From biophysical to economic impacts of climate change: an integrated perspective

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Abstract

Estimates of climate change's economic impacts vary widely, depending on applied methodology. This uncertainty is a barrier for policy makers seeking to quantify 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 the identification of the most socio-economically relevant types of impacts. A structured model inter-comparison related to economic impacts is noted as crucial next step.

Introduction

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 modeling efforts and model intercomparisons, helping to assess ranges and uncertainties (*1, 2*). The assessment of biophysical climate change impacts like changes in yields, water availability or sea-level rise as been greatly advanced in recent years by consistent cross-sectoral modeling initiatives like the Intersectoral Impact Model Intercomparison Project (ISIMIP) (*3*). However, a robust understanding and quantitative assessment of their full future socioeconomic impacts remains a significant challenge. The quantitative estimates of global economic impacts provided in the literature vary widely (*4*), depending on the methods used to assess them and the types of impacts included. In particular, the great advances of empirical studies linking climatic conditions and different aspects of socioeconomic systems (*5*) have widened the range of estimates, related also to the debate whether temperature affects level or growth of productivity (*6–8*). Integrating such empirical findings into global cost-benefit 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, policy makers and stakeholders alike. Multiple literature reviews have addressed aspects of this complex topics, focusing broadly on linkages between climate and the economy and related policy implications (*13*), on key open research questions (*14*), on econometric advances (*5, 15, 16*) or damage functions in cost-benefit models (*17*). The goal of this paper 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 (e.g. economists, integrated assessment modelers, biophysical impact modelers) to advance the integrated research on economic impacts, and as a guide for policy makers 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 modeling 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 i) direct losses of income and production; ii) the value of resources, goods, and services which become unavailable or of reduced quality; iii) damage to productive capital and infrastructure; iv) reductions in ecosystem services; v) effect on morbidity and mortality and vi) 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 (i–iii), directly valued within markets, and non-market impacts (iv-vi), 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, i.e. the purchase of goods and services, but also depends upon 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. Since the units of welfare are arbitrary, total economic damages are often reported as the equivalent loss in consumption which would result in the same welfare loss as the combined market and non-market damages (the Hicksian equivalent variation).

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 modeling approaches. As the models employed at the different levels depicted in Figure 1 increase in comprehensiveness, they invariably use parameterization to simplify constituent processes. For example, while process-based crop models represent biophysical growth processes of individual plants, 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 Material (see also Figure S2). Model parameterization forces the models to assume forms of stationarity and undermine the representation of adaptation at 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 (though see (*18*) for a relaxation of this assumption). This may be inadequate when projecting climate change impacts and adaptation policies over the long term (e.g., to 2100), as it fails to capture potentially radical changes in technical systems, investment patterns and consumption dynamics (see (*19*) for a general discussion of the issue of constant elasticity of subsitution in energy-climate- economy models). Note, that also models that describe fundamental biophysical relationships reflect current technologies (e.g. crop varieties, distribution systems, protective gear) and are likely to misrepresent impacts in the distant future.

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 like the value of statistical life to the use of partial equilibrium models (*20, 21*), CGE models (*22, 23*), or agent-based models (ABM) (*24–26*) (e.g. process-based crop models are used to calculate regional crop failures which are then valuated 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 impacts 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 like 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 (i.e. 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 cost-benefit (CBA) models for policy optimization. Diaz & Moore (*17*) provide a detailed review of the functions applied in the most prominent CBA models DICE (*29*), PAGE (*30*) and FUND (*31*). These damage functions tend to yield rather small losses (e.g., in the case of DICE, 2.1 % for a 3°C temperature increase over pre-industrial levels and of 8.5 % at 6°C), 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 e.g. (*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 processes (*32*). A number of studies extend the standard damage function in the DICE model to account for uncertainty in damages (*33*), the possibility of tipping points (*34*), or natural capital (*35*). Another increasing body of literature applies empirical damage estimates, yielding larger damages, either directly on output (*9, 36*) or through changes in capital depreciation or productivity (*10, 37*). As in this paper we focus on the damage assessemnts, see (*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 Figure S1 and associated discussion, 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, e.g. 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, e.g. in the context of the Climate Impact Lab (*38*).

Modeling approaches for global aggregate economic impacts

The estimates of global aggregate economic effects of climate change in the literature vary widely, reflecting the methodological diversity described above. In the following we provide a comparative overview (Table 1 and Figure 2) and methodological discussion for results along the different end points outlined in Figure 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, since earlier studies mostly have been updated or are build upon (*4*). We do not discuss the end point of final economic impacts with dynamic effects here since such estimates are rarely provided in the literature without the application in policy optimization (though see (*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.

Final economic impacts based on top-down econometrics

Top-down estimates of macroeconomic damages provide a simple representation for use in integrated assessment models, and recent panel-based econometric research improve their empirical basis (see (*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 (GDP per capita) and changes in regional temperatures. This relationship has been observed at multiple scales: global-national (*6, 7, 39–41*), global-ADM1 (*8*), global-household (*42*), EU-national (*43*), USA-ADM1 (*40, 44*), USA-ADM2 (*45*), USA-metro (*43*), Brazil-ADM1, and Indonesia-ADM1 (*43*). 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, 40*), and the effect of different sectors, seasons, and periods (*41, 44*). Resulting estimates vary widely, with GDP losses under RCP8.5 in 2100 between 7% (*40*) and 23% (*7*), and very high uncertainties (*39*). It remains an open question whether all countries are affected in a similar way (*7*) or if a negative relation only exists for poor countries, due to their level of development as well as dependence on sectors with high climate exposure like 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 effect (*8*). A shock to growth in one year can lead to higher, equivalent or permanently lower long-term outcomes, depending on rebound effects (*47*). Several authors have proposed functional forms for the dynamics of persistence (see Figure 3). Low impacts can derive from an quick return to the baseline per capita GDP after one-year temperature shocks (Level effects, (*8*)), while larger impacts emerge when the return is slow or non-existent (Growth effects, (*40, 45, 48*)), although this order may be reversed (*49*). Growth effects can also appear when temperature levels instead of temperature change are used as temperature measure, leading to an accumulation of damages for permanent temperature increases ((*7*) vs. (*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, data sets are short, estimates are noisy and the question remains unresolved at the national (*39*) and subnational (e.g., disagreement between (*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 this 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 level effects, and a wide gap opens between the two as time progresses (Figure 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 like the one described above (*36, 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 feedback (*27*). Level effects could result if the determinants of economic growth are unaffected by climate change (e.g., 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 (*36, 48*).

Besides persistency, 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 insignificant (*51*). 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 weather responses' climate contribution directly (*15, 38, 52*).

Finally, integrated assessment models cannot directly use parameter coefficients derived from econometric estimates (see also (*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 autocorrelation (*48*). Alternatively, the econometric models can be applied to weather data from GCM projections, and then a statistical relationship can be found between the average of these impacts and long-run climatic mean temperature (*38*).

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 indivdual economic agents (e.g., firms, households, or economic sectors). The most prominently covered impact channels in these approaches include agriculture, labor 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 econometrically (*53*), by coupling biophysical impact models with a CGE model (*54*), or via the valuation of literature-based relations of a given impact with temperature (*55*). 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 only tells 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 like 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 (i.e., 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 network (*59*). All of these mechanisms can increase or decrease the final aggregate impact. It is not *a priori* clear in which direction this goes (*28*).

Most CGE models suffer from similarly limited spatial resolution as compact IAMs, due to the computational challenges posed by solving optimization problems with high spatial and temporal dimensionality (*60*). (*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 cases (*61*). Finally, although CGE models can account for heterogeneity in land (*62*), labour (*63*) and capital (*64*), 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), either because they have a limited time horizon (*65*), the global aggregate masks large regional differences (e.g. over 20% in annual long run losses for some countries in (*60*)) 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 (*58*) and (*55*), for example, economic damages are limited to losses in labour and agricultural productivity, limited damages from sea level rise (i.e., losses in arable land only) and impacts on tourism. Therefore, comparing bottom-up assessments to each other requires detailed knowledge on included impact channels. Comparing them to top-down assessments or those based on aggregate damage functions is of limited value. The first agent-based integrated assessment model (*24*) captures climate impacts through micro-shocks and finds much larger impacts than standard IAMs or CGEs (up to 85% GDP loss in 2100 for labor productivity shocks). The reason is the presence of non-linearities and an endogenous emergence of economic tipping points through the interaction of heterogeneous agents.

One main issue for all types of bottom-up studies based on biophysical modeling is the reliance on one climate-impact model combination per channel. The handling of a multitude of very different process-based modeling 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 modeling. However, this uncertainty can be large (*66*). Results from projects like ISIMIP should be better utilized to provide input for CGE modeling, allowing for properly quantifying the uncertainty surrounding the resulting policy advice.

Methodological Gaps

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

Aggregation of Impacts

The empirical assessment and modeling of impacts described above is performed at the geospatial scale, country-level, or macro-region level, and with varying distributional resolution (in most studies only one representative household per unit of observation). With regard to the spatial dimension, aggregation (e.g., from country level to global) removes the substantial heterogeneity in impacts, and can even lead to a cancellation of positive and negative impacts. A significant advance achieved by (*67*) and (*68*), presenting dynamic spatial growth models at a 1°x1° spatial resolution. The same challenge likely 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, due 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 inter-temporal aggregation has been subject to a large debate with a focus on the social discount rate, see (*69*). This aggregation dimension is in particular relevant when aggregating impacts for computing the Social Cost of Carbon (*70*). Finally, in many cases, the impacts are uncertain, for example due 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 (*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 (i.e. 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 (*72*) for an example.

The role of inequality

When aggregating economic impacts, their distributional effect plays an important role (see also the review by (*56*)). Together with the spatial distribution of biophysical climate impacts (exposure), inequalities in income, wealth, education, health, etc. are crucial drivers of how severely different people are affected (vulnerability), and if 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 (e.g. (*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 likely regressive (*6–8*), so that climate impacts could exacerbate current and future global inequality (*74–76*). 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 model (*58*) working with 139 countries (Figure 4, see also section on bottom-up approaches).

In addition to inequality between countries, large disparities prevail also 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 scale (*79*).

Despite this, most IAM analyses do not include within-country inequality and the distribution of climate impacts yet, 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 households (*83*), calibrating multi-household general equilibrium models to survey data (*84*), and considering the interaction with national redistribution schemes (*85*).

Building upon 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 adaption 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 adaption to climate change (*15*), adaptation can occur in various sectors under different forms, and the adaptation decision can occur at a small scale (*86*) or at the wider global scale, in particular, the research and development of adaptive technologies (*6*). Some studies found substantial impact reductions through adaptation to future climate (*38,87,88*), but empirical evidence for adaptation to ongoing climate is mixed (*7,89,90*). Different assumptions on the level of future adaptation lead to significantly 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 integrated assessment models. Endogenous adaptation has been introduced in the DICE model by splitting the global damage function into residual damage and protection cost (*86*). 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 adaptation (*91*). The PAGE and FUND models also represent adaptation (*17*). However, in most cases, explicit adaptation is modeled as an exogenous input in specific sectors where the adaptation costs and climate impact are both available, as for example for sea-level rise (*88*). Some adaptation dynamics often already exists, even partially, in integrated assessment models, whether explicitly or implicitly, for example through the socio-economic development (i.e., enhancing adaptive capacity through poverty reduction or education), savings and capital accumulation dynamics, or in the modeling 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 (*38, 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 which will deeply change societies in the near and far future. However, available damage estimates vary strongly. One challenge is the wide variety of metrics (e.g., 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 impacts or impact channels, 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 modeling and innovative approaches with increased dimensionality open new avenues.

Top-down econometric assessments can provide relations which 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, e.g. through applying different empirical relations or modeling different degrees of persistence. Through collaboration between empirical and IAM modelers, 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, like extreme events, effects on economic growth, or distributional consequences. Damage estimates including such factors can be significantly 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 modeling-based estimates of other impact channels, like biodiversity, mortality, conflict or migration is 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 significant economic (growth) effect (*97*). Biophysical models could then be used to assess if 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 socio-economic resolution is required to capture distributional effects both between and within countries. Adaptation needs a price, and both targeted adaptation measures like sea walls and system responses like factor reallocation, structural change or migration need to be captured where this is not the case yet. 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 (*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 inter-model 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 like 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, to be truly useful for policy advice. This research endeavour needs to bring together all the major modeling paradigms as well as biophysical and empirical impact modelers.

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Additional Information

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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, the Supplementary Table was developed by N.T. with contributions by all authors.

Competing Interests

The authors declare no competing interests.

Figure legends

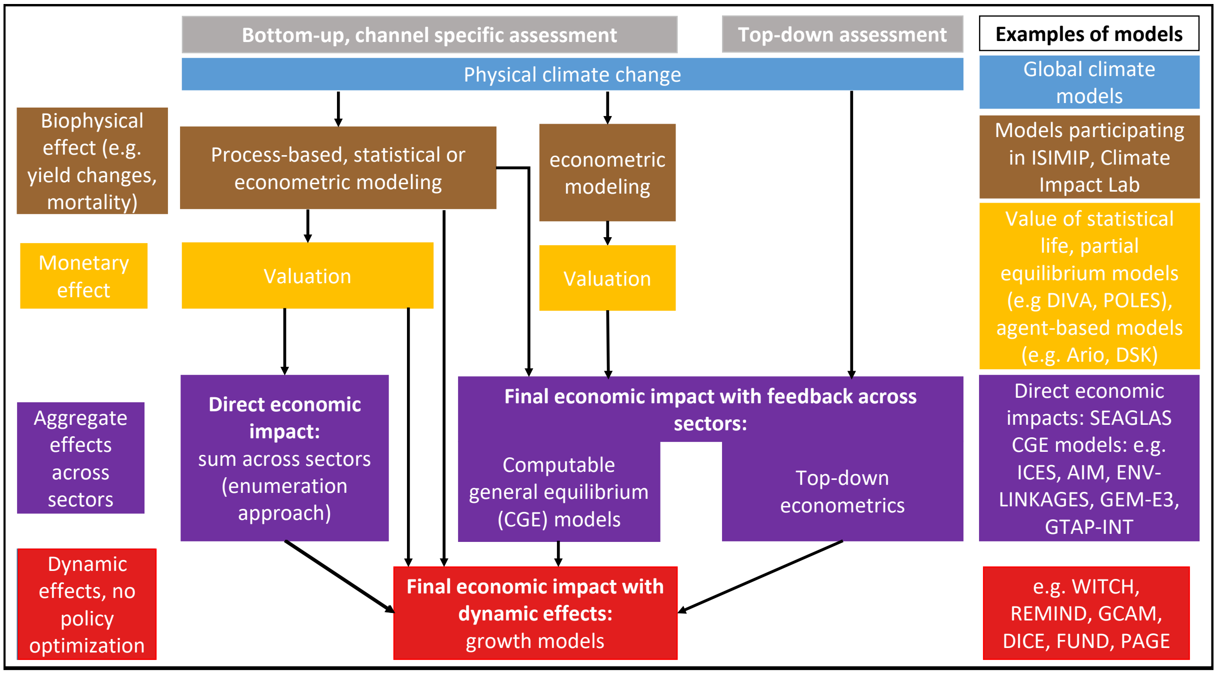

Figure 1: **Taxonomy of approaches to capture economic impacts of climate change.** The different end points capture different levels of feedback effects. The column on the right lists some examples for models and studies applying the methodologies. Model references: global climate models (*98*), ISIMIP - www.isimip.org/impactmodels, Climate Impact Lab - http://www.impactlab.org/, DIVA (*20*), POLES (*21*), ARIO (*26*), DSK (*24*), SEAGLAS (*53*),ICES (*22*), AIM (*54*), ENV-LINKAGES (*23*), GEM-E3 (*57*), GTAP-INT (*58*), WITCH (*99*), REMIND (*36*), GCAM (*100*), DICE (*29*), FUND (*31*), PAGE (*30*)

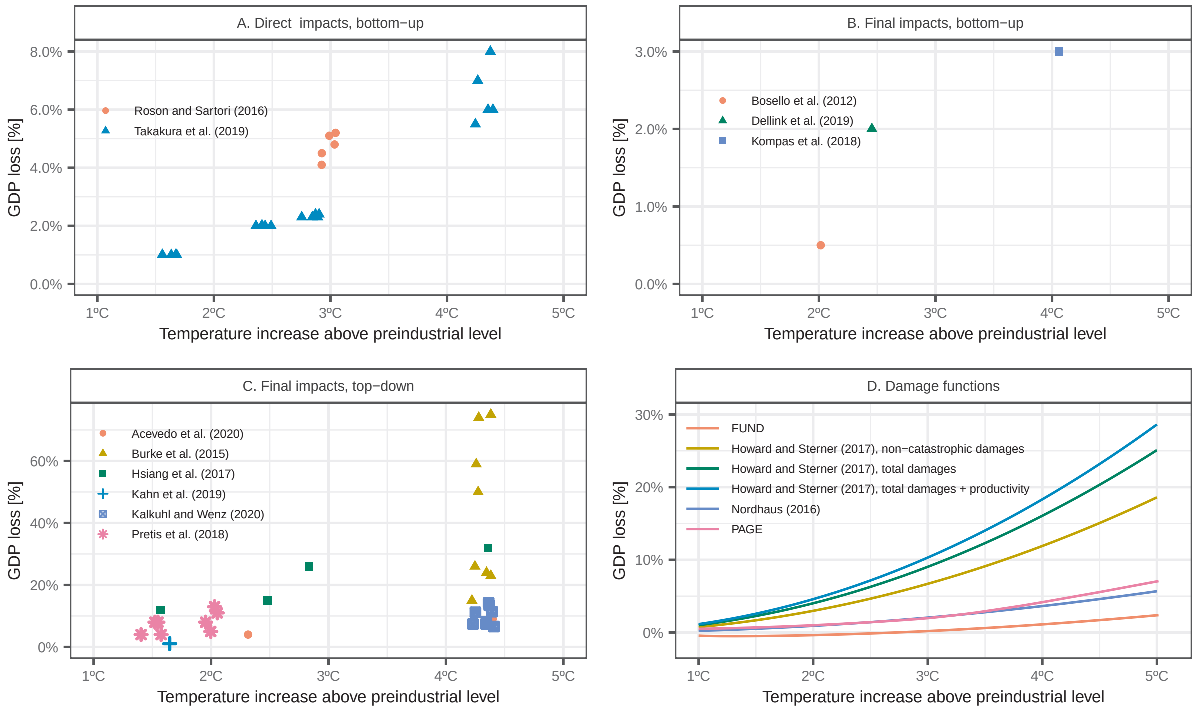

Figure 2: **Global GDP losses at increasing warming levels, estimated with different modeling approaches.** Panel A: direct economic impacts based on bottom-up assessment; Panel B: final economic impacts with sectoral feedback effects based on bottom-up assessment; Panel C: final economic impacts with sectoral feedback effects based on top-down econometric studies; Panel D: aggregate damage functions from the prominent cost-benefit models DICE, FUND and PAGE, and from the meta-analysis by (*4*) (with different specifications).

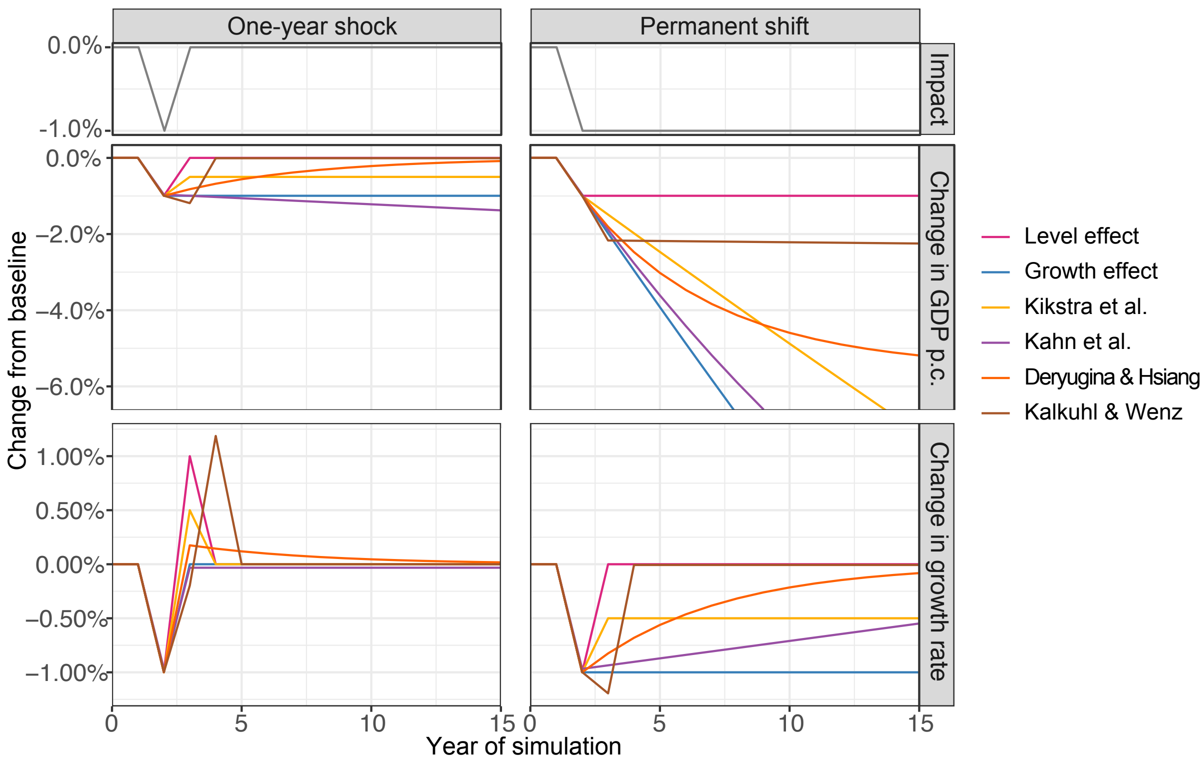

Figure 3: **Level and growth effects:** Simulations of different models of levels and growth effects, from a one-year weather shock (left) or a step-change in climate (right). The top panels show the simulated shock for each column, consisting of a 1% GDP loss is incurred either only once or continuously due to a change in climate in year 2. The middle panel shows percent 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. **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. **Kikstra et al.** (*48*), $Y_t = Y_{t-1}(1 + G - \rho D_{t-1})(1 + D_{t-1} - D_t)$: A parameter moderates between level damages ($\rho = 0$) and growth damages ($\rho = 1$), without explicit reference to a baseline trajectory (set to 0.528). **Kahn et al.** (*40*), $Y_t = Y_{t-1}(1 + G - |\bar{D}_{t-1} - D_t|)$: Deviations from a N-year average climate determine damages (N = 30). **Deryugina & Hsiang** (*45*), $Y_t = \bar{Y}_{t-1}(1 + G + \sum_{s=0} \rho^s D_{t-s}) = (\rho Y_{t-1} + (1 - \rho)\bar{Y}_{t-1})(1 + G - D)$: Damages persist according to an exponential decay, with $\rho = 0.825$. **Kalkuhl & Wenz** (*8*), $Y_t = Y_{t-1}(1 + G + ((\beta_1 + \beta_2(13 + D_t))\Delta D_t + (\beta_3 + \beta_4(13 + D_t))\Delta D_{t-1} + \beta_5(13 + D_t))$: Damages are related to both first-differences and contemporaneous temperatures, shown assuming 13° C baseline temperatures.

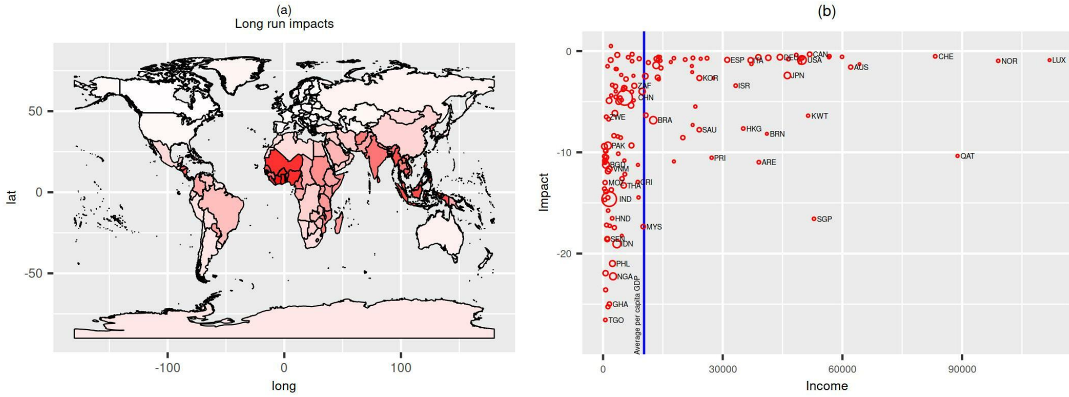

Figure 4: **Climate impacts between countries (*58*)**: **Left panel:** Long run annual losses in GDP using a 139-country/region climate change and trade model: Long run annual percentage losses in GDP by country for an average global temperature increase in 2100 of 4°C. Losses in GDP range from less than 2% to 28% (from lighter to darker red) between countries, with an unweighted global average of over 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. **Right panel:** 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 the left panel. The vertical blue line indicates average global per capita GDP (calculated from the GTAP data base) 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 (e.g., ARE: United Arab Emirates; AUS: Australia; BRA: Brazil; BRN: Brunei Darussalam; CHE: Switzerland; CHN: China; DEU: Germany; ESP: Spain; GHA: Ghana; HKG: Hong Kong; HND: Honduras; IDN: Indonesia; IND: India; ISR: Israel; JPN: Japan; KOR: South Korea; KWT: Kuwait; 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; ZWE: Zimbabwe).

Tables

Table 1: Comparative overview of aggregate global economic damage estimates following three main different approaches as shown in Figure 1. Final economic impacts with dynamic effects are not included in this table 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 shown, together with recent damage functions based on meta-analysis of the damage literature (*4*). For the FUND and PAGE models we show the implied damage functions based on (*17*). The meta-analysis by (*4*) provides three different specifcations: only non-catastrophic damages, total damages including catastrophic events and total damages plus productivity effects based on the empirical literature. For space reasons we only provide one example reference per approach, for a more extensive literature overview including methodological details of the studies see Supplementary Table 1.

	Direct economic impacts Bottom-up assessment	Final economic impacts with sectoral feedback effects Bottom-up assessment	Final economic impacts with sectoral feedback effects Top-down assessment	Aggregate damage functions
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 e.g. from investment; often used for CBA to derive abatement decisions
Impact channels	various, most prominently agriculture, labor productivity, tourism, health (infectious diseases, heat-related mortality), energy demand, limited sea-level rise	various, most prominently agriculture, labor productivity, tourism, health (infectious diseases, heat-related mortality), energy demand, limited sea-level rise	(Total) Factor Productivity or growth	Output loss
Example	Roson & Satori (2016) (*55*)	Kompas et al. (2018) (*58*)	Burke et al. (2015) (*7*)	Howard & Sterner (2017) (*4*)
Global GDP loss for different warming levels (see also Figure 2)	1.5°C: 1% 4.3°C: 6-8% (based on 2 studies)	1.8°C: 0.5% 4°C: 3% (based on 3 studies)	1.5°C: $<$10% 4.3°C: 5-65% (based on 6 studies)	1.5°C: slight gains under the FUND damage function, up to 3% loss under Howard & Sterner (2017) with productivity effects 4°C: 1-18% loss
Advantages	Transparency; high detail on impact side	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 (e.g. mortality impacts via VSL); 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)	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 like extreme events; opacity about included channels	Focus on output/productivity effects – rarely includes other channels like 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 I/O data	out-of-sample projections; unclear role of adaptation; assumes stationarity in slow-moving processes (e.g. cannot capture sea-level rise); does not include non-market damages	difficult to derive; high aggregation masks spatial/social heterogeneity