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Quantifying the economic risks of climate change

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Understanding the value of reducing greenhouse-gas emissions matters for policy decisions and climate risk management, but quantification is challenging because of the complex interactions and uncertainties in the Earth and human systems, as well as normative ethical considerations. Current modelling approaches use damage functions to parameterize a simplified relationship between climate variables, such as temperature change, and economic losses. Here we review and synthesize the limitations of these damage functions and describe how incorporating impacts, adaptation and vulnerability research advances and empirical findings could substantially improve damage modelling and the robustness of social cost of carbon values produced. We discuss the opportunities and challenges associated with integrating these research advances into cost–benefit integrated assessment models, with guidance for future work.

Climate change poses an extremely wide-ranging set of risks, and in some cases benefits, to the things that people value and produce. Quantifying and aggregating these climate impacts in a meaningful way is extremely challenging, owing to the complex uncertainty that pervades the coupled human–Earth system, the long time horizon of the problem with temporal dynamics such as thermal inertia and other lags, and the heterogeneous nature of climate impacts across regions, sectors and generations. Nevertheless, estimating the economic damages of climate change is critically important for social decision-making: it tells us how the benefits of reducing greenhouse-gas emissions stack up against the costs, as well as the value of spending on climate mitigation relative to other social investments.

The social cost of carbon (SCC) is a monetary estimate of the climate change damages to society over time from an additional tonne of carbon dioxide, including market impacts such as agricultural productivity, energy costs and infrastructure damage as well as impacts on non-marketed goods such as ecosystems and human health. The SCC is increasingly being used to inform policy decisions ranging from the international to the local level. In the United States, federal agencies are required to account for the benefits of reductions in greenhouse-gas emission as part of rulemaking cost–benefit analysis[1], while other institutions such as state governments and public companies are also considering using the SCC. (Although a 2017 executive order terminated the working group establishing official US government SCC estimates, individual federal agencies must still consider the avoided costs of emissions as part of regulatory impact analysis.)

Alongside this growth in SCC application has come increased scrutiny of the modelling approaches involved, specifically a subset of integrated assessment models (IAMs) that represent key Earth and human system components in order to monetize climate impacts[2]. Despite the important role of quantitative tools for policy and risk management, a clear disconnect exists between the current scientific literature on climate change impacts, adaptation and vulnerability (IAV) and the representation of climate change impacts in these cost–benefit models[3–5]. A National Academy of Sciences committee recently examined the four principal components of SCC estimation (the socioeconomic, climate, damage and discounting modules) and, with respect to the damage module, recommended improvements to the SCC IAMs so that the damage modules would reflect the current state of scientific knowledge, characterize and quantify key uncertainties, and be transparent, reproducible and clearly documented[6]. There is therefore both an opportunity and a need to improve the economic quantification of climate damages by integrating recent advances in climate impact research and empirical findings into IAMs. Here, we first review the existing state of damage functions in cost–benefit IAMs, then summarize critiques of the current representation, and close by suggesting pathways for improvement based on advances in IAV science. The goal is to link ongoing research into climate change impacts with the requirements of the global economic models used to produce the SCC, thereby highlighting near-term opportunities as well as areas for further development.

State of climate damage functions in IAMs

Climate change damages are represented in cost–benefit IAMs through a damage function, which relates climate variables (such as temperature, CO_2 concentrations and sea-level rise (SLR)) to economic welfare. Although the function itself may be simple, it parameterizes a complex series of physical and socioeconomic relationships to aggregate the net impacts of climate change in a particular region and sector. The costs associated with a particular change in a climate driver (typically global or regional temperature change) depend on the exposure and sensitivity of the sector to the climate driver, the capacity for natural or technological adaptations, the available economic margins of adjustment and the structure of economic preferences in the sector (Fig. 1). Climate damages in an impact sector are the sum of the residual changes in welfare after these adjustments and the costs of adaptation.

We focus our review of damage functions on the three IAMs used by the US government to estimate the SCC: DICE (ref. 7), FUND (ref. 8) and PAGE (ref. 9). In contrast to the complexity of full-scale Earth system models, these IAMs have simplified representations of the economy, climate and impact mechanisms in order to explore trade-offs in policy design and be computationally tractable; for example, DICE is typically run as an intertemporal optimization (that is, it chooses consumption and other decision variables to maximize social welfare over the model time horizon, typically a century or more) with a nonlinear objective function, and FUND and PAGE often perform parametric uncertainty analysis using tens of thousands of runs in a Monte Carlo simulation. Despite common elements, the models differ substantially

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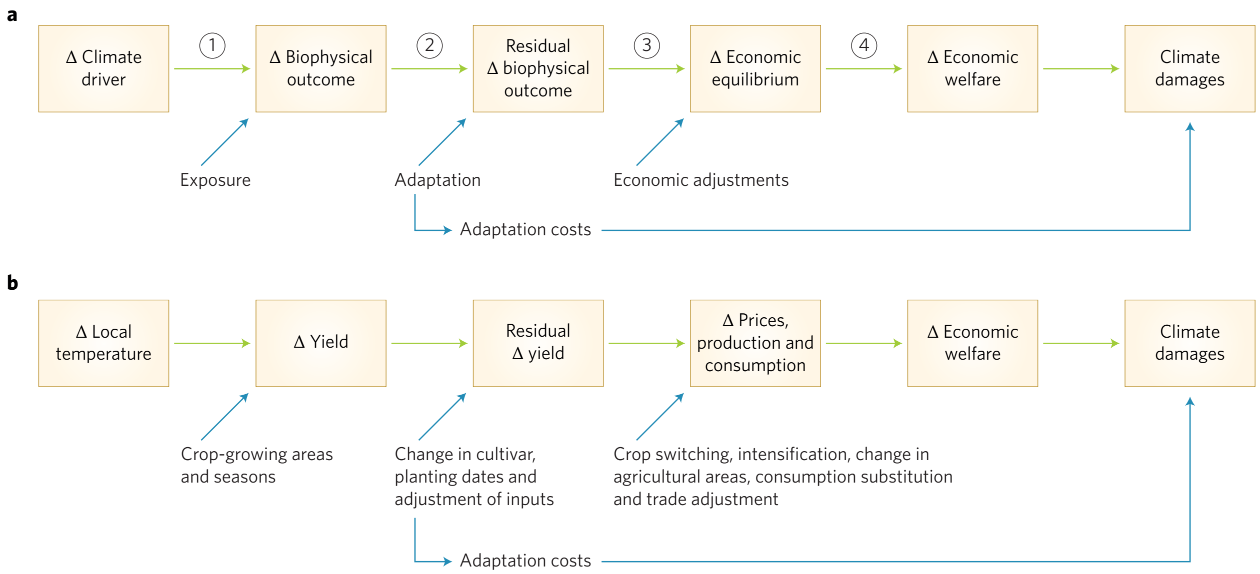

Figure 1 | Schematic representation of the complex series of physical and socioeconomic processes and relationships encompassed by a damage function. a, Generalized stages involved in determining damages, where Δ represents the change in the parameter and numbered connections represent (1) biophysical sensitivity to climate driver, (2) adaptation effectiveness, (3) general-equilibrium effects, and (4) economic preferences. **b**, Specific example for the agriculture sector.

in terms of their input assumptions and structure, notably in the degree of regional and sectoral disaggregation, formulation of climate damages, and treatment of adaptation and uncertainty (Table 1).

The defining characteristics summarized in Table 1 cause the models to project different damage outcomes for the same socioeconomic and climate conditions[2,10]. The models differ in the composition of damages across sectors and regions at 2 °C and 4 °C (Fig. 2a), as well as in aggregate, shown through the implied damage functions with respect to temperature (Fig. 2b). DICE and PAGE estimate similar levels of total damages, but FUND projects very different impacts from climate change, with global net benefits at lower levels of warming. At 4 °C, projected damages from DICE and PAGE are substantially higher than those from FUND, about 4% of gross domestic product (GDP) compared with about 1% of GDP, respectively.

The DICE model projects most damages in the aggregate 'non- sea-level rise' (non-SLR) damage category, with sea-level rise (SLR) comprising less than one-fifth of total damages over this century (Fig. 2a). The FUND model projects substantial net benefits from increased agricultural productivity and reduced heating demand (that is, avoided energy costs), while the dominant damages are due to increased cooling costs and water resource damages. PAGE damages at low levels of warming are dominated by non-economic and SLR damages, as economic damages can be avoided by higher adaptation capacity, while PAGE's discontinuity damage category shows up after crossing a threshold of 3 °C. The cost of adaptation in PAGE is constant, small and unresponsive to temperature.

In addition to the level of damages, the slopes of the implied damage functions of temperature (Fig. 2b) are particularly relevant for SCC estimates, as they indicate the marginal damage response to incremental warming, which is what the SCC measures. The PAGE damage function is most responsive to warming, with the slope increasing substantially after 3 °C when the risk of a discontinuity is present and adaptation capacity is reduced. DICE damages increase smoothly with warming, reflecting the two quadratic damage functions of temperature and SLR. FUND projects net benefits below 2.5 °C (for example, avoided heating demand, agriculture benefits from CO_2 fertilization) and impacts increase only gradually with temperature, in large part because higher per-capita incomes reduce damages in the health impact sectors over time, a characteristic termed 'dynamic vulnerability' in FUND[11].

The role that these types of structural assumptions such as dynamic vulnerability and adaptation play in determining damage estimates can be illustrated by modifying the IAMs and recalculating damages. Dynamic vulnerability in FUND is formulated uniquely for each sector through both positive and negative income elasticities[12]. We introduce a comparable dynamic vulnerability effect into DICE and PAGE, with an aggregate income elasticity equivalent to the implied total response in FUND (Fig. 2c). We also estimate damages in a version of FUND with static vulnerability, fixing income elasticities to zero, to compare to the standard DICE and PAGE results that have no explicit income elasticity of damages (see Supplementary Information for methods). Matching the vulnerability assumptions in the three models brings them into closer agreement and produces substantively similar damages. For example, comparing similar modes for dynamic vulnerability and static vulnerability reduces the spread at 4 °C by roughly a factor of three, indicating that different assumptions about whether higher incomes lead to lower sensitivity to climate change are an important driver of differences in aggregate damages. Removing adaptation from the two models that represent it explicitly has a much smaller effect on the damage function, although note that because SLR accumulates over time and damages are less sensitive to temperature change, coastal adaptation has little impact on the damage function (Fig. 2d).

Irrespective of income elasticity and adaptation assumptions, the relatively low level of climate damages for all models, particularly at warming less than 3 °C, has long been a subject of discussion and debate in the arena of global carbon policy. A warming of 2 °C by 2100 implies only a 1% GDP loss in DICE and PAGE and modest benefits in FUND, impacts that, given estimates of the cost of mitigation, are insufficient to justify the global temperature limit adopted by the international community[13]. These damage functions have also been the subject of criticism for more specific reasons, both technical and theoretical. Table 2 synthesizes some of the main critiques of existing damage functions from the economics literature (additional details in Supplementary Information).

Prospects for incorporating IAV research into IAMs

Although some of the critiques in Table 2 are difficult to address for reasons both conceptual and practical, there are opportunities for

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Table 1 | Key dimensions and damage function characteristics of three IAMs.

Model details	Dynamic Integrated model of Climate and the Economy[7] (DICE2010)	Climate Framework for Uncertainty, Negotiation and Distribution[8] (FUND v.3.8)	Policy Analysis of the Greenhouse Effect[9] (PAGE09)
Regions	One region (world)	Sixteen regions	Eight regions
Sectors	Two sectors Market: SLR, aggregate non-SLR Non-market: aggregate non-SLR	Fourteen sectors Market: SLR, agriculture, forests, heating, cooling, water resources, tropical and extratropical storm damages Non-market: biodiversity, cardiovascular/respiratory, vector-borne diseases, diarrhoea, morbidity, tropical and extratropical storm deaths, migration	Four sectors Market: SLR, economic, discontinuity (for example, abrupt change or catastrophe) Non-market: non-economic
Damage functional form	Estimates damages *D* as a per cent loss of global GDP Quadratic function of climate variable, for example: $D = \delta_1 \Delta T + \delta_q \Delta T^2$ Where δl and δq are linear and quadratic damage coefficients and ΔT is temperature change	Estimates damages *D* as a per cent change in regional productivity Uniquely formulated by sector, with damage function *f* scaled by a dynamic vulnerability term, for example: $D = f(\Delta T^x)\left(\frac{\mathrm{YPC}_t}{\mathrm{YPC}_0}\right)^{-\varepsilon}$ Where *x* is the climate variable exponent, YPC is per capita income, *t* and 0 are the current and reference time periods, and ε is income elasticity	Estimates residual damages *D* after adaptation as a percent loss of regional GDP Power function of residual climate variable plus adaptation costs *C*, for example: $D = \delta\Delta(T_r - T_{\mathrm{adapt}})^x + C_{\mathrm{adapt}}$
Climate variable	Global mean temperature change, global mean SLR	Global mean or regional temperature change (all), rate of warming (agriculture), CO_2 concentrations (agriculture, forestry, storms), global mean sea-level change (SLR), ocean temperature (storms)	Regional mean temperature change, global mean SLR
Socioeconomic drivers	Global income	Population, income, per capita income, population density, technological change, production cost, land value 'Dynamic vulnerability' allows climate resiliency or exposure to change over time in response to income growth or technological change[12]	Income, per capita income, regional adaptation capacity and costs, regional scaling factor relative to European Union, modest equity weights
Calibration	DICE2010 is loosely calibrated to the IPCC (ref. 64) and a meta-analysis of net damages for 1–3 °C (ref. 65) via RICE-2010 (ref. 13)	Calibrated to sector-specific impact studies, mostly published between 1992 and 1998 (ref. 2)	SLR calibrated to ref. 66; economic and non-economic calibrated to a review of damage estimates for 3 °C (from four IAMs, including DICE, FUND and PAGE)[67]; discontinuity calibrated to refs 68 and 69
Adaptation	Implicit: calibrated to estimates of damages net of adaptation	Explicit: agriculture includes lagged rate component that fades with adaptation, SLR assumes cost-effective adaptation with sea-walls or retreat Implicit otherwise: calibrated to econometric studies of net response to warming	Explicit: two types of exogenous adaptation, modelled as fixed regional policies (constant regardless of climate change and socioeconomics) that reduce impacts for a cost
Uncertainty representation	Deterministic design	Probabilistic design represents parametric uncertainty with thin-tailed (for example normal) distributions	Probabilistic design represents parametric uncertainty with triangular distributions
Catastrophic risk	Implicit: net damage includes the expected value of catastrophic loss per Nordhaus expert survey[68]	Potential for catastrophic outcome through tails of parameter distributions	'Discontinuity' impact occurs with a positive probability linked to temperatures over 3 °C

Data shown are for the versions of the three IAMs[7-9] used to calculate the most recent US government SCC estimates, adapted from ref. 2. Additional description and background provided in the Supplementary Information, including examples for agricultural and coastal damages.

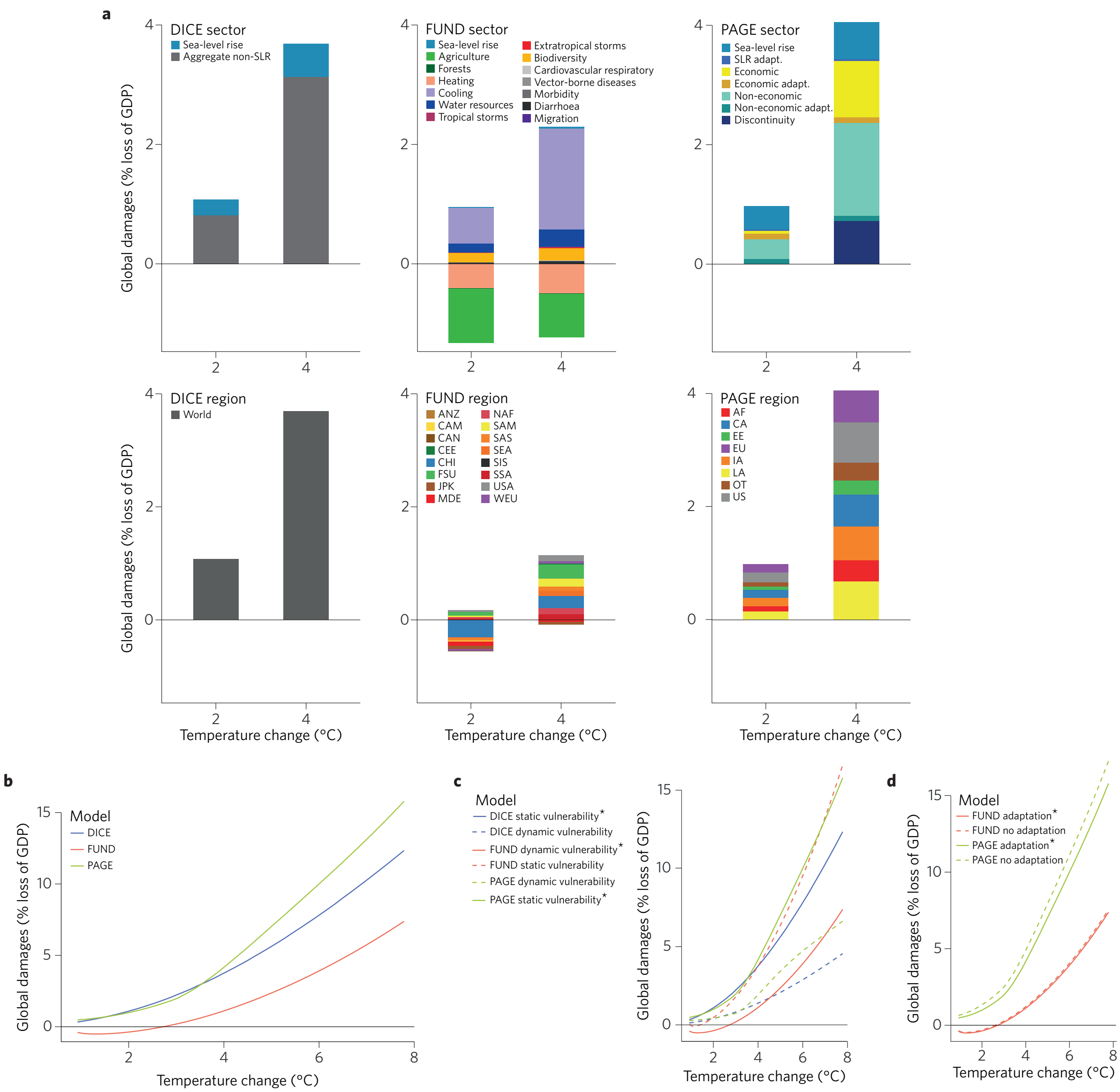

Figure 2 | Damage estimates projected by the DICE, FUND and PAGE models at different levels of temperature change, corresponding to 2100 socioeconomics. See Supplementary Information for methods. **a**, Decomposition of total damages for 2 °C and 4 °C above pre-industrial temperature by IAM region and sector for the standard model in deterministic mode. Regional abbreviations are as given in the IAMs; adapt., adaptation. **b**, Implied aggregate damage functions with respect to temperature change for each IAM, following ref. 2. **c**, Comparison of IAM damage functions modified with comparable implementations of static or dynamic vulnerability, where asterisks denote standard model mode. **d**, Similar to **c** for adaptation feature.

near-term and future advances using the large IAV literature that has developed since damage functions were first introduced. The empirical basis of IAM damage functions is necessarily constrained by the studies available in each region and sector. Despite recent growth in studies of climate change impacts, incorporating this research into current economic damage functions is not straightforward. Impact studies that can most readily inform IAM damage functions will ideally meet these criteria:

C1. Use a common framework with consistent assumptions around population growth, economic growth and technological change
C2. Report impacts with respect to physical climate driver such as temperature change, SLR, CO_2 concentration or rate of change, and socioeconomics if possible, rather than (or in addition to) time-paths based on a particular emissions scenario or representative concentration pathway (RCP)
C3. Have global coverage
C4. Incorporate the effects of all the costs and benefits of climate change in a particular sector
C5. Consider inter-region and inter-sectoral interactions, to the extent possible
C6. Include the costs and benefits of available, cost-effective adaptations
C7. If applicable, account for general- or partial-equilibrium economic adjustments to biophysical impacts
C8. Be reported in economic units, ideally as welfare changes;
C9. Quantify uncertainty in impacts

Although not necessarily possible or appropriate for every analysis, studies that meet many of these criteria will be most easily incorporated into IAMs, supporting the recommendations in the National Academies of Sciences report[6] for traceable and transparent damage functions calibrated to current science. Below, we describe three main classes of IAV research that could be that could be used

Table 2 | Synthesis of published damage function critiques, with key references.

Damage function characteristic	Critique description	Model examples and implications for damage estimates	Key references
Extrapolation to high temperatures	Damage functions are calibrated based on impact studies of 1–3 °C warming, but extrapolated beyond this range when computing damages or SCC estimates for many emissions scenarios Damage estimates for higher levels of warming are extremely speculative and do not inform the choice of functional form (for example linear or quadratic)	DICE and FUND are calibrated to impact estimates for 1–3 °C warming, PAGE to 3 °C DICE damage function extrapolated to 6 °C and 12 °C implies yield global GDP losses of 8% and 26% respectively; Weitzman[69] suggests that this is implausibly low and finds that a steeper slope (50% and 99% loss at 6 °C and 12 °C respectively) raises the SCC	70–72
Extrapolation to other regions	IAMs estimate global damages, but underlying impact studies focus disproportionately on a few regions (for example the United States and European Union), which are then extrapolated to other regions for global coverage	PAGE applies ad hoc regional adjustments based on coastline length to scale damage functions that are calibrated to European Union impact studies	9, 67, 73–75
Coverage of impact categories	Damage functions have incomplete coverage of climate change impact categories, often because underlying studies for calibration are lacking Represented sectors may have secondary impacts that are omitted (for example health effects from malnutrition due to impacts in the agricultural sector)	Sectors with limited or missing representation include ocean acidification, wildfires, energy supply, labour and capital productivity, crime, infrastructure, geopolitical instability and cultural heritage Many authors suggest that SCC estimates might thus be viewed as a lower bound, although some climate benefits are also missing from damage functions	3, 75–80
Treatment of inter-sectoral and inter-regional interactions	Damage functions tend to be independent (additive) across both regions and sectors and therefore do not capture interactions between climate impacts Underlying impact studies often examine sectors individually without quantifying inter-sectoral interactions, meaning any interactions may also not be accounted for implicitly through calibration	Missing interactions from many damage functions include the effects of water scarcity, geopolitical conflicts, migration, and partial- or general-equilibrium responses to direct impacts Many of these interactions have the potential to amplify damage estimates, although general equilibrium adjustments could be offsetting in some cases FUND considers inter-regional migration driven by land inundation from SLR, although the costs are arbitrary and likely to be incomplete	14, 25, 75, 76, 79, 81, 82
Representation of adaptation	Many damage functions implicitly include private adaptation, which assumes a smooth, instantaneous transition to equilibrium in a new climate state, ignoring adjustment costs, which may be substantial, and imperfect knowledge of future climate Lack of data on the aggregated costs and benefits of adaptation makes explicitly incorporating adaptation decisions into IAMs challenging	Some studies have attempted to represent adaptation explicitly in cost–benefit IAMs in order to examine trade-offs between adaptation and optimal mitigation policy FUND assumes perfect foresight and efficient adaptation to SLR, neglecting market and other institutional barriers to adaptation Market failures associated with learning about a changing climate or the development of adaptation technologies may be substantial, meaning that damages would be higher than under perfect adaptation	4, 80, 83–88
Outdated scientific understanding	Damage projections fail to reflect the current understanding of climate impacts from the IAV community (see extended discussion in Supplementary Information)	Damage functions are often calibrated directly or indirectly to older literature, much dating back to the 1990s	2, 3, 5, 10
Representation of uncertainty	Damage functions fail to capture the full range of parametric and stochastic uncertainty Underlying studies used for calibration typically estimate the effects of equilibrium changes in mean temperature (or sea level), but not necessarily the effects of extremes (such as heatwaves) or stochastic variability (storm-surges)	DICE is formulated as deterministic optimization with perfect foresight; PAGE and FUND are designed for probabilistic analysis (Monte Carlo simulation) The scientific basis of the parameter distributions as well as the choice of distribution (for example, tailed in FUND versus triangular in PAGE) is not documented Tail events with very low probabilities but the potential for very high consequences can, under certain assumptions, greatly increase damages	2, 70, 80, 89

Continued

Table 2 | (continued)

Damage function characteristic	Critique description	Model examples and implications for damage estimates	Key references
System dynamics and thresholds	Damage functions ignore or inadequately represent potential tipping points within the Earth system or the socioeconomic system Damage functions of current temperature change imply that climate impacts are the same whether warming is increasing or decreasing, effectively ruling out system irreversibilities or hysteresis	Potential system irreversibilities that are not well captured include species extinction or ice-sheet disintegration, underestimating damages in 'temperature overshoot' scenarios PAGE discontinuity represents an uncertain but high-impact irreversible tipping-point (taken in expectation) Recent studies modify DICE to incorporate random tipping points and generally find this increases the SCC substantially	3, 67, 78, 90–93
Damages to growth rates	Damages in IAMs affect economic output, but the underlying factors driving economic growth are largely specified exogenously and unaffected by temperature, counter to some empirical evidence that warmer temperatures slow growth rates, particularly in poorer countries	The growth rate in a DICE optimization run is determined endogenously, meaning climate damages indirectly affect growth through savings Proposed mechanisms for impacts on growth rates include slowing the productivity of research and development, and increasing the depreciation of capital Impacts to economic growth are permanent and cumulative and therefore have the potential to substantially increase damage estimates	5, 63, 71, 94, 95
Substitutability of environmental goods	Damage functions assume that losses from climate impacts are perfectly substitutable with increased consumption (that is, that the costs of climate impacts can be fully compensated by higher incomes) which may be implausible for non-market impacts such as biodiversity or health Measuring the degree of substitution between climate impacts and consumption is extremely difficult	Imperfect substitutability between climate impacts and increased consumption would increase damage estimates	96–98
Utility function preference parameters	Damage functions parameterize economic losses but the value of those economic losses depends on the utility function The constant elasticity of substitution (CES) utility function has been most widely used, which uses a single parameter (η) to describe time preferences, risk aversion and inequality aversion. (Discount rates are a preference parameter with a large effect on the SCC, but have been extensively discussed elsewhere and are not a focus of this Review)	Recent evidence suggests that time and risk preferences are not the same. Using a utility function that separates these, calibrated to asset price data, substantially increases the SCC. Damages are also aggregated across people and regions with very different incomes. Aversion to inequality is a preference parameter that determines how these should be weighted and can have a substantial impact on the SCC	60, 70, 72, 96, 99–105

Additional description and references are provided in the Supplementary Information, with discussion of related issues and implications for climate impact valuation.

to inform damage functions, and the opportunities and challenges associated with each.

Detailed process impact IAMs

In contrast to the relatively simple and stylized cost–benefit IAMs that have been used to calculate the SCC, there is a class of IAMs with higher spatial and process resolution that couple biogeophysical and economic models to represent climate impacts at finer scales, referred to as detailed process IAMs by Weyant[14]. Examples of these types of IAMs include the Global Change Assessment Model (GCAM)[15], the Integrated Global Systems Model (IGSM)[16] and the Integrated Model to Assess the Global Environment (IMAGE)[17], among others.

These models play an integral role in global scenario assessments (for example the RCPs[18] and shared socioeconomic pathways (SSPs)[19]), but have not typically been used to estimate economic risks directly because they report outcomes in terms of resources or other physical measures, as opposed to monetized impacts, consumption or welfare. However, using them to inform the calibration of IAM damage functions is promising because they meet several criteria outlined above. Specifically, these models are global in scope (C3), their assumptions regarding population and economic growth are internally consistent (C1), and because they incorporate partial- or general-equilibrium models of the economy they can account for economic adjustments to biophysical changes (C7) and could be applied to produce results in terms of economic units (C8). Moreover, as they incorporate multiple economic regions and sectors, they are a natural tool for accounting for inter-region and inter-sectoral interactions (C5). Detailed process models offer improved characterization of the focus domain, although they are still prone to limitations in uncertainty characterization as well as system dynamics and thresholds. Previous assessments of climate impacts in key sectors that could inform damage functions include agriculture[20,21], energy demand[22] and water resources[23,24]. Where possible, reporting results of these studies in terms of changes in economic welfare (C8) in relation to global temperature change (C2) would aid the incorporation of these results into IAM damage functions.

Multisector coordinated modelling projects

Several large multimodel efforts are underway to evaluate climate change impacts systematically either across multiple sectors[25–27] or within a single sector[28]. These efforts are structured with interdisciplinary teams of physical, natural, and social scientists. These multisector or model intercomparison projects are resource intensive but are a promising source for updating damage functions. Many such collaborations have been designed with consistent input assumptions and scenarios (C1), often using the RCPs and SSPs. This standardized, multimodel ensemble approach (pioneered in the climate modelling community[29]) strengthens uncertainty quantification and enables defensible error bars to be generated around impact estimates and the resulting damage functions (C9).

Although these projects advance understanding of climate change impacts, the direct applicability of results to IAM damage functions is mixed. While several projects are global[25,30–33], some have a more limited geographical scope, typically in data-rich regions such as the United States[26,34] and Europe[35,36]. In addition, although some projects monetize damages[26,31,35], many quantify impacts in various non-monetary units such as percentage changes to productivity or crop yields, number of people affected or coastal area flooded[27]. A subsequent analysis monetizing these results would be needed before they could inform damage functions, often requiring substantial further work[6,37].

Empirical studies

A large and rapidly growing IAV literature uses statistical relationships between socioeconomic outcomes and weather or climate variables to estimate the impacts of climate change[38,39]. Rather than explicitly modelling distinct processes, including the effects of individual adaptations, or pathways by which climate change affects outcomes of interest, this approach parameterizes impacts in a simple (reduced-form) relationship between climate and outcome. Although the exact pathway of impacts is a 'black box', impact estimates are derived directly from observed, real-world outcomes. Moreover, these approaches benefit from today's data-rich environment and are relatively inexpensive to implement. They can also offer the opportunity to study climate impacts in sectors that have previously been omitted from damage functions, such as conflict, political turnover or labour productivity[40–43]. Conversely, empirical studies can be challenging or impossible to implement for impacts that have no historical analogue or where the spatial or temporal variation of the climate driver is insufficiently large (such as ocean acidification, CO_2 fertilization or SLR).

Relevant empirical studies can be divided into individual, sector-specific studies and top-down, whole-economy studies. Empirical studies of the relationship between climate or weather and socioeconomic outcomes are now wide-ranging and cover agriculture[44–47], energy demand[48,49], morbidity and mortality[41,50–53], labour supply and productivity[42,54,55], conflict[40], politics[43] and crime[56]. Results from several of these studies were recently combined[57] with process models in certain sectors to estimate new damage functions for the United States. The empirical studies have largely focused on developed economies, partly owing to the data needs of statistical models. In particular, panel models that use fixed-effects ('dummy variables') to control for time-invariant differences between locations require long-term observations not available in all parts of the world. This means that empirically based damage functions may require global extrapolation (C3).

The extent to which empirical models capture the net benefits of adaptations or equilibrium economic adjustments (C6, C7) depends on details of the statistical model used and the kinds of adaptation technologies available[58]. Sector-specific statistical studies often, although not exclusively[44,59], report impacts in physical units (for example change in yield, additional deaths or illnesses, or change in likelihood of event). Monetizing the identified impacts (C8) requires additional analysis that, in the case of non-market impacts such as conflict, crime, illness or mortality, may be contentious. The reduced-form of most empirical studies means that they integrate over multiple impact pathways to give the net effects of climate change in a particular region and/or sector (C4). In addition, statistical confidence intervals on parameter estimates make quantifying uncertainty in damage estimates fairly straightforward (C9).

A smaller set of top-down empirical studies has used global data on GDP growth rates to estimate the relationship between temperature variation and total economic output[60–62]. Because these impact estimates have global coverage (C3) and are reported in monetary units (C8), they can be readily incorporated into IAM damage functions[60,63]. For instance, Moore and Diaz[63] used a damage function calibrated to empirical estimates of the relationship between temperature fluctuations and GDP growth in a modified version of the DICE model. They showed that impacts to the growth-rate produced much larger losses than the conventional representation of damages to annual output. Using this aggregate approach partly avoids the need for explicit representation of individual impact sectors, and the related critiques of omission of impact types, interaction effects and adaptation (C5). However, it fails to capture potentially very large welfare effects of non-market climate impacts, such as health or ecosystems, that are not included in GDP (C8), or the effect of climate variables that cannot be estimated empirically, such as SLR or ocean acidification.

Discussion

Damage functions play an important role in quantifying, comparing, aggregating and communicating the many different economic risks that society faces from climate change, and serve to explore trade-offs between the welfare costs and benefits (avoided climate risks) of investing in greenhouse-gas mitigation. But this simplified representation of climate change impacts in cost–benefit IAMs suffers from several limitations described here. Many of these gaps are further underscored by a disconnect between recent advances in our understanding of climate change impacts and their incorporation in IAM damage functions. Many IAV research streams present promising opportunities for improving damage functions, although there are challenges to closer integration. Continuing to strengthen the connection between IAV literature and IAM damage functions will allow a more robust scientific basis for decision-making and policy for climate risk management.

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References

1. Interagency Working Group on Social Cost of Carbon. *Technical Support Document: Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866* 1–50 (United States Government, Washington DC, 2010).
2. Rose, S. K., Diaz, D. B. & Blanford, G. J. Understanding the social cost of carbon: a model diagnostic and inter-comparison study. *Clim. Chang. Econ.* **8,** 1750009 (2017).
   An in-depth examination of the DICE, FUND and PAGE integrated assessment models used by the US Government to estimate the social cost of carbon with detailed decomposition and comparison of intermediate results.
3. Revesz, R. *et al.* Improve economic models of climate change. *Nature* **508,** 173–175 (2014).
4. Burke, M. *et al.* Opportunities for advances in climate change economics. *Science* **352,** 292–293 (2016).
5. Stern, N. The structure of economic modeling of the potential impacts of climate change: grafting gross underestimation of risk onto already narrow science models. *J. Econ. Lit.* **51,** 838–859 (2013).
6. National Academies of Sciences, Engineering, and Medicine. *Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide* (National Academies Press, 2017).
   Comprehensive report examining potential approaches for updating the methodology for estimating the social cost of carbon dioxide for US regulatory analysis.

7. Nordhaus, W. *RICE-2010 and DICE-2010 Models* (last accessed 20 March 2012); http://www.econ.yale.edu/~nordhaus/homepage/RICEmodels.htm
8. Anthoff, D. & Tol, R. S. J. FUND v.3.8 Scientific Documentation (2014); http://www.fund-model.org/versions
9. Hope, C. W. *The PAGE09 Integrated Assessment Model: A Technical Description*. Working Paper (Cambridge Judge Business School, 2011).
10. Ackerman, F. & Munitz, C. Climate damages in the FUND model: a disaggregated analysis. *Ecol. Econ.* **77,** 219–224 (2012).
11. Tol, R. S. J. Estimates of the damage costs of climate change, Part II. Dynamic estimates. *Environ. Resour. Econ.* **21,** 135–160 (2002).
A methodology for modeling dynamic factors such as socioeconomic levels affecting vulnerability for eight major climate impact categories.
12. Anthoff, D. & Tol, R. S. J. in *Climate Change and Common Sense: Essays in Honour of Tom Schelling*, 260–273 (Oxford Univ. Press, 2012).
13. Nordhaus, W. D. Economic aspects of global warming in a post-Copenhagen environment. *Proc. Natl Acad. Sci. USA* **107,** 11721–11726 (2010).
14. Weyant, J. Some contributions of integrated assessment models of global climate change. *Rev. Environ. Econ. Policy* **11,** 115–137 (2017).
Comprehensive overview of the use of IAMs in global policy analysis, discussing challenges and open issues.
15. Calvin, K. *et al.* GCAM Wiki documentation (Pacific Northwest National Laboratory, 2011); http://jgcri.github.io/gcam-doc/
16. Sokolov, A., Schlosser, C., Dutkiewicz, S. & Paltsev, S. *MIT Integrated Global System Model (IGSM) Version 2: Model Description and Baseline Evaluation* (2005); https://dspace.mit.edu/handle/1721.1/29789
17. Stehfest, E., Vuuren, D. van, Bouwman, L. & Kram, T. *Integrated Assessment of Global Environmental Change with Image 3.0: Model Description and Policy Applications* (2014); http://dspace.library.uu.nl/handle/1874/308545
18. Moss, R. H. *et al.* The next generation of scenarios for climate change research and assessment. *Nature* **463,** 747–756 (2010).
19. O'Neill, B. C. *et al.* A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic Change* **122,** 387–400 (2014).
20. Calvin, K., Wise, M., Clarke, L., Edmonds, J. & Kyle, P. Implications of simultaneously mitigating and adapting to climate change: initial experiments using GCAM. *Climatic Change* 117, 545–560 (2013).
21. Kyle, P., Müller, C., Calvin, K. & Thomson, A. Meeting the radiative forcing targets of the representative concentration pathways in a world with agricultural climate impacts. *Earth's Future* **2,** http://dx.doi.org/10.1002/2013EF000199 (2014).
22. Zhou, Y., Eom, J. & Clarke, L. The effect of global climate change, population distribution, and climate mitigation on building energy use in the US and China. *Climatic Change* **119,** 979–992 (2013).
23. Hejazi, M. I. *et al.* Integrated assessment of global water scarcity over the 21st century under multiple climate change mitigation policies. *Hydrol. Earth Syst. Sci.* **18,** 2859–2883 (2014).
24. Blanc, E. *et al.* Modeling U. S. water resources under climate change. *Earth's Future* **2,** 197–224 (2014).
25. Huber, V. *et al.* Climate impact research: beyond patchwork. *Earth Syst. Dyn.* **5,** 399–408 (2014).
26. Waldhoff, S. T. *et al.* Overview of the special issue: a multi-model framework to achieve consistent evaluation of climate change impacts in the United States. *Climatic Change* **131,** 1–20 (2015).
27. O'Neill, B. C. *et al.* The Benefits of Reduced Anthropogenic Climate changE (BRACE): a synthesis. *Climatic Change* https://doi.org/10.1007/s10584-017-2009-x (2017).
28. Rosenzweig, C. *et al.* Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proc. Natl Acad. Sci. USA* **111,** 3268–3273 (2014).
29. Knutti, R., Furrer, R., Tebaldi, C., Cermak, J. & Meehl, G. A. Challenges in combining projections from multiple climate models. *J. Clim.* **23,** 2739–2758 (2010).
30. Warszawski, L. *et al.* The Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP): project framework. *Proc. Natl Acad. Sci. USA* **111,** 3228–3232 (2014).
Example of recent multisector coordinated modeling initiative using standardized scenarios and input assumptions.
31. Roson, R. & Sartori, M. *Estimation of Climate Change Damage Functions for 140 Regions in the GTAP9 Database* (World Bank, 2016).
32. Greenstone, M., Houser, T., Hsiang, S. M. & Kopp, R. E. *Climate Impact Lab;* http://www.impactlab.org/
33. Arnell, N. W. *et al. The Impacts of Climate Change Avoided by Future Reductions in Emissions as Defined in the Intended Nationally-Determined Contributions* (AVOID 2, UK Government, 2015).
34. Houser, T., Hsiang, S., Kopp, R. & Larsen, K. *Economic Risks of Climate Change: An American Prospectus* (Columbia Univ. Press, 2015).
35. Ciscar, J.-C. *et al. Climate Impacts in Europe — The JRC PESETA II Project*, Vol. 26586 (Publications Office of the European Union, 2014).
36. Bosello, F., Eboli, F. & Pierfederici, R. Assessing the economic impacts of climate change — an updated CGE point of view. *SSRN Electron. J.* http://dx.doi.org/10.2139/ssrn.2004966 (2012).
37. Moore, F. C., Baldos, U., Hertel, T. W. & Diaz, D. B. New science of climate change impacts on agriculture implies higher social cost of carbon. *Nat. Commun.* (in the press); https://doi.org/10.1038/s41467-017-01792-x
38. Carleton, T. & Hsiang, S. Social and economic impacts of climate change. *Science* **353,** aad9837 (2016).
39. Dell, M., Jones, B. F. & Olken, B. A. What do we learn from the weather? The new climate-economy literature. *J. Econ. Lit.* **53,** 740–798 (2014).
Comprehensive review of the growing empirical literature on weather effects using panel data, with implications for economic research.
40. Hsiang, S. M., Burke, M. & Miguel, E. Quantifying the influence of climate on human conflict. *Science* **341,** 1235367 (2013).
41. Fishman, R., Russ, J. & Carrillo, P. *Long-Term Impacts of High Temperatures on Economic Productivity* (2015); https://ideas.repec.org/p/gwi/wpaper/2015-18.html
42. Seppanen, O., Fisk, W. J. & Lei, Q. *Effect of Temperature on Task Performance in Office Environments* (LBNL, 2006).
43. Obradovich, N. Climate change may speed democratic turnover. *Climatic Change* **140,** 135–147 (2017).
44. Mendelsohn, R., Nordhaus, W. D. & Shaw, D. The impact of global warming on agriculture: a Ricardian analysis. *Am. Econ. Rev.* **84,** 753–771 (1994).
45. Schlenker, W. & Roberts, D. L. Nonlinear temperature effects indicate severe damages to US corn yields under climate change. *Proc. Natl Acad. Sci. USA* **106,** 15594–15598 (2009).
46. Tack, J., Barkley, A. & Nalley, L. L. Effect of warming temperatures on US wheat yields. *Proc. Natl Acad. Sci. USA* **112,** 6931–6936 (2015).
47. Lobell, D. B., Banziger, M., Magorokosho, C. & Vivek, B. Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nat. Clim. Change* **1,** 42–45 (2011).
48. Auffhammer, Maximilian and Anin Aroonruengsawat. *Hotspots of Climate-Driven Increases in Residential Electricity Demand: A Simulation Exercise Based on Household Level Billing Data for California.* Publication number: CEC-500-2012-021 (California Climate Change Center, California Energy Commission, 2012).
49. Davis, L. W. & Gertler, P. J. Contribution of air conditioning adoption to future energy use under global warming. *Proc. Natl Acad. Sci. USA* **112,** 5962–5927 (2015).
50. Deschênes, O. & Greenstone, M. Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US. *Am. Econ. J. Appl. Econ.* **3,** 152–185 (2011).
51. Barreca, A., Clay, K., Deschenes, O., Greenstone, M. & Shapiro, J. S. Adapting to climate change: the remarkable decline in the US temperature–mortality relationship over the 20th century. *J. Polit. Econ.* **124,** 105–159 (2013).
52. Barreca, A. Climate change, humidity, and mortality in the United States. *J. Environ. Econ. Manage.* **63,** 19–34 (2012).
53. Deschênes, O., Greenstone, M. & Guryan, J. Climate change and birth weight. *Am. Econ. Rev. Pap. Proc.* **99,** 211–217 (2009).
54. Heal, G. & Park, J. *Feeling the Heat: Temperature, Physiology & the Wealth of Nations* (2013); http://www.nber.org/papers/w19725
55. Graff Zivin, J. & Neidell, M. Temperature and the allocation of time: implications for climate change. *J. Labor Econ.* **32,** 1–26 (2014).
56. Ranson, M. Crime, weather, and climate change. *J. Environ. Econ. Manage.* **67,** 274–302 (2014).
57. Hsiang, S. *et al.* Estimating economic damage from climate change in the United States. *Science* **356,** 1362–1369 (2017).
Recent multisector assessment of US climate damages at high spatial resolution of both physical and economic impacts, with a focus on empirical support for sectoral damage functions.
58. Hsiang, S. Climate econometrics. *Ann. Rev. Res. Econ.* **8,** 43–75 (2016).
59. Deschênes, O. & Greenstone, M. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *Am. Econ. Rev.* **97,** 354–385 (2007).
60. Lemoine, D. & Kapnick, S. A top-down approach to projecting market impacts of climate change. *Nat. Clim. Change* **6,** 51–55 (2016).
61. Dell, M., Jones, B. F. & Olken, B. A. Temperature shocks and economic growth: evidence from the last half century. *Am. Econ. J. Macroecon.* **4,** 66–95 (2012).
62. Burke, M., Hsiang, S. M. & Miguel, E. Global non-linear effect of temperature on economic production. *Nature* **527,** 235–239 (2015).
63. Moore, F. C. & Diaz, D. B. Temperature impacts on economic growth warrant stringent mitigation policy. *Nat. Clim. Change* **5,** 127–131 (2015).
64. IPCC: Summary for Policymakers. In *Climate Change 2007: Impacts, Adaptation and Vulnerability* (eds Parry, M. L. *et al.*) (Cambridge Univ. Press, 2007).
65. Tol, R. S. J. The economic effects of climate change. *J. Econ. Perspect.* **23,** 29–51 (2009).

66. Anthoff, D., Nicholls, R. J., Tol, R. S. J. & Vafeidis, A. T. *Global and Regional Exposure to Large Rises in Sea-Level: A Sensitivity Analysis* (2006); http://www.tyndall.ac.uk/sites/default/files/wp96_0.pdf
67. Warren, R. *et al. Spotlighting Impacts Functions in Integrated Assessment* (Tyndall Centre for Climate Change Research, 2006).
68. Nordhaus, W. D. Expert opinion on climatic change. *Am. Sci.* **82,** 45–51 (1994).
69. Ackerman, F., Stanton, E. A., Hope, C. W. & Alberth, S. Did the Stern Review underestimate US and global climate damages? *Energy Policy* **37,** 2717–2721 (2009).
70. Weitzman, M. L. GHG targets as insurance against catastrophic climate damages. *J. Public Econ. Theory* **14,** 221–244 (2012).
Describes how fat-tailed climate risks affect the cost–benefit analysis of climate change, highlighting limitations in the treatment of: uncertainty, risk, discounting and welfare (in the face of catastrophic outcomes).
71. Dietz, S. & Stern, N. Endogenous growth, convexity of damage and climate risk: how Nordhaus' framework supports deep cuts in carbon emissions. *Econ. J.* **125,** 574–620 (2015).
72. Ackerman, F. & Stanton, E. A. Climate risks and carbon prices: revising the social cost of carbon. *Economics* **6,** 1–25 (2012).
73. van den Bergh, J. C. J. M. & Botzen, W. J. W. A lower bound to the social cost of CO_2 emissions. *Nat. Clim. Change* **4,** 253–258 (2014).
74. Nordhaus, W. D. To slow or not to slow: the economics of the greenhouse effect. *Econ. J.* **101,** 920–937 (1991).
75. Warren, R. The role of interactions in a world implementing adaptation and mitigation solutions to climate change. *Phil. Trans. R. Soc. A* **369,** 217–41 (2011).
76. Marten, A. L. *et al.* Improving the assessment and valuation of climate change impacts for policy and regulatory analysis. *Climatic Change* **117,** 433–438 (2013).
77. Watkiss, P. Aggregate economic measures of climate change damages: explaining the differences and implications. *Wiley Interdiscip. Rev. Clim. Change* **2,** 356–372 (2011).
78. Howard, P. *Omitted Damages: What's Missing from the Social Cost of Carbon*. (2014); http://go.nature.com/2wKYTcF
79. Watkiss, P. & Downing, T. E. The social cost of carbon: valuation estimates and their use in UK policy. *Integr. Assess. J. Bridg. Sci. Policy* **8,** 85–105 (2008).
80. Neumann, J. E. & Strzepek, K. State of the literature on the economic impacts of climate change in the United States. *J. Benefit Cost Anal.* **5,** 411–443 (2014).
81. Kopp, R. E. & Mignone, B. B. K. The US government's social cost of carbon estimates after their first two years: pathways for improvement. *Economics E-Journal* **6,** 1–41 (2012).
82. Bell, A., Zhu, T., Xie, H. & Ringler, C. Climate–water interactions: challenges for improved representation in integrated assessment models. *Energy Econ.* **46,** 510–521 (2014).
83. Li, J., Mullan, M. & Helgeson, J. Improving the practice of economic analysis of climate change adaptation. *J. Benefit Cost Anal.* **5,** 445–467 (2014).
84. de Bruin, K. C., Dellink, R. B. & Tol, R. S. J. AD-DICE: an implementation of adaptation in the DICE model. *Climatic Change* **95,** 63–81 (2009).
85. Farmer, J. D., Hepburn, C., Mealy, P. & Teytelboym, A. A third wave in the economics of climate change. *Environ. Resour. Econ.* **62,** 329–357 (2015).
86. Kelly, D., Kolstad, C. & Mitchell, G. Adjustment costs from environmental change. *J. Environ. Econ. Manage.* **50,** 468–495 (2005).
Conceptual framework for understanding adjustment costs and equilibrium response, with an empirical application for US agriculture.
87. Schneider, S. H., Easterling, W. E. & Mearns, L. O. Adaptation: sensitivity to natural variability, agent assumptions and dynamic climate changes. *Climatic Change* **45,** 203–221 (2000).
88. Hornbeck, R. The enduring impact of the American Dust Bowl: short and long-run adjustments to environmental catastrophe. *Am. Econ. Rev.* **102,** 1477–1507 (2012).
89. Heal, G. & Millner, A. Reflections: uncertainty and decision making in climate change economics. *Rev. Environ. Econ. Policy* **8,** 120–137 (2014).
90. Cai, Y., Judd, K. L., Lenton, T. M., Lontzek, T. S. & Narita, D. Environmental tipping points significantly affect the cost-benefit assessment of climate policies. *Proc. Natl Acad. Sci. USA* **112,** 4606–4611 (2015).
Example of recent advances using stochastic dynamic programming to model uncertain climate thresholds with an endogenous hazard rate and incorporate catastrophic uncertainty into IAMs.
91. Lemoine, D. & Traeger, C. Watch your step: optimal policy in a tipping climate. *Am. Econ. J. Econ. Policy* **6,** 137–166 (2014).
92. Diaz, D. B. & Keller, K. A potential disintegration of the West Antarctic Ice Sheet: implications for economic analyses of climate policy. *Am. Econ. Rev. Pap. Proc.* **106,** 1–5 (2016).
93. Kopp, R. E., Shwom, R. L., Wagner, G. & Yuan, J. Tipping elements and climate–economic shocks: Pathways toward integrated assessment. *Earth's Future* **4,** 346–372 (2016).
94. Moyer, E., Woolley, M., Glotter, M. & Weisbach, D. Climate impacts on economic growth as drivers of uncertainty in the social cost of carbon. *J. Legal Stud.* **43,** 401–425 (2014).
95. Pindyck, R. S. Climate change policy: what do the models tell us? *J. Econ. Lit.* **51,** 860–872 (2013).
96. Sterner, T. & Persson, U. M. An even sterner review: introducing relative prices into the discounting debate. *Rev. Environ. Econ. Policy* **2,** 61–76 (2008).
97. Weitzman, M. L. On modelling and interpreting the economics of catastrophic climate change. *Rev. Econ. Stat.* **91,** 1–19 (2009).
98. Weitzman, M. L. What is the 'damages function' for global warming — and what difference might it make? *Clim. Chang. Econ.* **1,** 57–69 (2012).
99. Anthoff, D., Tol, R. S. J. & Yohe, G. W. Risk aversion, time preference, and the social cost of carbon. *Environ. Res. Lett.* **4,** 24002 (2009).
100. Anthoff, D., Hepburn, C. & Tol, R. S. J. Equity weighting and the marginal damage costs of climate change. *Ecol. Econ.* **68,** 836–849 (2009).
101. Dennig, F., Budolfson, M. B., Fleurbaey, M., Siebert, A. & Socolow, R. H. Inequality, climate impacts on the future poor, and carbon prices. *Proc. Natl Acad. Sci. USA* **112,** 1513967112 (2015).
102. Newbold, S. C. & Daigneault, A. Climate response uncertainty and the benefits of greenhouse gas emissions reductions. *Environ. Resour. Econ.* **44,** 351–377 (2009).
103. Crost, B. & Traeger, C. P. Optimal CO_2 mitigation under damage risk valuation. *Nat. Clim. Change* **4,** 631–636 (2014).
104. Jensen, S. & Traeger, C. P. Optimal climate change mitigation under long-term growth uncertainty: stochastic integrated assessment and analytic findings. *Eur. Econ. Rev.* **69,** 104–125 (2014).
105. Daniel, K. D., Litterman, R. B. & Wagner, G. *Applying Asset Pricing Theory to Calibrate the Price of Climate Risk* (2015); http://go.nature.com/2xw8SSL

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Author contributions

D.B.D. and F.C.M. designed and wrote the manuscript. F.C.M. produced Fig. 1. D.B.D. performed the analysis and produced Fig. 2.

Additional information

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Competing financial interests

The authors declare no competing financial interests.