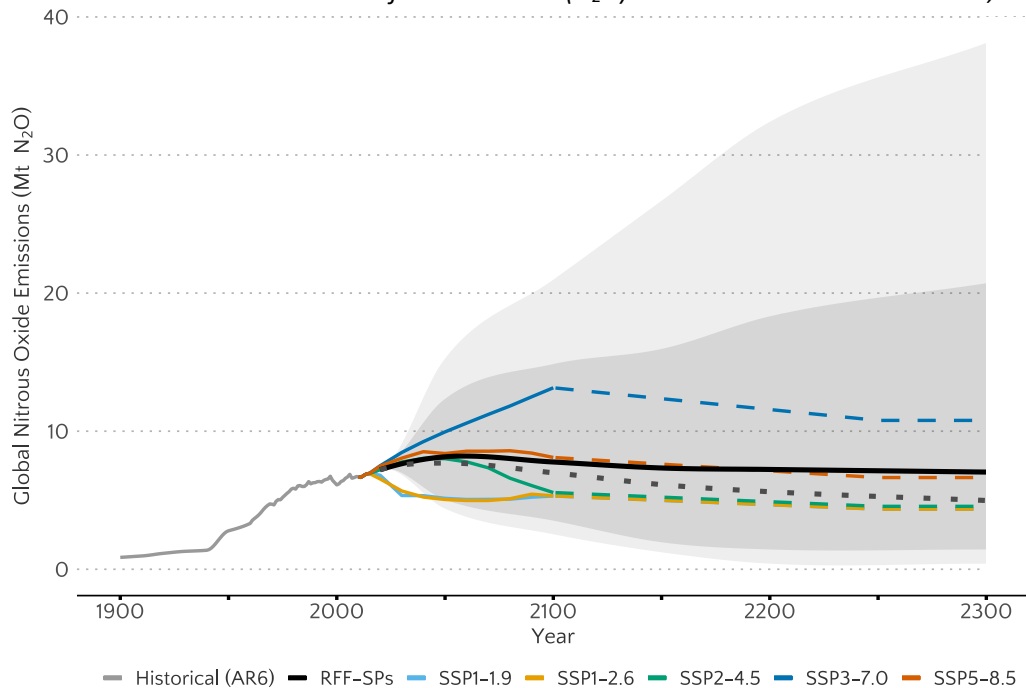*Figure A.5.1: Net Annual Global Emissions of Methane (CH$_4$) under the RFF-SPs and the SSPs, 1900-2300*

Figure A.5.2: Net Annual Global Emissions of Nitrous Oxide (N$_2$O) under the RFF-SPs and the SSPs, 1900-2300

RFF-SP projections based on RFF-SPs (Rennert et al. 2022a). Black lines represent the mean (solid) and median (dotted) projections along with the 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges. SSP data through 2100 from International Institute for Applied Systems Analysis (IIASA) SSP Database (Riahi et al. 2017). SSPs beyond 2100 (dashed) are based on the commonly used extensions provided by the Reduced Complexity Model Intercomparison Project (Nicholls et al. 2020).

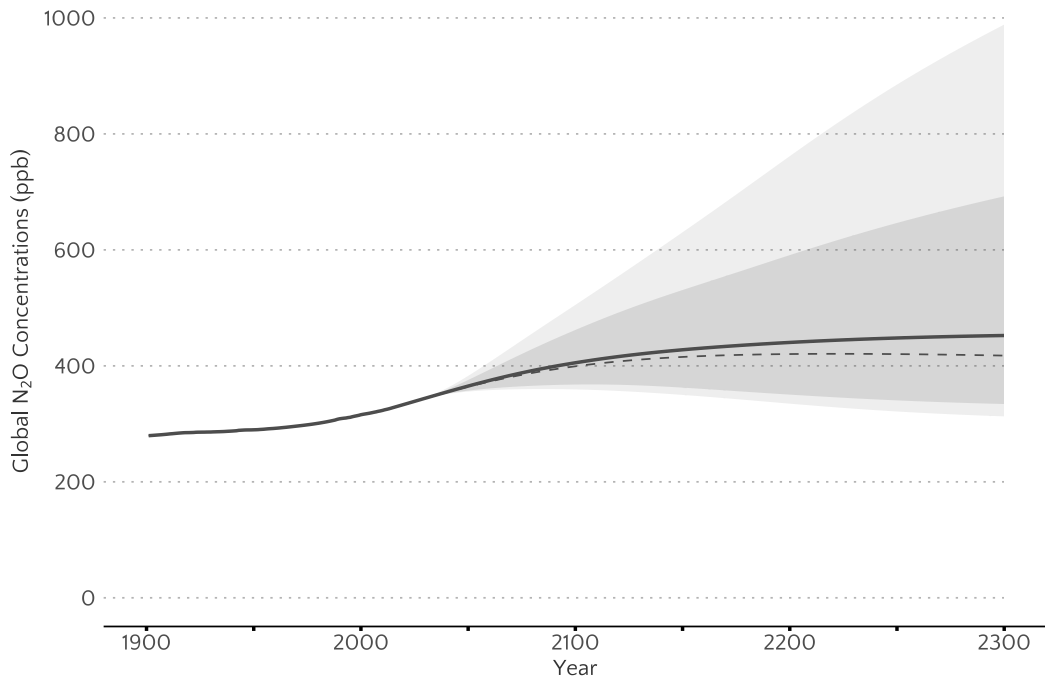*Figure A.5.3: Global Atmospheric Concentrations of Methane (CH4), 1900-2300*
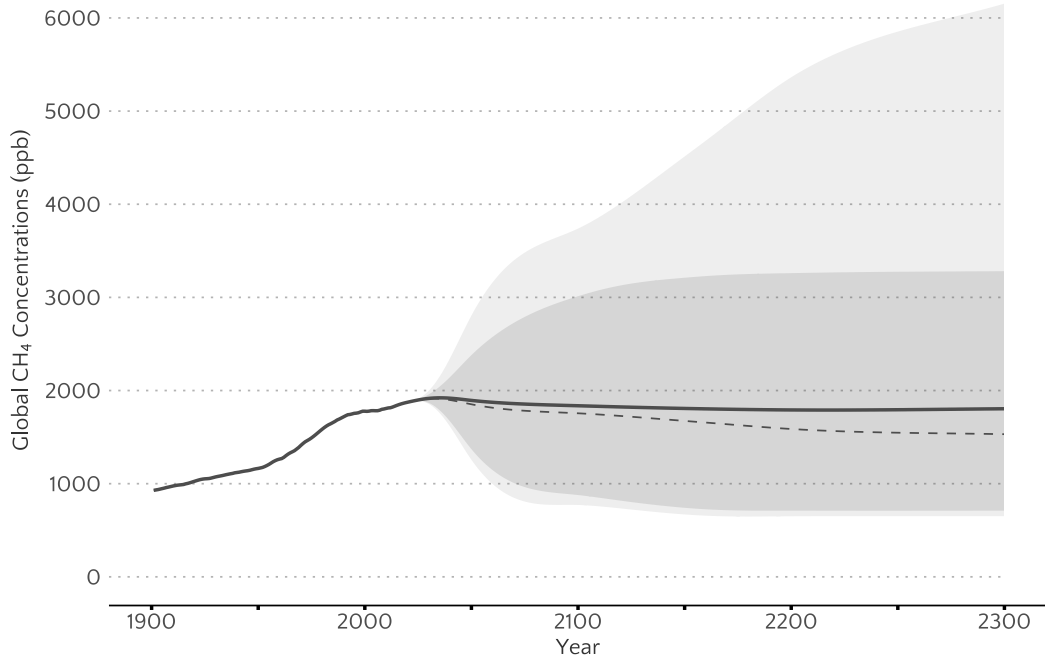
Figure A.5.4: Global Atmospheric Concentrations of Nitrous Oxide (N2O), 2020-2300

Historical and future concentrations of methane (CH4, top) and nitrous oxide (N2O, bottom) are based on the range of emissions from the sampled RFF-SP scenarios used as inputs into FaIR 1.6.2. FaIR 1.6.2 is run with the full, AR6 calibrated (constrained) uncertainty distribution. Therefore, the uncertainty ranges in this figure represent both emissions and physical carbon cycle uncertainty. Mean (solid) and median (dashed) lines along with 5th to 95th (dark) and 1st to 99th (light) percentile ranges.

Figure A.5.5: Global Temperature Anomaly from a Pulse of Methane (1MtCH$_4$) Emissions, 2020-2300
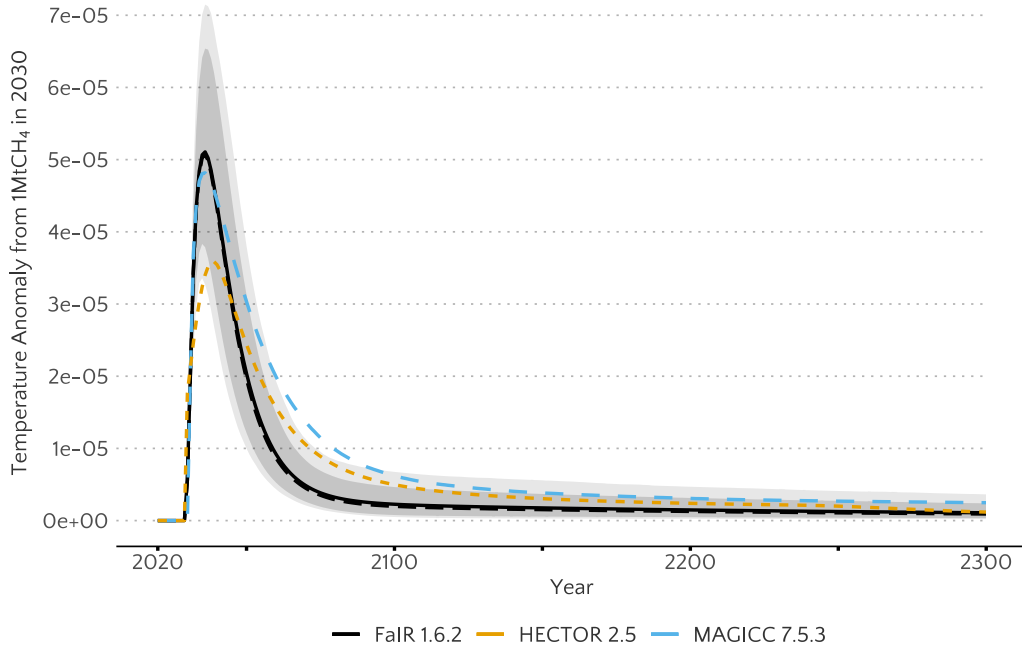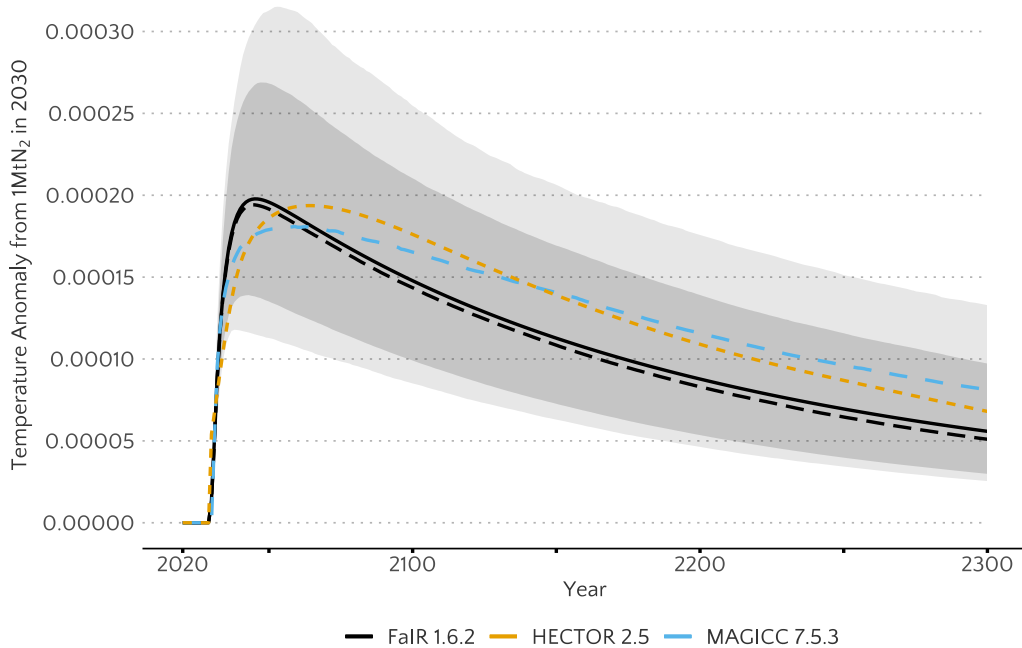

Figure A.5.6: Global Temperature Anomaly from a Pulse of Nitrous Oxide (1MtN$_2$) Emissions, 2020-2300

The global temperature response resulting from a pulse of emissions of CH$_4$ (top) and N$_2$O (bottom) in 2030 as projected by FaIR1.6.2, Hector 2.5, and MAGICC 7.5.3. This represents the difference between a reference scenario (using SSP2-RCP4.5 for the figure) and the same scenario including the pulse of emissions. The emission pulse size is 1 GtC for carbon dioxide. Mean (solid) and median (dashed) lines are shown along with the 5th to 95th (dark shade) and 1st to 99th (light shade) percentile ranges.

Figure A.5.7: Dynamic temperature response of 256 climate science models (the CMIP5 ensemble) and seven IAMs
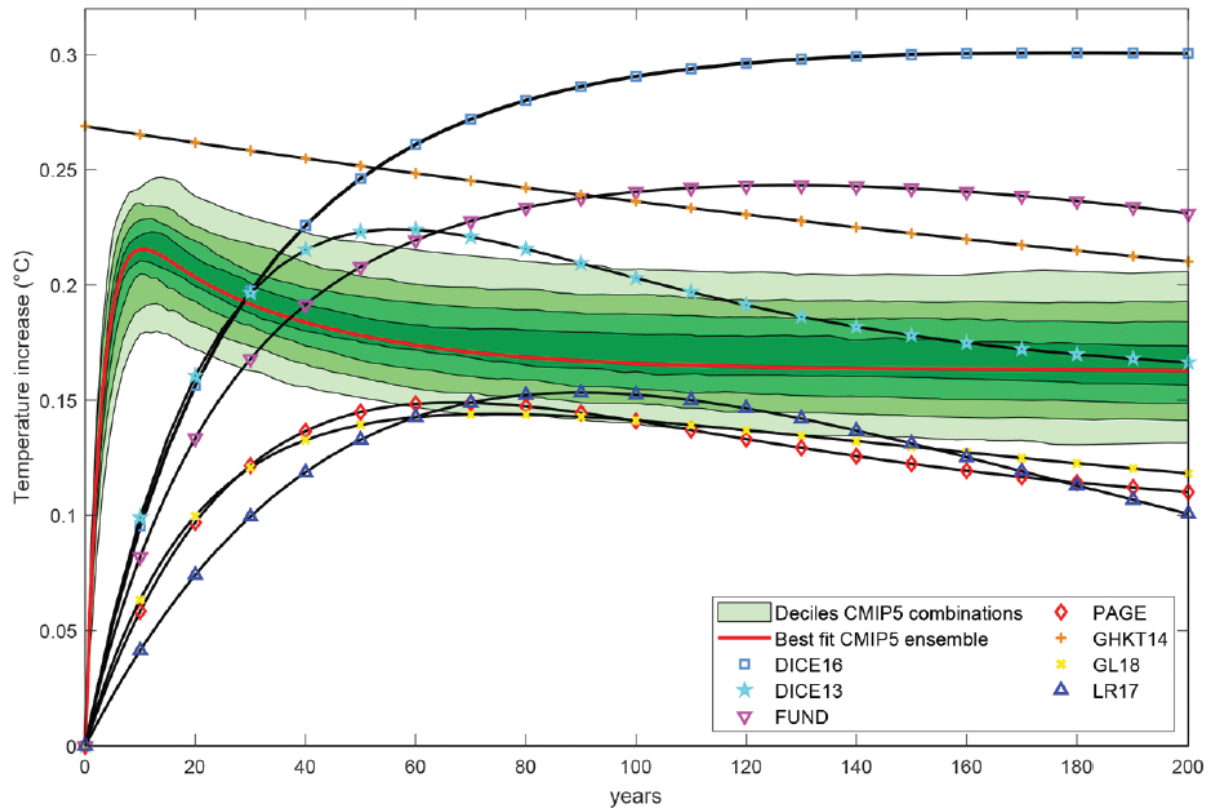
Source: Dietz et al. (2021). The figure displays the dynamic temperature response of 256 climate science models (the CMIP5 ensemble) and seven IAMs to an instantaneous 100 GtC emission impulse against a constant background atmospheric CO2 concentration of 389 ppm. The temperature response of the IAMs is much slower than the climate science models, except Golosov et al. (2014). After 200 years, the temperature response of the IAMs is often well outside the range of the climate science models. The CMIP5 model responses are emulated/fitted by combining the Joos et al. (2013) carbon cycle model and the Geoffroy et al. (2013) warming model.

Figure A.5.8: Distribution of SC-CH₄ Estimates for 2030, by Damage Module and Discount Rate
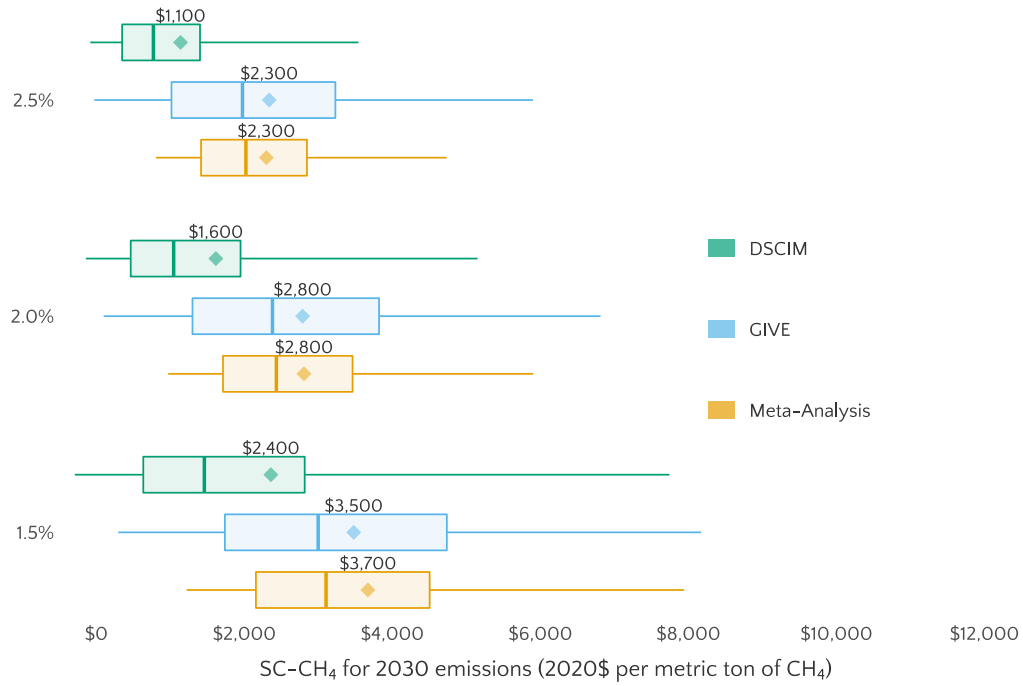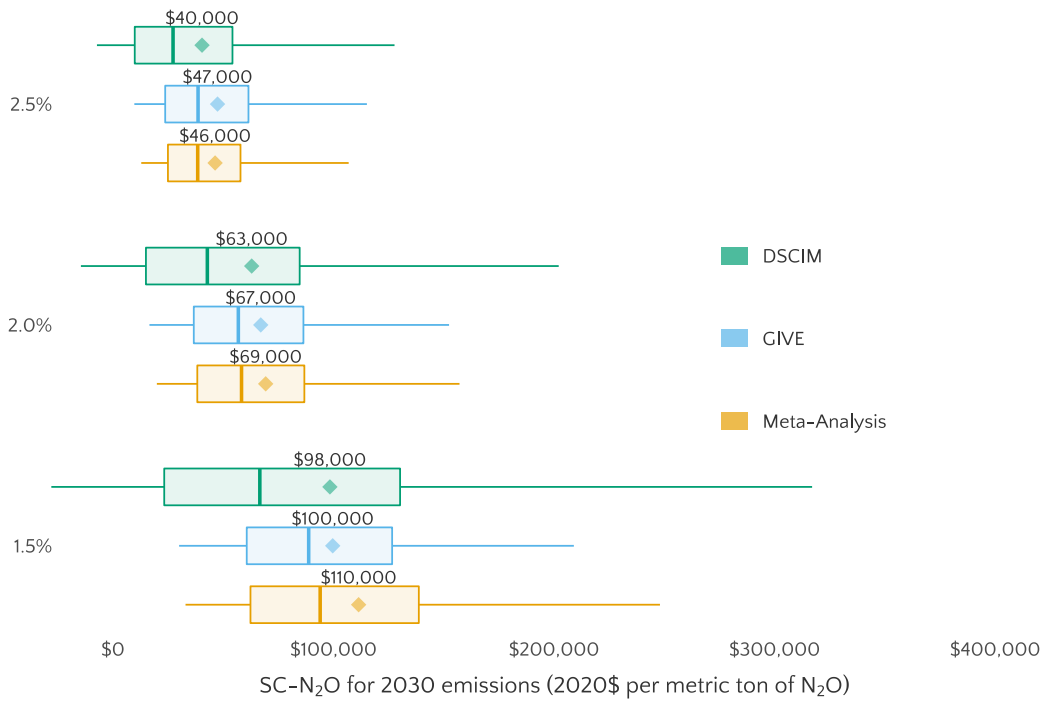

Figure A.5.9: Distribution of SC-N₂O Estimates for 2030, by Damage Module and Discount Rate

Boxes span the inner quartile range (25th to 75th percentiles), whiskers extend to the 5th (left) and the 95th (right) quantiles. The vertical lines inside of the boxes mark the median of each distribution, and the points inside of the boxes and dollar estimates on top of the boxes mark the simple mean (average).

A.6. Valuation Methodologies to Use in Estimating the Social Cost of GHGs

The EPA will continue to review developments in the literature, including new and robust methodologies for estimating the magnitude of the various direct and indirect damages from climate impacts. EPA will also continue to assess whether there are other parts of this literature or other methodologies to evaluate for potential inclusion in SC-GHG estimation.

Both DSCIM and the GIVE model incorporate sector-specific damage functions published in the peer-reviewed literature. One advantage of the modular approach used by these models is that new or alternative damage functions can be incorporated in a relatively straightforward way, while maintaining the state-of-the-science modules dealing with socioeconomic scenarios, emission trajectories, discounting, and climate modeling used in this report.

As explained in Section 2.3, the damage module component of SC-GHG estimation translates changes in temperature and other physical impacts of climate change into monetized estimates of net economic damages based on the willingness to pay of individuals to avoid those damages. The developers of the damage functions used in this report applied valuation methods that are consistent with the theoretical underpinning of EPA's benefit-cost analysis (BCA) – the Kaldor-Hicks criterion.[140] For example, in DSCIM and GIVE, changes in agricultural output due to climate change are valued using expected market prices for key agricultural commodities. Use of prices to value commodities traded in markets is generally consistent with the Kaldor-Hicks criterion, sometimes called an economic efficiency test. For damage categories that involve non-market impacts (commodities or services not traded in the market, like changes in mortality risks) there is no readily observed price information and there are challenges in capturing the value of something as precious as changes in life expectancy. However, economists have developed a robust literature to infer values for these non-market commodities using methods that are consistent with the economic efficiency test. Because of data limitations and other constraints to performing original research to develop location- and context- specific values to assign to each non-market impact, analysts regularly need to draw upon existing value estimates for use in benefits analysis

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[140] The Pareto criterion maintains that if an economic change does not harm any individual and makes at least one individual better off, there is an increase in social welfare. The Kaldor-Hicks criterion captures the intuition of the Pareto criterion, but allows for the identification of potential improvements in social welfare under conditions where some may be made worse off by the economic change. For a potential increase in social welfare, there needs to be a "potential" Pareto improvement, which occurs when those who gain from the economic change would be willing to fully compensate those made worse off from the economic change. From this criterion, the rules of BCA as an economic efficiency test follow, including the use of the consumer sovereignty principle whereby BCA must value benefits and costs based on individuals' willingness to pay. If the impacts to individuals are measured using a value other than their willingness to pay, the results of the BCA will be unable to identify potential Pareto improvements under the Kaldor-Hick criterion and their interpretation may be unclear. The discipline of the private market to allocate resources cannot work for pollution, so the BCA helps provide this information as one input, amongst many, in the decision-making process. As in a private market, the price in the simulated market test should equal the willingness to pay of individuals on the margin, as any other valuation would cause the test to fail in answering its question. See EPA (2010) for more discussion.

through "benefits transfer."[141] The benefits transfer methods used by the developers of the DSCIM and GIVE damage functions used in this report are also consistent with the economic efficiency test.

The challenge of valuing climate-related mortality risks provides an illuminating application of these methods. As shown in Section 3.1, net costs of expected premature mortality associated with climate change driven changes in hot- and cold weather comprise the largest share of the DSCIM and GIVE based SC-GHG estimates presented in this report.[142] It is worth noting that valuing premature mortality risks in EPA BCAs is a routine occurrence. Particulate matter, ozone, lead, and many other environmental contaminants can increase mortality risks through various modes of action including, increased cardiovascular disease, cancer, and respiratory disease. To value changes in these mortality risks, EPA uses published research that estimates individuals' willingness to pay to reduce mortality risks in their own lives – a number that is inaptly termed the "Value of Statistical Life" (VSL) [143] – and then transfers these willingness to pay (WTP) estimates to the risk reductions expected from EPA policy options.[144,145]

EPA's benefit transfer also recognizes that as per capita income increases, willingness to pay for mortality risk reductions also increases. This parallels the fact that as their income increases individuals are willing to pay more for most goods and services.[146] EPA increases the willingness to pay estimate over time to reflect projected per capita income growth (i.e., by applying a positive income elasticity) as a way to capture that the wealthier we are, the greater our willingness to pay to avoid mortality risks consistent with the empirical evidence. For example, applying an income elasticity of one implies that for every one percent increase in per capita income, the value of mortality risk reductions increases by one percent, such that the willingness to pay for mortality risk reductions remains a constant share of people's income. EPA's VSL methodology is peer reviewed by its Science Advisory Board (SAB). EPA periodically engages in a consultation with the SAB on the appropriate range of income elasticities.

In estimating the SC-GHG, the question becomes what VSL to use to monetize expected mortality risk reductions occurring in other countries. Given the small number of high-quality VSL studies in many countries, the vast majority of countries do not have their own official recommended VSL estimates or

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[141] Benefits transfer is the process of applying values estimated in previous studies to a new context. See EPA (2010) for an overview of current EPA guidance on best practices in benefits transfer.

[142] Mortality risk changes are also partially captured in the coastal damage category in each model. See Section 2.3 for more discussion.

[143] As noted by the SAB, "the conventional term used to describe the value of risk reduction (the "value of a statistical life," or VSL) is easily misinterpreted, leading to confusion about key concepts" (EPA 2011). As explained in OMB Circular A-4 the "phrase can be misleading because it suggests erroneously that the monetization exercise tries to place a "value" on individual lives"; "…. these terms refer to the measurement of willingness to pay for reductions in only small risks of premature death. They have no application to an identifiable individual or to very large reductions in individual risks. They do not suggest that any individual's life can be expressed in monetary terms. Their sole purpose is to help describe better the likely benefits of a regulatory action" (OMB 2003). Put another way, the VSL "represents the rate at which an individual views a change in the money he or she has available for spending as equivalent to a small change in his or her own mortality risk within a specific time period, such as one year" (Robinson et al. 2019b).

[144] For more details on the derivation of EPA's values for mortality risk reductions, see EPA's Guidelines for Preparing Economic Analyses (2010), p. 7-8. https://www.epa.gov/sites/default/files/2017-09/documents/ee-0568-07.pdf

[145] A willingness to pay to reduce mortality risk is a ratio, where the numerator reflects the marginal disutility of (usually small) increases in probability of experiencing premature mortality, usually within the next year, and the denominator is the marginal utility associated with additional income/consumption.

[146] In economics, goods for which individuals increase their demand as their income rises, signifying an increased willingness to pay, are called normal goods.

estimates from the empirical literature that can be readily adopted (Robinson et al. 2019a). Therefore, analysts must rely on benefits transfer techniques to develop VSL estimates for other countries that are extrapolated from existing estimates in the U.S. or other countries with robust empirical estimates.

With respect to this report, both the GIVE and DSCIM based damage modules explicitly model changes in the risk of premature mortality due to GHG emissions driven climate change and monetize these climate-related mortality risks consistent with the economic efficiency paradigm. Specifically, as described in Section 2.3, projected changes in premature mortality in the U.S. are monetized using the same value of mortality risk reduction as in the EPA's regulatory analyses ($4.8 million in 1990 (1990USD)) and adjusted for income growth and inflation following current EPA guidelines and practice (EPA 2010) and consistent with SAB advice (see e.g., EPA 2011, OMB 2003), resulting in a 2020 value of $10.05 million (2020USD). Valuation of mortality risk changes outside the U.S. is based on an extrapolation of the EPA value that equalizes willingness-to-pay as a percentage of per capita income across all countries (i.e., using an assumed income elasticity of 1). The use of a benefits transfer approach based on a positive income elasticity is consistent with the approach used in the default version of the damage functions and published studies used in this report (e.g., Rennert et al. 2022b, Carleton et al. 2022, and Diaz 2016), other academic literature (e.g., Hasegawa et al. 2016, Springmann et al. 2016, Sarofim et al. 2017, Markandya et al. 2018, and the Lancet Commission on pollution and health (Landrigan et al. 2018)), advice given to the IWG by experts at the 2011 U.S. EPA and U.S. DOE Workshop on Improving the Assessment and Valuation of Climate Change Impacts for Policy and Regulatory Analysis (ICF International 2011), and other prominent domestic and international guidance documents that speak to international mortality risk reduction valuation. See, for example, the 2019 Gates Foundation Reference Case Guidelines for Benefit-Cost Analysis in Global Health and Development Guidelines (Robinson et al. 2019a) and literature cited therein (e.g., Robinson et al. 2018, 2019b, OECD 2016, World Bank and IHME 2016, Viscusi and Masterman 2017a, 2017b, Masterman and Viscusi 2018), and the U.S. Millennium Challenge Corporation guidance for conducting benefit-cost analysis (MCC 2021). Many international organizations also regularly use country-level measures of the willingness-to-pay for mortality risk reductions based on a positive income elasticity in cross country analyses (see, for example, Tan-Soo 2021, Roy and Braathen 2017, Roy 2016, Laxminarayan et al. 2007).

Given that the methodology in this report is grounded in a willingness to pay concept and the empirical evidence shows a positive relationship between income and the willingness to pay for mortality risk reductions, the willingness to pay for mortality risk reductions in countries with lower average incomes is less than the willingness to pay for mortality risk reductions in higher income countries. It is important to stress that this metric does not reflect the "value" that this approach places on mortality risks in different parts of the world. Rather, it reflects an estimate of the willingness to pay for mortality risk reductions by the average resident of countries or regions conditional on their income. EPA's Science Advisory Board, while reviewing our methodology to assign monetized estimates to mortality risk reductions also recognized this challenge:

"While it is clear from economic theory that individual WTP may vary with individual and risk characteristics, the SAB acknowledges that the objectives, methods, and principles underlying benefit cost analysis and particularly the values of mortality risk reductions and other non-market goods are often misunderstood or rejected as inappropriate by many participants and commentators on the policymaking process. In the past, for example, the Agency was criticized for considering VRRs [VSL] that differ by

individuals' age. However, as acknowledged in the White Paper, values for health risk reductions are not "one size fits all." Applying a willingness to pay value to a targeted population (such as low income or elderly) that exceeds that group's willingness to pay for reduced risk could result in decisions that ultimately reduce the well-being of the targeted group. The proposed change of terminology and application of VRRs [VSL] that differ with individual and risk characteristics provide an opportunity for constructive engagement with the public and other interested parties concerning these topics."[147] (EPA 2011).

It is important to note that EPA's BCAs, based on the economic efficiency criterion, is one of several economic analyses done to inform decision making and the public. Notably, distributional considerations are also paramount. In general, when a BCA is undertaken, EPA also conducts an environmental justice analysis, examining the incidence of environmental impacts both in the baseline and those that would result from the policy options under review.[148] This is in addition to economic impact analyses that are conducted by EPA to examines how different populations are affected by other expected outcomes of the policy options.

There is also a separate literature that argues that equity and other concerns should be addressed directly throughout all elements of a BCA (e.g., Scitovsky 1951, Lutz 1995, Farrow 1998, Persky 2001, Little 2002). This issue comes up with regard to climate change, since the impacts of climate change are not manifesting uniformly across space and populations, as highlighted in Section 3.2, with some of the most vulnerable populations living in locations that will experience some of the most severe effects. These facets of climate change have led some analysts (e.g., Azar and Sterner 1996; Fankhauser et al. 1997; Azar 1999; Anthoff et al. 2009; Anthoff and Tol 2010; Dennig et al. 2015, Anthoff and Emmerling 2019) to employ "equity weighting" to incorporate distributional equity objectives into estimates of the SC-GHG. As noted by Anthoff and Emmerling (2019), "[e]xisting equity weighting studies assume a social welfare

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[147] In that same review, the SAB opined more specifically on whether EPA should use a country-wide average VSL or more granular VSL estimates. While this SAB review was addressing how mortality risks for domestic EPA regulations should be valued, the insight is easily extended to how the mortality risks in other countries are valued in this report. "Recognizing that VRR [VSL] is a metric that can vary with both individual and risk characteristics, the conceptually appropriate method to estimate the benefits to the U.S. population of a change in mortality risk that results from environmental policy is to estimate the risk changes faced by each individual over time, value these changes using the appropriate individual VRRs [VSLs], and sum the results over the population. In contrast, an alternative "short-cut" approach is conventionally applied. The short-cut approach is to multiply the number of people in the population by the population-mean risk reduction (yielding the number of "lives saved") and multiply that by the population-mean VRR [VSL]. The short-cut approach yields an approximation to the conceptually appropriate method. It requires information on only the average VRR [VSL] and risk reduction, not on how VRR [VSL] and risk reduction vary across individuals. The approximation is exact when any of three conditions hold: (a) all individuals face the same risk reduction; (b) all individuals have the same VRR; or (c) individual risk reductions and VRRs [VSLs]are uncorrelated in the population. If none of these conditions holds, the short-cut approach introduces bias as a result of "premature aggregation" (Cameron 2010, Hammitt and Treich 2007)" EPA (2011).

[148] EPA has detailed technical guidance on conducting environmental justice analyses. See Technical Guidance for Assessing Environmental Justice in Regulatory Analysis, EPA 2015. https://www.epa.gov/environmentaljustice/technical-guidance-assessing-environmental-justice-regulatory-analysis

function (SWF) that exhibits inequality aversion over per capita consumption levels." As defined by EPA's SAB "[a] social welfare function essentially involves two stages. In the first stage, each group has its own definition of welfare, which is impacted by the various effects set out in this chapter. In the second stage, the groups are weighted to account for distributional concerns" (EPA 2021f). The argument for equity weighting in this strand of literature is "that a given (say one dollar) cost which affects a poor person (in a poor country) should be valued as a higher welfare cost than an equivalent cost affecting an average [high income country] citizen" to reflect a decreasing marginal utility of income (Azar and Sterner 1996). The degree to which the valuations differ across those individuals will, in part, be dependent upon the degree of society's intra-temporal inequality aversion specified within the SWF.

In place of directly incorporating distributional equity objectives through the specification of a SWF, a couple of studies have explored the impact of alternative VSL assumptions within the analysis of mortality impacts of climate change. Bressler (2021), in an effort to reflect distributional concerns, considered the use of a constant VSL across all countries in place of an income adjusted VSL designed to reflect willingness to pay. This approach weights the value of mortality risk changes to residents of lower income countries such that it is higher than their willingness to pay and weights mortality risk changes to higher income countries such that they are valued less than their willingness to pay. Carleton et al. (2022) included an empirical exploration in sensitivity analyses of how climate-related mortality damages change under a variety of valuations. They found net damages from climate change mortality risk changes of \$15-\$65 per ton CO_2 when using a WTP-based VSL (similar to the approach used in this report) and damages of \$46-\$144 per ton CO_2 when using a global average VSL, where the range is across the socioeconomic-emissions scenario modeled.[149]

While EPA will continue to assess the broader literature on BCA, social welfare, and equity as it seeks to apply the best available science in its analyses, this report develops SC-GHG estimates that are consistent with the Kaldor-Hicks criterion that underlies all the other elements of the EPA's BCAs. In addition, this approach is consistent with the benefits transfer approaches used in the default versions of the damage functions and published studies used in this report. This approach also ensures that U.S. mortality risks from climate impacts are valued consistently with how EPA values U.S. mortality risks from other causes. In addition to conducting a Kaldor-Hicks based BCA, EPA has and will continue to conduct detailed analyses of environmental justice concerns of climate change in its rulemakings as required and appropriate[150] and the distributional outcomes of climate change in detailed quantitative analyses,[151] so as to ensure that decision-makers and the public have robust information as to the damages of climate change and their distributional effects.

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[149] These values were calculated using a constant 2% discount rate and only reflect damages from net changes in mortality risks from climate change using a different scenarios and climate modeling than was applied in this report.

[150] For example, https://www.epa.gov/regulations-emissions-vehicles-and-engines/final-rule-revise-existing-national-ghg-emissions.

[151] For example, 2021 Climate Change and Social Vulnerability report (EPA 2021e).