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► To cite this version:

Franziska Piontek, Laurent Drouet, Johannes Emmerling, Tom Kompas, Aurélie Méjean, et al.. Integrated perspective on translating biophysical to economic impacts of climate change. *Nature Climate Change*, 2021, 11 (7), pp.563-572. 10.1038/s41558-021-01065-y . hal-03320249

HAL Id: hal-03320249

<https://hal.science/hal-03320249>

Submitted on 18 Dec 2021

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Integrated perspective on translating biophysical to economic impacts of climate change

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Abstract

Estimates of climate change's economic impacts vary widely, depending on the applied methodology. This uncertainty is a barrier for policymakers seeking to quantify the benefits of mitigation. In this Perspective, we provide a comprehensive overview and categorization of the pathways and methods translating biophysical impacts into economic damages. We highlight the open question of the persistence of impacts as well as key methodological gaps, in particular the effect of including inequality and adaptation in the assessments. We discuss the need for intensifying interdisciplinary research, focusing on the uncertainty of econometric estimates of damages as well as identification of the most socioeconomically relevant types of impact. A structured model intercomparison related to economic impacts is noted as a crucial next step.

Support for the great societal transformations required to reach the goals of the Paris Agreement can be built by a comprehensive integrated assessment weighting the costs of mitigation and adaptation measures against the corresponding avoided impacts. Mitigation strategies and their associated costs can be robustly assessed due to extensive collaborative modelling efforts and model intercomparisons, helping to assess ranges and uncertainties^{1,2}. The assessment of biophysical climate change impacts such as changes in yields, water availability or sea-level rise has been greatly advanced in recent years by consistent cross-sectoral modelling initiatives such as the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)³. However, a robust understanding and quantitative assessment of their full future socioeconomic impacts remains a substantial challenge. The quantitative estimates of global economic impacts provided in the literature vary widely⁴, depending on the methods used to assess them and the types of impact included. In particular, the great advances of empirical studies linking climatic conditions and different aspects of socioeconomic systems⁵ have widened the range of estimates, related also to the debate on whether temperature affects level or growth of productivity^{6–8}. Integrating such empirical findings into global cost–benefit analysis (CBA) models leads to larger social costs of carbon and more stringent mitigation pathways, as does the integration of distributional aspects^{9–12}. This disparate and inconclusive understanding of economic impacts is a challenge for researchers, policymakers and stakeholders alike. Multiple literature reviews have addressed aspects of this complex topic, focusing broadly on linkages between climate and the economy and related policy implications¹³, on key open research questions¹⁴, on econometric advances^{5,15,16} or on damage functions in CBA models¹⁷. The goal of this Perspective is to add a comprehensive, accessible and structured overview of the methods used to derive final economic damages from biophysical impacts, explicitly without consideration of adaptation or mitigation measures, including their advantages and disadvantages. This is aimed as a foundation for researchers from different disciplines (for example, economists, integrated assessment modellers, biophysical impact modellers) to advance the integrated research on economic impacts, and as a guide for policymakers to contextualize new cost estimates and their uncertainties. While not aiming for a complete literature review, we provide an overview of key methodological characteristics of recent global studies of economic impacts. Furthermore, we contribute a discussion of the key empirical question of persistence of impacts, highlight the status of modelling adaptation and inequality as key determinants of final impacts, and outline next research steps.

Translating biophysical into economic damages

Quantifying the total economic losses resulting from climate change requires a comprehensive analysis of social welfare. Generally, they include (1) direct losses of income and production; (2) the value of resources, goods and services that become unavailable or of reduced quality; (3) damage to productive capital and infrastructure; (4) reductions in ecosystem services; (5) effects on morbidity and mortality; and (6) the loss of subjective well-being from less tangible benefits, such as the extinction of species or deterioration of ecosystems. These are divided into market impacts (1–3), directly valued within markets, and non-market impacts (4–6), which are not traded. In order to compare different policy options, market and non-market impacts are translated into commensurate units of ‘welfare’. Welfare is assumed to increase with consumption, that is, the purchase of goods and services, but also depends on non-market

determinants. This allows for the evaluation and comparison of different policies balancing income levels with subjective benefits. Non-market damages can be included through a translation into monetary units, such as the willingness-to-pay to avoid a given subjective loss, or by employing a welfare damage function accounting for both aspects of damages. As the units of welfare are arbitrary, total economic damages are often reported as the equivalent loss in consumption that would result in the same welfare loss as the combined market and non-market damages (the Hicksian equivalent variation).

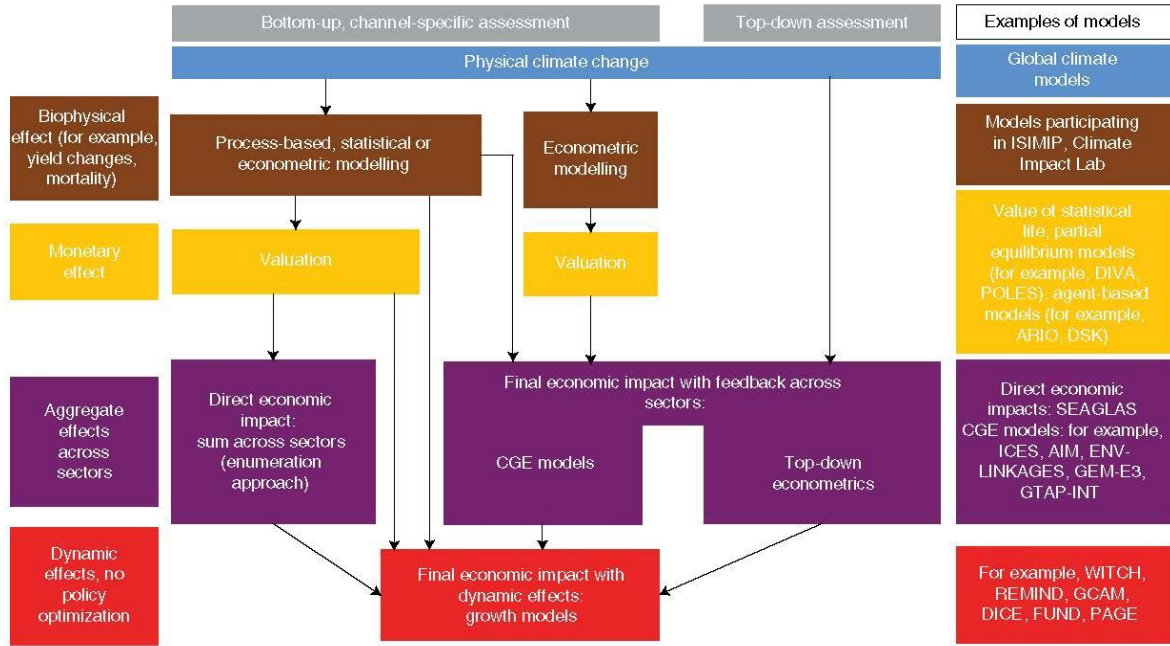


Fig. 1 | Taxonomy of approaches to capture economic impacts of climate change. The different end points capture different levels of feedback effects. The column on the right lists some examples for models and studies applying the methodologies. Model references: global climate models⁹⁸, ISIMIP (www.isimip.org/impactmodels), Climate Impact Lab (<http://www.impactlab.org/>), DIVA²⁰, POLES²¹, ARIO²⁶, DSK²⁴, SEAGLAS⁵³, ICES²², AIM⁵⁴, ENV-LINKAGES²³, GEM-E3⁵⁷, GTAP-INT⁵⁸, WITCH⁹⁹, REMIND³⁷, GCAM¹⁰⁰, DICE³⁰, FUND³² and PAGE³¹

Figure 1 shows a taxonomy of the different possible approaches to derive economic damages from physical climate change, with examples of models. The result crucially depends on the type of feedback and dynamic processes captured in the different modelling approaches. As the models employed at the different levels depicted in Fig. 1 increase in comprehensiveness, they invariably use parameterization to simplify constituent processes. For example, process-based crop models represent the biophysical growth processes of individual plants, whereas statistical yield models parameterize the relationship between weather and yields, while encompassing the dynamic feedbacks between farmers and their fields. Detailed examples are discussed in the Supplementary Information (see also Supplementary Fig. 2). Model parameterization forces the models to assume forms of stationarity and undermine the representation of adaptation on scales below the model’s scale. In particular, macro- and microeconomic econometric estimates assume stationarity of the biophysical process as reflected in the observational record. Computable general equilibrium (CGE) models allow redistribution of economic activity, but typically assume that supply and demand elasticities are constant (but see ref. 18 for a relaxation of this assumption). This may be inadequate when projecting climate change impacts and adaptation policies over the long term (for example, to 2100), as it fails to capture

potentially radical changes in technical systems, investment patterns and consumption dynamics (see ref. 19 for a general discussion of the issue of constant elasticity of substitution in energy–climate–economy models). Note also that models that describe fundamental biophysical relationships reflect current technologies (for example, crop varieties, distribution systems, protective gear) and are likely to misrepresent impacts in the distant future.

	Direct economic impacts	Final economic impacts with sectoral feedback effects		Aggregate damage functions
	Bottom-up assessment	Bottom-up assessment	Top-down assessment	
Approach	Add up damages from individual sectors (either from biophysical models or from econometric studies)	Overall economic effect of direct sectoral damages including equilibrium effects, autonomous adaptation endogenous	Econometric study of aggregate climate effect as well as individual channels	Apply aggregate damage functions in growth models to capture economic feedback, for example, from investment; often used for CBA to derive abatement decisions
Impact channels	Various, most prominently agriculture, labour productivity, tourism, health (infectious diseases, heat-related mortality), energy demand, limited sea-level rise		(Total) factor productivity or growth	Output loss
Example ref.	55	58	7	4
Global GDP loss for different warming levels (see also Fig. 2)	1.5 °C: 1%	1.8 °C: 0.5%	1.5 °C: <10%	1.5 °C: slight gains under the FUND damage function, up to 3% loss under ref. 4 with productivity effects
	4.3 °C: 6–8%	4 °C: 3%	4.3 °C: 5–65%	4 °C: 1–18% loss
	(based on two studies)	(based on three studies)	(based on six studies)	(based on four studies)
Advantages	Transparency; high detail on impact side		Close derivation from observed data; full representation of (historical) uncertainty; simple representation for use in IAMs (with caveats)	Simple function for use in IAMs; high flexibility; difficult to derive
	Includes non-market damages (for example, mortality impacts via the value of statistical life); direct consideration of explicit adaptation measures	Captures economic response dynamics for different impact channels; high sectoral detail; propagation of impacts across sectors		
Disadvantages	Little flexibility on impact side, rare uncertainty analysis (often a single biophysical impact model per channel)		Focus on output/productivity effects—rarely includes other channels such as extreme events; opacity about included channels	
	No feedback/interaction effects between sectors, from the general economy or to the climate system	No forward-looking investment processes; cannot capture economic transformations; spatial resolution limited by input/output data	Out-of-sample projections; unclear role of adaptation; assumes stationarity in slow-moving processes (for example, cannot capture sea-level rise); does not include non-market damages	Difficult to derive; high aggregation masks spatial/social heterogeneity

Final economic impacts with dynamic effects are not included as these are typically combined with policy optimization in the literature. Instead, for comparison, aggregate damage functions as used in the most prominent CBA models DICE, FUND and PAGE are featured, together with recent damage functions based on meta-analysis of the damage literature⁴. For brevity we provide only one example reference per approach; for a more extensive literature overview including methodological details of the studies see Supplementary Table 1.

Table 1 | Comparative overview of aggregate global economic damage estimates following three main different approaches as shown in Fig. 1

A main differentiation in the assessment of impacts is between bottom-up and top-down approaches. Bottom-up approaches quantify impacts specifically for individual impact channels. The valuation of biophysical impact indicators is a crucial step. Different techniques can be used, ranging from simple conversion factors such as the value of statistical life to the use of partial equilibrium models^{20,21}, CGE models^{22,23} or agent-based models^{24–26} (for example,

process-based crop models are used to calculate regional crop failures, which are then valued by agro-economic partial equilibrium models). By contrast, in top-down approaches, climate damages are quantified by econometrically estimating aggregate impacts on economic output.

Furthermore, we classify different end points for a final assessment: the direct economic impact, which is simply the sum of sectoral impacts, and two types of final impact capturing system readjustment. These are the final impact accounting for interplay between different impacts and sectors, and the final impact accounting additionally for dynamic effects such as savings or capital accumulation in the economic system. The latter is normally obtained using growth models^{27,28}. These feedback effects can increase or decrease overall damages (that is, have an adaptation effect) and are crucial for a complete or overall picture. Aggregate damage functions, relating temperature change to output change, can be derived from all end points. They are used in CBA models for policy optimization. Ref. 17 provides a detailed review of the functions applied in the most prominent CBA models DICE^{29,30}, PAGE³¹ and FUND³². These damage functions tend to yield rather small losses (for example, in the case of DICE, 2.1% for a 3 °C temperature increase over pre-industrial levels and 8.5% for a 6 °C increase), possibly due to the high level of aggregation, outdated underlying impact estimates, and ambitious assumptions about adaptation and substitutability. One attempt to improve them includes meta-analysis of economic damage assessments (see, for example, refs. 4,29), which can lead to larger effects. Damage functions have been criticized for embedding many, typically opaque assumptions and poor linkages to the underlying processes³³. A number of studies extend the standard damage function in the DICE model to account for uncertainty in damages³⁴, the possibility of tipping points³⁵ or natural capital³⁶. Another increasing body of literature applies empirical damage estimates, yielding larger damages, either directly on output^{9,37} or through changes in capital depreciation or productivity^{10,38}. As we focus on the damage assessments here, see ref. 17 for a further review of the critiques as well as a research agenda to improve damage functions.

A key issue in economic damage assessment is the coverage of impact channels (see Supplementary Fig. 1 and associated discussion, and Table 1). No approach is complete, but while this is fairly transparent for bottom-up approaches detailing the channels captured, the coverage is less clear for top-down approaches or aggregate damage functions. Top-down econometric estimates generally capture market effects driven by temperature fluctuations, for example, productivity effects, but not sea-level rise, extreme events or non-market effects, some of which are included in the CBA models. All available estimates are lower bounds in that context, and for many of the missing channels we do not know how large the additional effect will be. First steps are being taken now to remedy this gap, for example, in the context of the Climate Impact Lab³⁹.

Modelling approaches for global aggregate impacts

The estimates of global aggregate economic effects of climate change in the literature vary widely, reflecting the methodological diversity described above. Here, we provide a comparative overview (Table 1 and Fig. 2) and methodological discussion for results along the different end points outlined in Fig. 1. Supplementary Table 1 provides a categorization of individual studies from the literature with more methodological detail. Note that, for reasons of clarity and manageability, we focus on studies from recent years, as most earlier studies have been updated

or built upon⁴. We do not discuss the end point of final economic impacts with dynamic effects here because such estimates are rarely provided in the literature without the application in policy optimization (although see ref. 27 for estimations of the size of the dynamic effects). This constitutes an important gap in analyses, preventing, for example, the calculation of benefits of mitigation or the quantification of the contribution of dynamic effects to the overall damage.

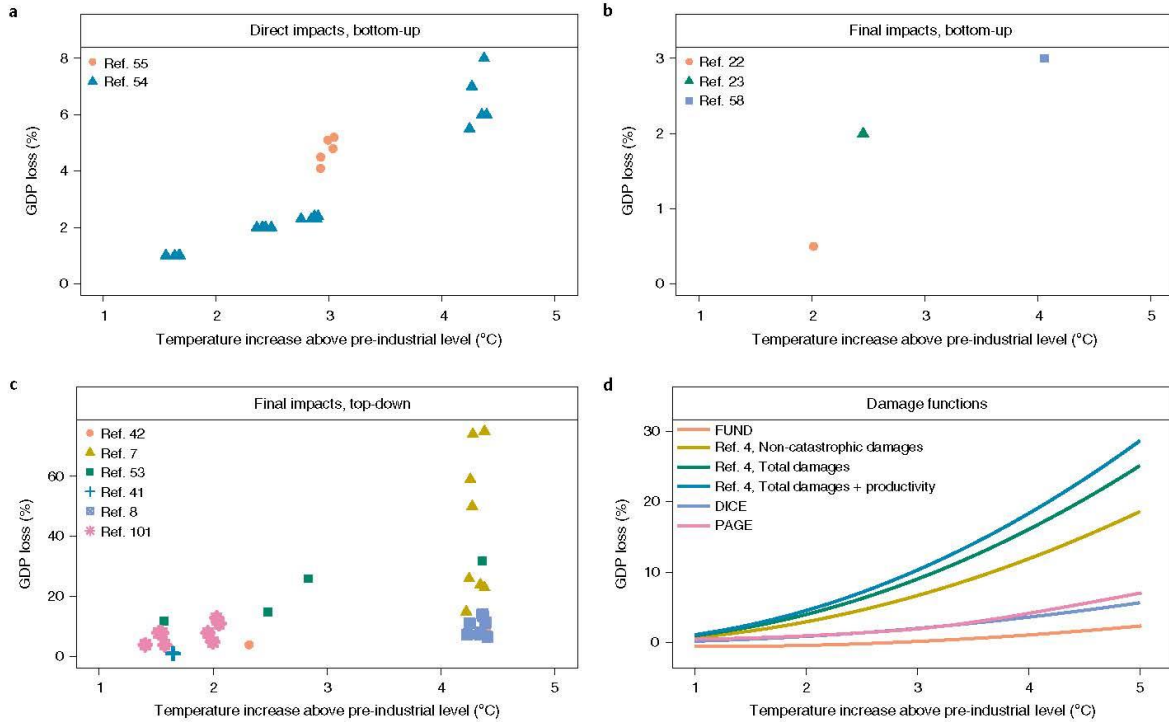


Fig. 2 | Global GDP losses at increasing warming levels, estimated with different modelling approaches. a, Direct economic impacts based on bottom-up assessment. b, Final economic impacts with sectoral feedback effects based on bottom-up assessment. c, Final economic impacts with sectoral feedback effects based on top-down econometric studies. d, Aggregate damage functions from the prominent CBA models DICE, FUND and PAGE, and from the meta-analysis by ref. 4 (with different specifications). For the FUND and PAGE models, we show the implied damage functions based on ref. 17. The meta-analysis by ref. 4 provides three different specifications.

Final economic impacts based on top-down econometrics

Top-down estimates of macroeconomic damages provide a simple representation for use in integrated assessment models (IAMs), and recent panel-based econometric research improves their empirical basis (see ref. 4 for a discussion of earlier cross-sectional estimates). However, these results come with important assumptions and limitations, described below. A robust observed relationship exists between changes in aggregate economic output (gross domestic product (GDP) per capita) and changes in regional temperatures. This relationship has been observed on multiple scales (ADM1 and ADM2 indicate first-order and second-order administrative units of countries): global-national^{6,7,40–42}, global-ADM1⁸, global-household (M. Burke and S. Hsiang, unpublished results), European Union-national⁴³, United States-ADM1^{41,44}, United States-ADM2⁴⁵, United States-metro⁴³, Brazil-ADM1 and Indonesia-ADM1⁴³. The main differences include the measure of temperature (level or change), the functional form (typically linear, polynomial or binned), and the inclusion of interaction terms and fixed effects. Innovations have focused on functional forms that explore nonlinearity,

adaptation^{8,41} and the effect of different sectors, seasons and periods^{42,44}. The resulting estimates vary widely, with GDP losses under Representative Concentration Pathway 8.5 in 2100 of between 7%⁴¹ and 23%⁷, and very high uncertainties⁴⁰. It remains an open question whether all countries are affected in a similar way⁷ or if a negative relation exists only for poor countries, due to their level of development as well as dependence on sectors with high climate exposure, such as agriculture^{6,46}. One of the most important open questions is for how long climate-induced economic losses persist. In general, shifts in climate can have an immediate, transitory and long-run effect⁸. A shock to growth in one year can lead to higher, equivalent or permanently lower long-term outcomes, depending on rebound effects⁴⁷. Several authors have proposed functional forms for the dynamics of persistence (see Fig. 3). Low impacts can derive from a quick return to the baseline per capita GDP after one-year temperature shocks (level effects⁸), whereas larger impacts emerge when the return is slow or non-existent (growth effects^{41,45,48}), although this order may be reversed⁴⁹. Growth effects can also appear when temperature levels instead of temperature change are used as the temperature measure, leading to an accumulation of damages for permanent temperature increases (ref. 7 versus ref. 8). The question of whether a climate shock results in permanently lower economic output is fundamentally an empirical question. One approach to resolving it is to construct a multi-annual impulse response curve, describing the effect of temperatures from multiple past years^{5,6}. Unfortunately, datasets are short, estimates are noisy and the question remains unresolved on the national⁴⁰ and subnational (for example, disagreement between refs. 8 and 43) scales. In the face of this uncertainty, we should distinguish the empirical question of persistence from the effects of the modelling decisions taken when using these results. An empirical relationship can be modelled with different persistence assumptions, offering a way to represent this uncertainty.

Two basic approaches are used in IAMs to project economic output. When the trajectory of economic output is derived from exogenous growth rates, we call it a ‘growth projection’; when it is derived from a scenario of economic output levels, we call it a ‘level projection’. Applied to a single-year response, growth projections produce growth effects and level projections produce level effects, and a wide gap opens between the two as time progresses (Fig. 3). However, both modelling approaches could result in either effect: a growth projection can produce a level effect when there is full rebound, and a level projection can become a growth effect with an infinite impulse response. In the face of empirical uncertainty, either projection approach can be applied to an empirical relationship such as the one described above^{37,50}.

Either assumption seems plausible a priori. Physically, a growth rate effect could emerge because of capital destruction, under-investment, or human capital effects, resulting in long-term feedback²⁷. Level effects could result if the determinants of economic growth are unaffected by climate change (for example, if damages are applied after savings), reflecting resilience (with rebound) or adaptation (with a diminishing impulse response). Some authors have developed models of partial persistence in response, based on existing approaches^{37,48}.

Besides persistence, other dimensions of the response of economies to climate change are not captured by current top-down empirical assessments. Most importantly, these include distributional effects (between producers and consumers, rich and poor, and rural and urban), non-market effects, the effects of sea-level rise or extreme events. Recent work suggests that

aggregation masks the important effect of precipitation on growth in developing countries, which is usually found to be insignificant⁵¹. Finally, these empirical estimates assume basic stationarity of the climate–economic system: that historical responses can inform future responses. This will no longer hold if climate shifts drastically (for example, with widespread desertification), or when the economy changes strongly. This reflects the challenge of econometric analysis to distinguish the effects of weather (isolated shocks) from climate (persistent states that admit adaptation). While econometric papers studying GDP effects generally find that the response to shocks has not changed much over the historical record, suggesting little adaptation, new methods are emerging to estimate the climate contribution of weather responses directly^{15,39,52}.

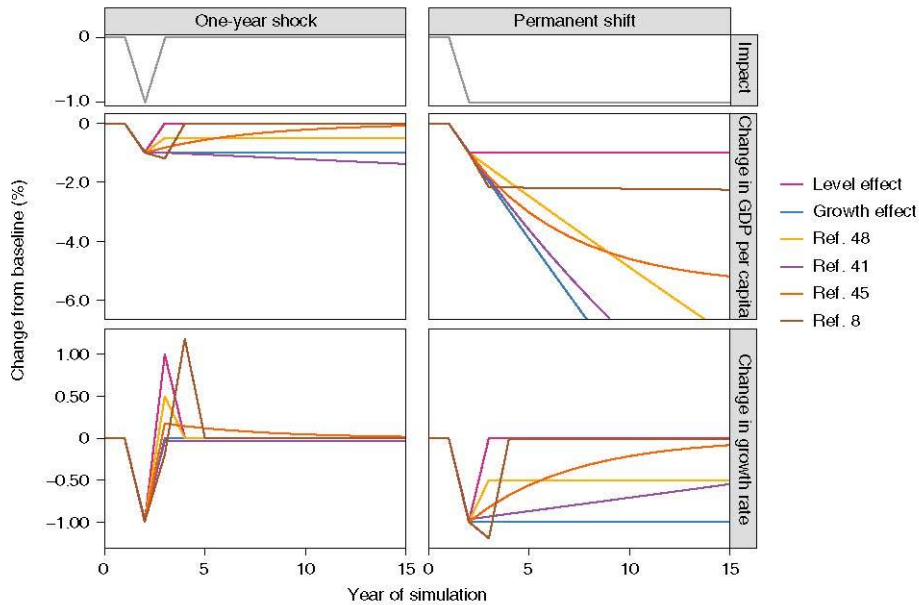


Fig. 3 | Level and growth effects. Simulations of different models of levels and growth effects from a one-year weather shock (left) or a step-change in climate (right). The top panels show the simulated shock for each column, consisting of a 1% GDP loss, incurred either only once or continuously due to a change in climate in year 2. The middle panels show per cent differences in GDP levels, relative to a baseline without damages. The bottom panels show differences in growth rate per year relative to the baseline growth rate. In the following, Y indicates GDP, G is the growth rate absent climate change, D is the effect of warming on growth, t is the year. Level effect, $Y_t = Y_t(1 - D)$: damages are applied in each year to the baseline trajectory; this results in a compensating rebound to a single-year shock and a return to a parallel, lower trend for permanent climate shifts. Growth effect, $Y_t = Y_{t-1}(1 + G - D)$: after a shock, growth follows a new baseline; this results in permanently lower growth rates and a large gap from the baseline trajectory.

Finally, IAMs cannot directly use parameter coefficients derived from econometric estimates (see also ref. 16). These estimates rely on temperature shocks, and their temperature variables are local and include annual variability, which is typically missing from IAMs. Jensen’s inequality implies that the expected value of one of these convex functions applied to variable temperatures will not equal the result of one of these functions applied to the expected value of temperature. Two basic approaches can be used to resolve this. One option is to stochastically downscale global temperatures to variable, local temperature, with the inclusion of random noise accounting for temporal and spatial autocorrelation⁴⁸. Alternatively, the

econometric models can be applied to weather data from general circulation model projections, and then a statistical relationship can be found between the average of these impacts and long-run climatic mean temperature³⁹.

Bottom-up approaches

Macroeconomic losses from climate change can be estimated using bottom-up approaches, either through the enumeration of direct economic impacts, or by assessing aggregate impacts using a sector-detailed CGE model, agent-based supply chain models or agent-based IAMs resolving impacts on individual economic agents (for example, firms, households or economic sectors). The most prominently covered impact channels in these approaches include agriculture, labour productivity, tourism, health (infectious diseases, heat-related mortality), energy demand, sea-level rise and more recently extreme events (tropical cyclones, fluvial floods). Enumeration is given by the assessment of damages from individual impact channels, either econometrically⁵³, by coupling biophysical impact models with a CGE model⁵⁴, or via the valuation of literature-based relations of a given impact with temperature⁵⁵. These are then simply summed up for the aggregate result. However, the enumeration approach ignores possible direct feedback effects between different impact channels, even before accounting for their impact on the economy. It also usually ignores resulting interactions within the economic system (except in the case of CGE coupling).

However, the assessment of direct economic impacts tells only part of the story. Alternatively, individual impact channels can be applied jointly in a multi-channel CGE model, which gives the aggregate equilibrium effects of climate change impacts^{22,23,56-58}. Such models apply impacts directly on stocks such as land or capital, factor productivity and demand. They account for the propagation of impacts across sectors and their economic effects, in particular in terms of the redistribution of economic activity (that is, structural change, changes in trade patterns, prices and carbon emissions). Similarly, global agent-based supply chain models can capture the spreading of, and changes in trade patterns resulting from local climate damages induced by extreme weather events across sectors and in the global trade network⁵⁹. All of these mechanisms can increase or decrease the final aggregate impact. It is not a priori clear in which direction this goes²⁸. Most CGE models suffer from similarly limited spatial resolution as IAMs, due to the computational challenges posed by solving optimization problems with high spatial and temporal dimensionality⁶⁰. Ref. 58 provides an exception, with a large-dimensional CGE climate and trade model including 139 countries and 57 commodity sectors. CGE models do not effectively incorporate uncertainty, save for a few rare and small-dimensional cases⁶¹. Finally, although CGE models can account for heterogeneity in land⁶², labour⁶³ and capital⁶⁴, global CGE multi-channel climate change models do not, which is a serious limitation for damage functions that aim at incorporating extensive damages from sea-level rise or age cohort effects in labour. Existing global assessments of damages using CGE models yield fairly low numbers (see Table 1 and Fig. 2) because they have a limited time horizon⁶⁵, the global aggregate masks large regional differences (for example, more than 20% in annual long-run losses for some countries⁶⁰), or more importantly the damage functions used in global CGE models are, by construction, very specific to commodity sector or factors of production and do not, at least until now, cover the full range of possible impacts. In refs. 58,55, for example, economic damages are limited to losses in labour and agricultural productivity, limited damages

from sea-level rise (that is, losses in only arable land) and impacts on tourism. Therefore, comparing bottom-up assessments with each other requires detailed knowledge on included impact channels. Comparing them with top-down assessments or those based on aggregate damage functions is of limited value. The first agent-based IAM²⁴ captures climate impacts through microshocks and finds much larger impacts than standard IAMs or CGEs (up to 85% GDP loss in 2100 for labour productivity shocks). The reason is the presence of nonlinearities and an endogenous emergence of economic tipping points through the interaction of heterogeneous agents.

One main issue for all types of bottom-up study based on biophysical modelling is the reliance on one climate-impact model combination per channel. The handling of a multitude of very different process-based modelling approaches and the aggregation of data with high spatial and temporal resolution leads to a trade-off between the number of impact channels covered explicitly and the handling of the uncertainty stemming from impact modelling. However, this uncertainty can be large⁶⁶. Results from projects such as ISIMIP should be better utilized to provide input for CGE modelling, allowing for proper quantification of the uncertainty surrounding the resulting policy advice.

Methodological gaps

A number of open methodological questions are valid for all types of study discussed above and crucial for a robust assessment of economic damages.

Aggregation of impacts

The empirical assessment and modelling of impacts described above is performed on the geospatial scale, country level or macroregion level, and with varying distributional resolution (in most studies only one representative household per unit of observation). With regard to the spatial dimension, aggregation (for example, from country level to global) removes the substantial heterogeneity in impacts, and can even lead to a cancellation of positive and negative impacts. An important advance was achieved by refs. 67,68, presenting dynamic spatial growth models at a $1 \times 1^\circ$ spatial resolution. The same challenge probably applies to different income levels in the same spatial unit of observation and its correlation with impacts, which is addressed in more detail in the following section, owing to its prominence in current research. Moreover, the assessment of climate change impacts spans time frames from single-year observations to decades and centuries. The resulting intertemporal aggregation has been subject to a large debate with a focus on the social discount rate⁶⁹. This aggregation dimension is particularly relevant when aggregating impacts for computing the social cost of carbon⁷⁰. Finally, in many cases, the impacts are uncertain, for example, owing to different impact or climate models used or parametric uncertainties. Different methods and tools to aggregate uncertain impact estimates and parameters have been proposed and applied; see ref. 71 for an overview. As such, an aggregation across different dimensions is required when summarizing impact estimates. Notably, the common choice of decreasing marginal utility of consumption (that is, declining satisfaction for an additional unit of consumption with increasing consumption), and the related questions of inequality, intertemporal fluctuation and risk aversion matter for this aggregation. Note also that the dimensions of aggregation can interact: see ref. 72 for an example.

The role of inequality

When aggregating economic impacts, their distributional effect plays an important role (see also the review by ref. 56). Together with the spatial distribution of biophysical climate impacts (exposure), inequalities in income, wealth, education, health and so on are crucial drivers of how severely different people are affected (vulnerability), and whether or how quickly they can recover from the impact (resilience). A regressive distribution of climate impacts, together with the common assumption of decreasing marginal utility, leads to aggregate welfare losses being larger than average monetary losses (for example, ref. 73). These regressive impacts are rarely captured in most damage assessments, and especially not in those with high levels of sectoral and spatial aggregation. Regarding inequality between countries, recent climate econometric results indicate that the distribution of economic damages from climate change is probably regressive⁶⁻⁸, so that climate impacts could exacerbate current and future global inequality⁷⁴⁻⁷⁶. As an example for CGE analyses of climate impacts including heterogeneity between a large number of countries, we show the spatial distribution of country-level GDP damages and its variation with income level from one particular model⁵⁸ working with 139 countries (Fig. 4 ; see also ‘Bottom-up approaches’).

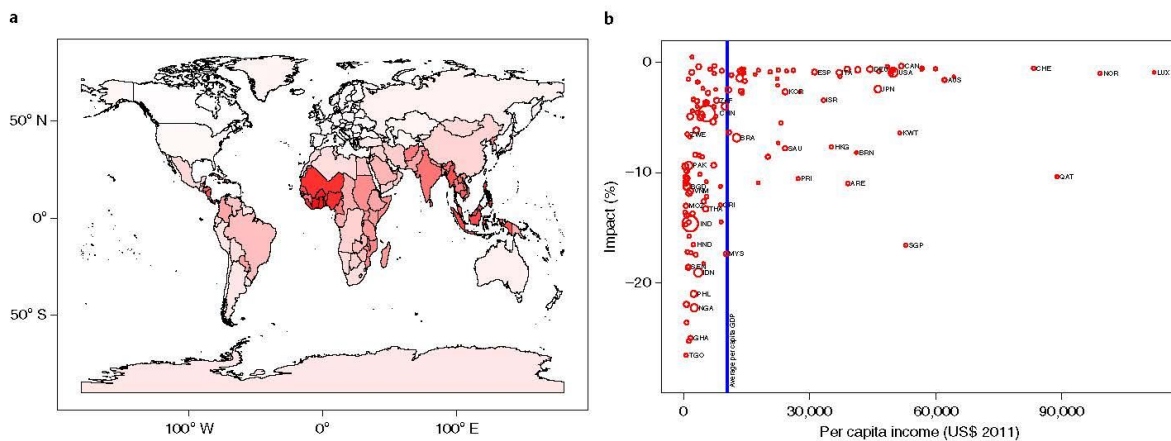


Fig. 4 | Climate impacts between countries. a, Long-run annual losses in GDP using a 139-country/region climate change and trade model: long-run annual percentage losses in GDP by country for an average global temperature increase in 2100 of 4°C. Losses in GDP range from <2% to 28% (from lighter to darker red) between countries, with an unweighted global average of >7% (note the still incomplete and limited coverage of damage channels). Losses in Antarctica capture island nations and other countries that do not have sufficient resolution in the global map. The map was produced with the R package ggmap (<https://www.rdocumentation.org/packages/ggmap/versions/3.0.0>). b, Inequality and climate change damages: the long-run economic damages from climate change measured as percentage falls in annual GDP (impact) and income measured as current per capita GDP (income), with the same temperature increase and limited damage channels as in a. The vertical blue line indicates average global per capita GDP (calculated from the database of the Global Trade Analysis Project, GTAP) and the size of each circle represents the size of population by country. The graphic shows that larger long-run annual percentage losses in GDP tend to correspond to lower current income levels per capita. The usual GTAP country indicators are used: ARE, United Arab Emirates; AUS, Australia; BGD, Bangladesh; BRA, Brazil; BRN, Brunei Darussalam; CAN, Canada; CHE, Switzerland; CHN, China; CRI, Costa Rica; DEU, Germany; ESP, Spain; GHA, Ghana; HKG, Hong Kong; HND, Honduras; IDN, Indonesia; IND, India; ISR, Israel; ITA, Italy; JPN, Japan; KOR, South Korea; KWT, Kuwait; LUX, Luxembourg; MOZ, Mozambique; MYS, Malaysia; NGA, Nigeria; NOR, Norway; PHL, Philippines; PRI, Puerto Rico; QAT, Qatar; SAU, Saudi Arabia; SEN, Senegal; SGP, Singapore; THA, Thailand; TGO, Togo; USA, United States; VNM, Vietnam; ZAF, South Africa; ZWE, Zimbabwe. Figure adapted with permission from: a, ref. 58, John Wiley & Sons.

In addition to inequality between countries, large disparities also prevail within countries. A number of recent econometric studies have combined spatial climatic data with distributional data and survey-based socioeconomic outcomes for selected countries^{53,77,78}, finding regressive impacts. Moving towards global coverage, district-level data^{8,43} has so far been the maximum degree of spatial resolution, confirming the regressivity of climate impacts. A regressive distribution within countries is also obtained when extrapolating the between-country trend to the subnational scale⁷⁹. Despite this, most IAM analyses do not yet include within-country inequality and the distribution of climate impacts, making it a high priority for future research^{80,81}. A number of approaches have already been pursued; for example, adding quintiles of the income distribution to the RICE model^{12,82}, simulations based on micro surveys focusing on poor households⁸³, calibrating multi-household general equilibrium models to survey data⁸⁴ and considering the interaction with national redistribution schemes⁸⁵. Building on these initial steps, capturing both the full spatial heterogeneity and the distributional effects of climate damages in impact models and IAMs would represent a major step forward in assessing the economic impacts of climate change.

The role of adaptation. The effects of climate change adaptation are often given little or no consideration in the aggregation of impacts, mainly because it is difficult to disentangle the adaptation, which is multi-faceted and multi-sectoral, from the resulting impact. Short-run adaptation to weather fluctuations should be distinguished from long-run adaptation to climate change¹⁵, adaptation can occur in various sectors under different forms and the adaptation decision can occur on a small scale⁸⁶ or on the wider global scale, in particular, the research and development of adaptive technologies⁶. Some studies found substantial impact reductions through adaptation to future climate^{39,87,88}, but empirical evidence for adaptation to ongoing climate is mixed^{7,89,90}. Different assumptions on the level of future adaptation lead to notably different results for the impacts of future climate change^{7,10}. A comprehensive integrated assessment should explicitly account for the costs and benefits of adaptation; however, this is still rare in IAMs. Endogenous adaptation has been introduced in the DICE model by splitting the global damage function into residual damage and protection cost⁸⁶. A more comprehensive framework can be found in the WITCH model, where several investment channels are represented such as adaptive capacity, proactive adaptation and reactive adaptation⁹¹. The PAGE and FUND models also represent adaptation¹⁷. However, in most cases, explicit adaptation is modelled as an exogenous input in specific sectors where the adaptation costs and climate impact are both available, for example, as for sea-level rise⁸⁸. Some adaptation dynamics often already exist— even partially—in IAMs, whether explicitly or implicitly, for example, through the socioeconomic development (that is, enhancing adaptive capacity through poverty reduction or education), savings and capital accumulation dynamics, or in the modelling of the damage persistency. A clear identification of the effects of adaptation during the estimation process of the impacts would help to integrate the damage functions in a coherent way in the assessment models, as proposed in refs. 39,92.

Discussion and suggestions for the way forward

The impacts of climate change are affecting societies already today^{93–96}: decision makers in politics, companies and the financial sector are setting the course for transformation processes that will deeply change societies in the near and far future. However, available damage

estimates vary strongly. One challenge is the wide variety of metrics (for example, GDP loss, changes in welfare, social cost of carbon). But the underlying methodology plays a major role. Bottom-up assessments serve well if the goal is a comparison of different types of impact or impact channel, a better understanding of feedback processes between impact channels, or a study of channel or sector-specific adaptation measures. They offer transparency and greater process detail. However, they are very resource intensive: adding new impact channels and performing uncertainty analysis is difficult. When using or comparing the—typically rather low—global damage results of bottom-up assessments, the coverage of channels has to be taken into account. Agent-based modelling and innovative approaches with increased dimensionality open new avenues. Top-down econometric assessments can provide relations that are more directly applicable in IAMs. However, crucial questions remain, in particular regarding the degree of persistence of damage, the treatment of adaptation and the applicability of such empirical relations for future projections. This uncertainty should be made explicit when applying the empirical results in IAMs, for example, through applying different empirical relations or modelling different degrees of persistence. Through collaboration between empirical and IAM modellers, improved empirical studies should be designed with the explicit link to future projections in mind. It is clear now that the true magnitude of climate change impacts is determined by factors we are just starting to capture, such as extreme events, effects on economic growth or distributional consequences. Damage estimates including such factors can be notably higher than previous estimates, shifting optimal emission pathways towards more stringency and in line with the Paris Agreement targets. An increasing number of empirical and modelling-based estimates of other impact channels, such as biodiversity, mortality, conflict or migration, are becoming available. Priorities should be developed to avoid a certain randomness and to ensure that the economically most relevant channels are represented. An expert elicitation of the ranking of channels could help to set priorities in this regard. In addition, economic models could be applied in sensitivity studies to assess how large an impact would have to be to yield a substantial economic (growth) effect⁹⁷. Biophysical models could then be used to assess whether a given driver can feasibly yield such an impact. On the other hand, the combination of top-down and bottom-up approaches while avoiding double counting should be investigated. Depending on the model type, models need to be advanced structurally in different respects. Higher spatial and socioeconomic resolution is required to capture distributional effects both between and within countries. Adaptation needs a price, and both targeted adaptation measures such as sea walls and system responses such as factor reallocation, structural change or migration need to be captured where this is not yet the case. An advanced discussion of the evaluation framework of impacts, appropriate welfare measures and embedded normative assumptions is necessary. Finally, progress can come from combining models of different types as well as their structured comparison, such as in ref. 88. For example, biophysical model outputs can be used as the independent variables for estimating micro- and macroeconomic econometric models, with the potential for both improving the predictability of these models and avoiding the parameterization of the biophysical relationship. Structured intermodel comparisons of economic models with a focus on damages can help to pinpoint the drivers of different outcomes and key dynamics for the assessment of economic effects such as investment dynamics or persistence of damage. Integrated assessment needs to take a leap to move away from the simple aggregate damage functions towards capturing the range of climate-impact estimations better, to appropriately account for uncertainty and to specifically quantify

avoided damages, if it is to be truly useful for policy advice. This research endeavour needs to bring together all the major modelling paradigms as well as biophysical and empirical impact modellers.

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Acknowledgements

We thank D. Diaz for providing the data for the implied damage functions for the FUND and PAGE models as shown in the final column of Table 1. We also thank the participants of the workshop ‘Integrating impacts, mitigation and inequality—state of the art and road ahead’, held in 2019 at the Potsdam Institute for Climate Impact Research, for input and discussions, as well as F. Moore for comments. The authors acknowledge the funding provided by the NAVIGATE project (H2020/2019-2023, grant agreement number 821124) of the European Commission. F.P. acknowledges funding through the ENGAGE project, funded through the Leibniz Competition (SAW-2016-PIK-1), and the CHIPS project, part of AXIS, an ERA-NET initiated by JPI Climate, funded by FORMAS (Sweden), DLR/BMBF (Germany, grant no. 01LS1904A), AEI (Spain) and ANR (France) with co-funding by the European Union (grant no. 776608).

Author contributions

F.P., J.R., J.E., T.K., N.T., A.M. and B.S. developed the synopsis. F.P., J.R., J.E., T.K., N.T., A.M., B.S. and L.D. wrote the manuscript with contributions by C.O. and M.T. The figures were developed by F.P., J.R., T.K., J.E. and N.T. All authors contributed to the literature review. Supplementary Table 1 was developed by N.T. with contributions by all authors.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s41558-021-01065-y>.