Quantifying climate loss and damage consistent with a social cost of carbon

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Climate change is causing measurable harm globally[1,2]. Political and legal efforts seek to link these damages with specific emissions, including in discussions of loss and damage (L&D)[3,4]; however, no quantitative definition of L&D exists[5,6], nor is there a framework to link past and future emissions from specific sources to monetized, location-specific damages. Here we develop such a framework, which is integrated with recent efforts to estimate the social cost of carbon[7]. Using empirical estimates of the non-linear relationship between temperature and aggregate economic output, we show that future damages from past emissions—one component of L&D—are at least an order of magnitude larger than historical damages from the same emissions. For instance, one tonne of CO_2 emitted in 1990 caused US$180 in discounted global damages by 2020 ($40–530) and will cause an additional $1,840 through 2100 ($500–5,700). Thus, settling debts for past damages will not settle debts for past emissions. In other illustrative estimates, a single long-haul flight per year over the past decade leads to about $25k ($6,000–77,000) in future damages by 2100, and US emissions since 1990 caused $500 billion ($180–1,300 billion) of damage in India and $330 billion ($110–820 billion) in Brazil. Carbon removal offers an alternative to transfer payments for settling L&D, but is increasingly ineffective in limiting damages as the delay between emission and recapture increases.

Decades of scientific advances establish that human activities are changing Earth's climate, that these changes are negatively impacting a range of human outcomes and that those experiencing the most harm are responsible for a small fraction of historical emissions[1,2,8]. These intersecting insights motivate calls that emitting entities pay for L&D, usually framed as the harms from climate change that parties were unable to avoid through adaptation or mitigation[4,9–11]. Similar claims have been made in ongoing litigation, in which claimants assert damages as a result of emissions from specific (and often distant) emitters[12,13].

Substantial headway has been made in understanding how anthropogenic forcing and its effects on climate extremes can be linked to specific national, regional or corporate emitters[14–16]; however, with a few exceptions[13,17], quantifying how these specific emissions can be linked to global and local damages has received less formal and empirical attention. A central empirical challenge is that emissions come from many sources and are well mixed in the atmosphere, and damages from these emissions must be inferred relative to a lower-emissions counterfactual that is unobserved. A key conceptual challenge is that since the language of L&D was agreed to[18], there have been multiple interpretations of what this language means in practice[5] and a formal definition has yet to be adopted[6].

Building on IPCC documents[4,9] and a growing academic literature[10,11], we propose that L&D is computed as the net present value of economic and non-economic impacts attributable to the emissions of greenhouse gases through their effect on the climate, net of any adaptation that was undertaken. We show how this source-agnostic measure of L&D can be equivalently computed as the theoretical payment schedule that would completely reimburse all harmed parties for the damages (or benefits) that they have experienced or will experience from climate change, paid for by the emitting parties. However, we emphasize that—consistent with Article 8 of the Paris agreement—these damage estimates do not necessarily equal what is owed by one entity to another, as that is a moral and legal question beyond the scope of this analysis.

The basic idea is to consider the emission of a unit of greenhouse gas (GHG) as the creation of an asset that produces a subsequent stream of value (Fig. 1). Unlike many assets, this value might be negative (for example, a liability) and its flow accrues to individuals who did not create the asset. These features are not unique to GHG assets, and similar assets are commonly traded in markets. For example, household garbage generates a flow of costs for whoever takes ownership, and households typically must compensate a waste disposal firm to take the garbage and store it on their premises. We compute an analogue to the value of unpaid garbage collection bills that would be owed for past GHG emissions if individuals were paid for the costs imposed on them by this waste. The total sum of these costs are the residual loss and damages suffered by populations due to climate change.

We show how L&D from CO_2 emissions can be computed from three components: the discounted historical damages that have already occurred due to past CO_2 emissions, the discounted future damages expected to occur from these past emissions, and the discounted future damages expected to occur from present or future

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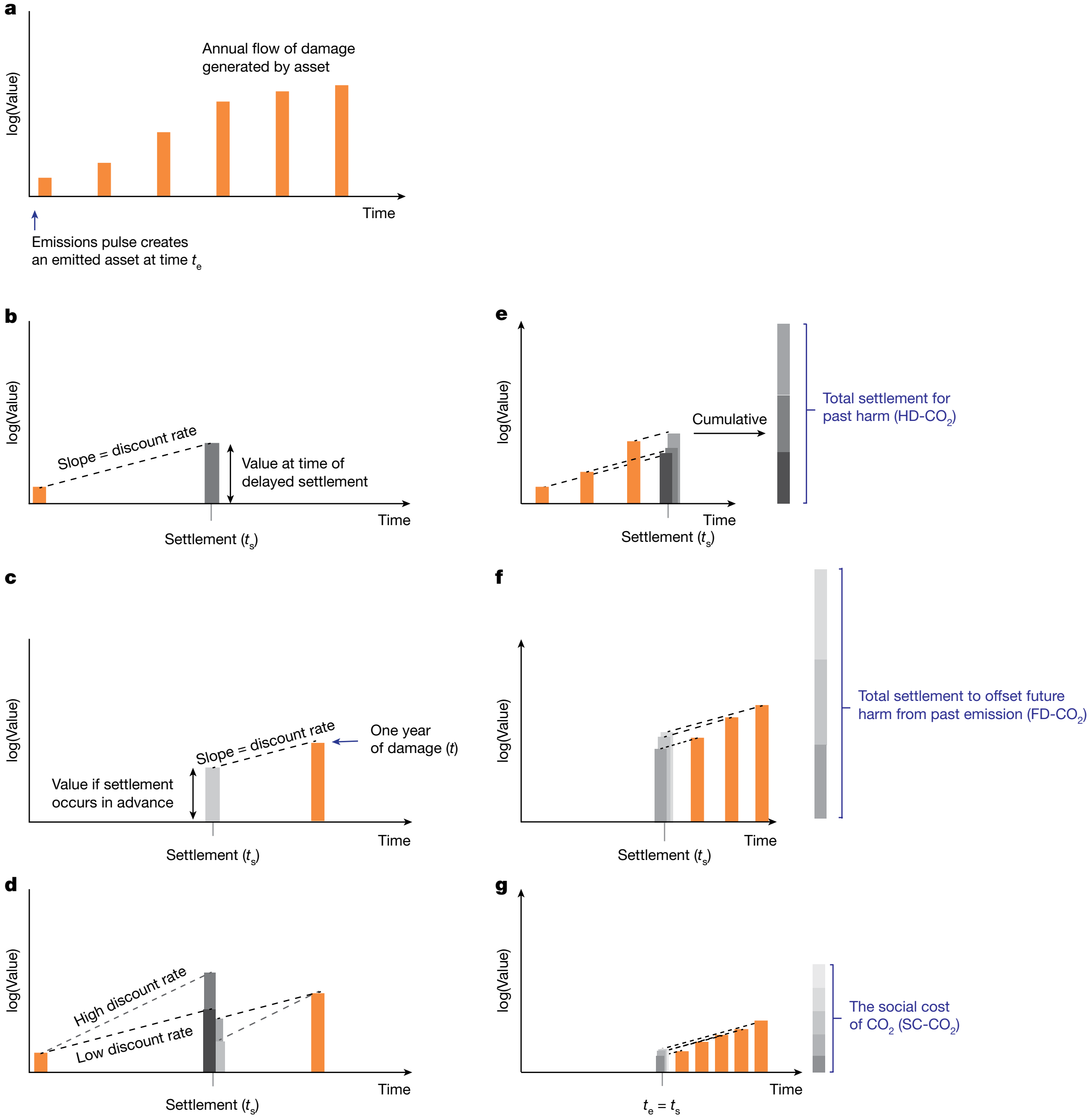

Fig. 1 | Framework for emissions damage accounting. a, A unit of emissions in year t_e generates an annual flow of damages in future year(s) t in population i. These damages can be compensated (that is, paid for in transfer payment from the emitter to i) in settlement year t_s. **b**, If the settlement year is after the damage year ($t_s > t$), then the damage accrues interest. **c**, If the settlement is in advance of anticipated future damage ($t_s < t$), then future damage is discounted back to the settlement year. **d**, A higher discount rate amplifies current value of past damages, and decreases present value of future damages, relative to a lower discount rate. **e**, Payment owed for multiple periods of uncompensated past damage (HD-CO_2) is additive. **f**, Past emission can continue to create future damage even if past damage is compensated (emissions remain in atmosphere), requiring additional compensation (FD-CO_2). **g**, SC-CO_2 is a special case in which settlement for future damages occurs at the time of emission.

emissions (Supplementary Methods). Total L&D is then the sum of each of these components, written in its simplest form as:

$$\begin{aligned}&\text{Total loss and damage}\\&\quad=\text{historical damages from historical emissions}\\&\qquad+\text{future damages from historical emissions}\\&\qquad+\text{future damages from future emissions}\end{aligned}\tag{1}$$

For a historical marginal emission—that is, an additional unit emitted above the existing background emissions in a given year—we denote the resulting discounted historical damages as HD-CO_2 and discounted future damages as FD-CO_2. For a present or future marginal emission, we denote the resulting discounted future damages as SC-CO_2. This approach enables decomposition of L&D into past and future damages, and aligns the financial accounting framework of L&D with the existing SC-CO_2 framework (refs. 7,19). The SC-CO_2 is commonly defined as the net-present value of total additional net future harm (or benefit) that accrues to society as a result of one additional unit of CO_2 emissions at a specific moment in time. Aligning the calculation of L&D with SC-CO_2 enables the application of established scientific tools used to compute SC-CO_2 (refs. 7,20), supports legal consistency around climate liability[12], and helps avoid incentives to delay emissions accountability, for instance, if damages from past and future emissions are valued differently.

We develop a formal framework for estimating equation (1), and an implementation of the framework that: combines (1) emissions inventories; (2) the reduced complexity model Finite Amplitude Impulse

Response (FaIR) to calculate the change in global mean surface temperature (GMST) from an emissions perturbation; (3) the CMIP6 ensemble of global climate models[21] to 'pattern scale' GMST changes to country-level changes; and (4) an updated statistical model that relates country-level per-capita economic growth rates to changes in contemporaneous and lagged average temperatures[22] to translate local temperature changes into damages (Extended Data Fig. 1 and Supplementary Methods). Relationships between mean annual temperature and GDP have been well explored in the literature[22–25] and probably capture many (but not all) channels through which a warming climate affects economic outcomes. The reduced-form temperature–GDP damage function we use is robust across statistical models, has not changed appreciably in the past 60 years (Extended Data Fig. 2), and provides strong evidence that temperature is affecting the growth rate of GDP, not just the level (Extended Data Figs. 3 and 4 and Supplementary Methods).

Implementation of our framework necessarily involves ethical and legal considerations, including the selection of a discount rate, a date when responsibility for emissions and their damages starts (for instance, the year when the possibility of widespread climate damages became known), and production-based versus consumption-based emissions accounting (Supplementary Methods). Damages are defined relative to an emissions year; a set of subsequent years in which damages occurs; a settlement year, which could be before (in the case of SC-CO2) or after (in the case of HD-CO_2) the damage years; and a discount rate (Fig. 1). Damages which occur before settlement are discounted similar to how damages in the future are discounted[26], implying that the value of past damages is larger at the time of settlement than at the time when they occurred, analogous to the effect of an interest rate on unpaid debt. The choice of a higher discount rate thus reduces the current value of future damages, but increases the present value of past damages.

Loss and damage per tonne of CO_2

Figure 2 shows estimates of HD-CO_2, FD-CO_2 and SC-CO_2 under different discount rates and different emission years from 1990–2020 (numerical values are provided in Extended Data Table 1, and confidence intervals are provided in Extended Data Fig. 5). Earlier emissions pulses generate larger cumulative damages, because earlier emissions act on an economy for more years and because growth effects compound; the use of other damage functions (for example, for mortality) will have this first feature but might not have the second.

We estimate that FD-CO_2 is many times larger than HD-CO_2, reflecting the longer time period over which future damages can occur and the fact that future warming will be acting on a warmer world. Differences are larger the lower the discount rate: under a 2% discount rate, 1 GtCO_2 emitted in 1990 causes $184 per tonne in cumulative discounted global damages by 2020, and $1,840 per tonne in cumulative damages between 2021 and 2100, a tenfold difference; at a 3% discount rate the difference is sixfold, and at 5% it is threefold. The implication is that under most discount rates, L&D settlements equivalent to estimated past damages will only account for a modest subset of the anticipated total damages that a historical emission will eventually cause. Settling debts for past damages will therefore not settle debts for past emissions.

Aggregate past and future damages from historical emissions are a mix of (1) modest benefits or limited damages in high-latitude countries, where we find that warming has a limited or uncertain effect on growth; and (2) widespread damage in mid-latitude and tropical countries, where warming harms growth with high confidence, and where damages are substantial as a percentage of current GDP (Fig. 2c,d and Extended Data Fig. 6). This geographic pattern is consistent with previous studies[17,22,27,28], although negative effects are more widespread than these earlier analyses due to the use of an updated response function that accounts for lagged effects of temperature on growth.

Given its policy importance, we estimate and report SC-CO_2 values under a broad range of analytic choices. Under relatively conservative assumptions (2% discount rate, no impacts past 2100; Supplementary Methods), we estimate a SC-CO_2 of $1,013 per tonne—a value that is much larger than recent bottom-up estimates produced by the US Federal Government[19] (Fig. 2). Cumulating impacts through 2300 instead of 2100, assuming lower fixed discount rates or using Ramsey discounting, and/or assuming higher counterfactual growth rates—all choices consistent with recent guidance[7]—yield even higher estimates (Extended Data Table 2). Using a response function that only allows temperature to affect contemporaneous growth yields substantially lower estimates, but is inconsistent with evidence that lagged effects are material (Extended Data Fig. 4). Similarly, allowing for growth rebounds following initial temperature-related declines, such that cumulative growth effects are eliminated, reduces SCC estimates by half; however, such a scenario finds mixed support in the existing literature[24], and rebounds are not apparent at least 15 years after an initial shock in our data (Extended Data Fig. 3). Finally, an accelerated adaptation scenario under which GDP is assumed to become successively less sensitive to temperature over time—a trend inconsistent with the observed stability in the temperature–GDP relationship over the past 60 years (Extended Data Fig. 2b, Extended Data Fig. 3d) and the general lack of observed change in sensitivity at the sectoral level[29]—could reduce future damages substantially, with the magnitude of reduction dependent on the assumed adaptation rate (Extended Data Table 2).

Loss and damage attributable to specific emitters

We use our framework to quantify components of L&D from individual-, company- and country-level emissions. Using estimates of average emissions reductions that would result from changes in individual behaviour[30,31] (Supplementary Methods), we estimate the reduction in global damage that would occur had these behaviours been sustained by an individual over the past decade (2010–2020). We find that taking one additional long-haul airline flight (8,000 km, or roughly one round trip from San Francisco to New York) per year for the past decade would have generated $165 ($55–385) in discounted global damages through 2020 and would be expected to generate $25,000 in discounted damages between 2021 and 2100 (2% discount rate; Fig. 3 and Supplementary Fig. 2). Switching from a representative non-vegetarian diet to a vegetarian diet, installing and using a heat pump, or reducing driving by 10% would have each resulted in about $6,000 of global economic benefits (reduced damages) through 2100 if undertaken for the past decade, and recycling or eating one fewer serving of beef per month over the same period would generate approximately $1,000 in global discounted future benefits. Past damages from these past emissions are roughly two orders of magnitude smaller than future damages from these past emissions, indicating the lasting global impact of even relatively small changes in individual behaviour.

Given the high estimated costs of airline travel in particular, we use public data on private jet flights and associated emissions by numerous American celebrities to calculate the future discounted damage of flights these celebrities (or their aircraft) took in 2022 (Supplementary Methods). We calculate that emissions from private flights taken by Bill Gates, Jeff Bezos, Floyd Mayweather, Elon Musk, Jay-Z and Taylor Swift in 2022 will each generate more than $1 million in discounted aggregate damages by 2100 (Fig. 3b), highlighting the substantial, and perhaps under-recognized, social cost of individual consumption choices.

Building on recent efforts to estimate firm-level emissions over time[32], we estimate the cumulative historical and future damage associated with emissions from the production and use of fossil fuels (that is, combined scope 1 and 3 emissions) produced by global carbon majors, or large state-owned, publicly owned or private companies that are substantial producers of oil, gas or coal. We estimate that emissions between 1988–2015 from the largest single company emitter, Saudi Aramco, resulted in $3 trillion in cumulative global economic

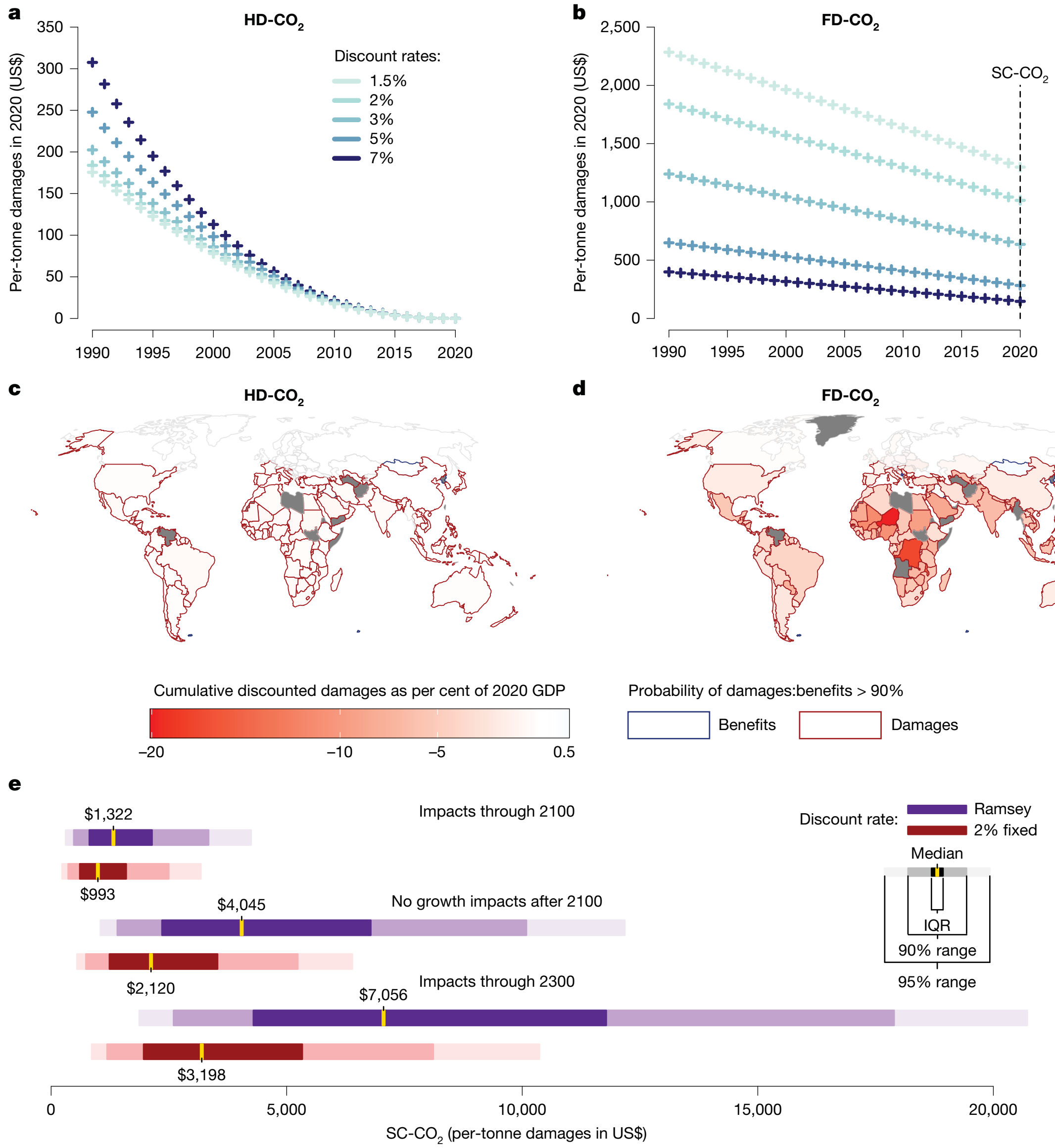

Fig. 2 | Estimated damage from a marginal unit of past or future emissions. **a**, Estimates of HD-CO$_2$, calculated as per-tonne cumulative impacts of a 1 Gt pulse of CO$_2$ emitted in a given year, from 1990 to 2020, under different fixed discount rates. **b**, Estimates of FD-CO$_2$, or the cumulative damages after 2020 of each of these pre-2020 emission pulses, under the same discount rates, assuming damages end in 2100. The post 2020 damage estimates for a pulse in 2020 are estimates of the SC-CO$_2$ in 2020. Numeric values are provided in Extended Data Table 1, and confidence intervals in Extended Data Fig. 5. Estimates account for the lagged effect of temperature on growth (Extended Data Figs. 3 and 4). **c**,**d**, Spatial distribution of HD-CO$_2$ and FD-CO$_2$ from a 1 tCO$_2$ emission in 1990, under a 2% discount rate, expressed as a percentage of total country GDP in 2020, showing impacts through 2020 (**c**) and projected impacts for 2021–2100 (**d**). Blue (red) shading indicates cumulative benefits (damages), whereas countries in grey have no data. Country borders are outlined if probability of damages or benefits exceeds 90%, accounting for both climate and econometric uncertainty. **e**, Estimate of the SC-CO$_2$ (here a 1 tCO$_2$ pulse in 2020) under three sets of analytic choices: impacts end in 2100, comparable to estimates in **b**; temperature has no effect on economic growth after 2100 but impacts cumulate through 2300 (see Supplementary Methods and Supplementary Fig. 1 for a schematic); and growth impacts continue through 2300. For each, SC-CO$_2$ is computed under two discounting schemes: a fixed 2% discount rate (red) and Ramsey discounting calibrated to a near-term rate of 2% (purple). Confidence bands account for both econometric and climate uncertainty (see Extended Data Fig. 5 for more details).

damages by 2020 (Fig. 3c and Supplementary Fig. 2c), or roughly eight years of company revenue. Future damages from these past emissions are more than 20 times larger, totaling $64 trillion in cumulative discounted damages through 2100. Cumulative damages through 2020 from the largest non-state-owned emitter, ExxonMobil, equalled $1.6 trillion, equal to about five years of annual revenue, whereas future damages through 2100 from ExxonMobil's past emissions total $29 trillion. Restricting attributed damages to scope 1 emissions (those resulting directly from the production of the products sold) yields damage estimates that are one order of magnitude smaller (Supplementary Fig 3).

For each country, we calculate the cumulative damages so far from historical emissions from other countries, for emissions between 1990–2020 (Fig. 4 and Extended Data Fig. 7). Carbon dioxide emissions in the US over the period were the largest source of damages, resulting in $10.2 trillion in cumulative damages by 2020 (2% discount rate), with approximately 30% (or $2.97 trillion) of these damages occurring in the US and approximately a further 14% ($1.39 trillion) in the European Union (EU), the two political units that we calculate have suffered the largest total damages to GDP. Emissions from China were the second largest source of damages over the period ($8.7 trillion), followed by the EU ($6.42 trillion). Damages are roughly twice as large for emissions

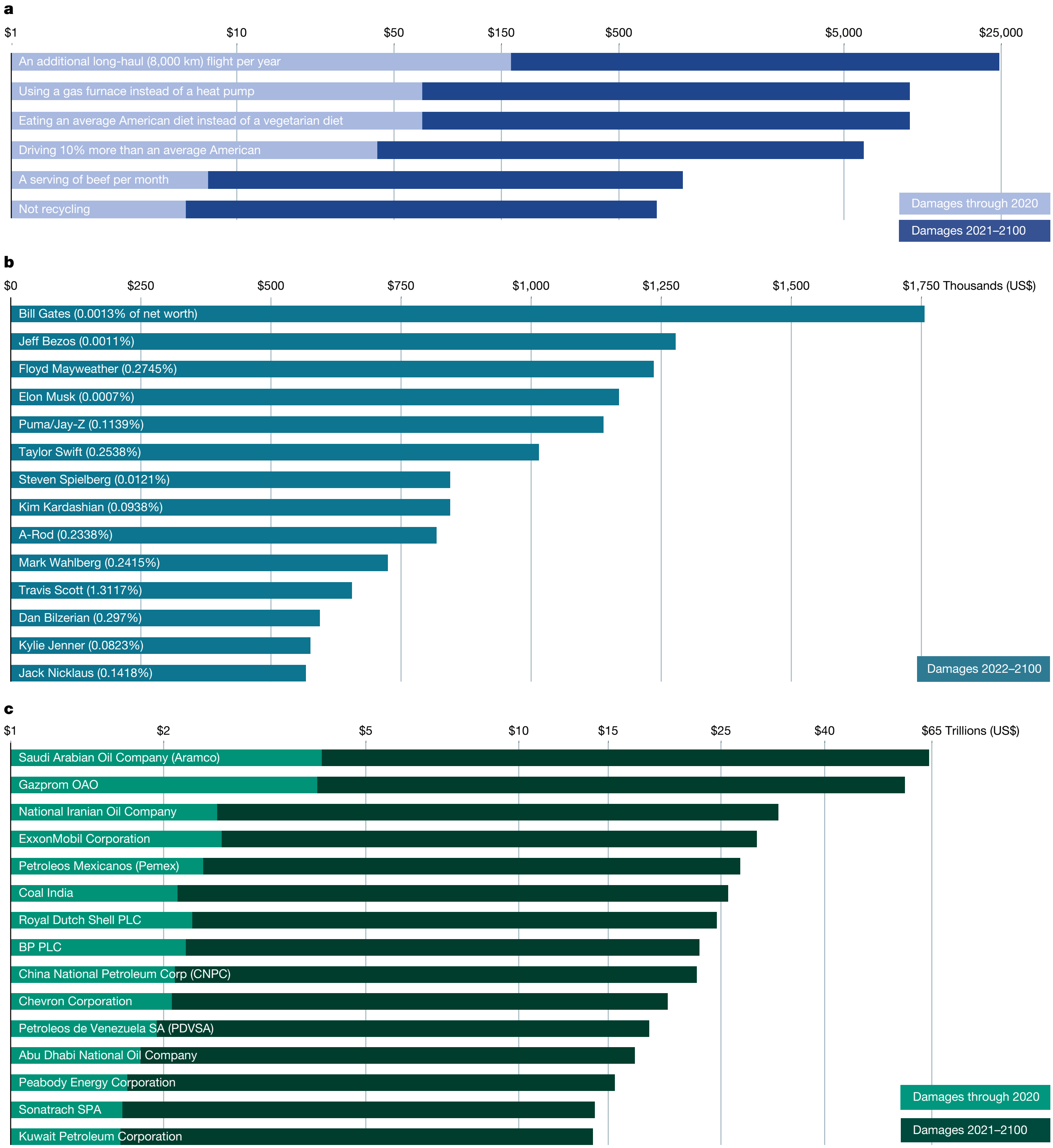

Fig. 3 | Estimated damages from emissions related to individual behaviors or firm output over varying time periods. Estimates show cumulative past (through 2020) and/or expected future damages (through 2100) from estimated emissions resulting from different choices by individuals or firms. Cumulative damages are discounted at 2%. **a**, Estimated past or future cumulative global damages from emissions associated with individual behaviours, under the assumption that each was conducted by one individual for the 2010–2020 decade (for instance, one more long-haul flight per year for a decade); future damages exceed past damages by two orders of magnitude (note the logarithmic scale). **b**, Cumulative damages (in thousands US$) through 2100 from emissions flights taken in 2022 by celebrities' private jets. Damage as a percentage of net worth of each individual shown in parentheses. **c**, Cumulative damages (in trillions US$) through 2020, and from 2021 through 2100, from the emissions associated with the production and use (scope 1 + 3) of products produced by different large oil and gas companies (carbon majors) between 1988–2015. Numerical values and confidence intervals are provided in Supplementary Fig. 2.

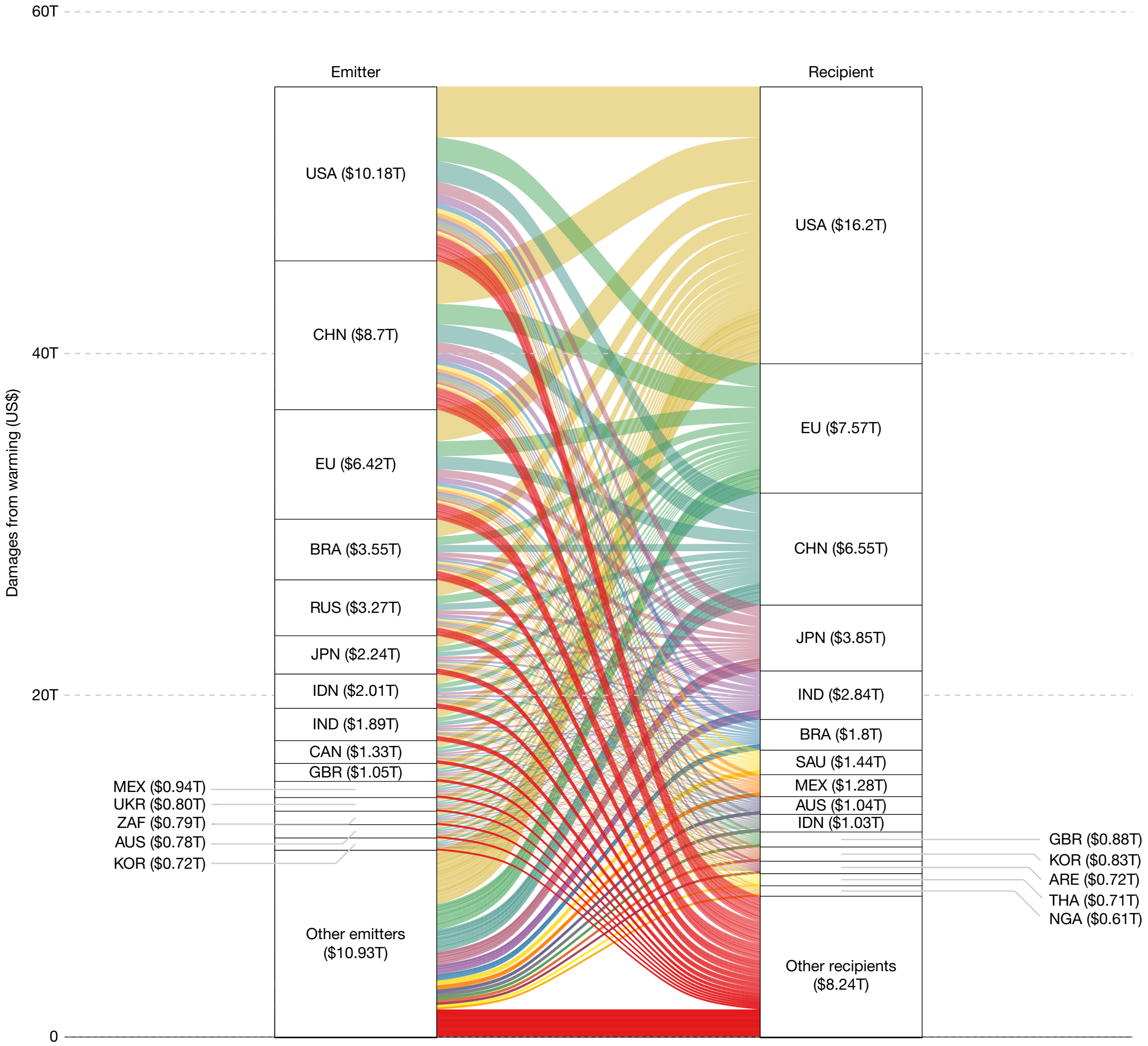

Fig. 4 | Bilateral attribution of historical damages due to country-level emissions since 1990, cumulated through 2020. Emissions include both fossil fuel and land use emissions. Emitting countries shown in the left column, whereas receiving countries are shown in the right column. Bar widths are proportional to damages or benefits. The total cumulative damages attributable to each emitter, or experienced by each recipient, are in parentheses. All estimates are under a fixed 2% discount rate.

starting in 1980 rather than 1990 (Supplementary Fig. 4), and more than five times larger for emissions starting in 1960 (Supplementary Fig. 5), with China representing a smaller share (and the EU a larger share) of damages the longer the time window. Estimates without land-use emissions or using consumption- rather than production-based emissions are roughly similar for most emitters (Supplementary Figs. 6 and 7).

Potential implications of CO_2 removal

Direct monetary compensation offers one approach for an emitting entity to address damages caused by its emissions, and is perhaps the only practical approach to address damages that have already occurred (HD-CO_2); however, for the future damages from past or current emissions (FD-CO_2, SC-CO_2), emitters could also consider greenhouse gas removal (including carbon dioxide removal, CDR) as a way to limit future damages, particularly if the per-ton cost of permanent and verifiable CDR fell below HD-CO_2 or SC-CO_2.

We abstract from the critically important and largely unresolved issues of feasibility, scale and economics of CDR[33], and consider a hypothetical scenario that assumes a CDR technology exists that can remove a desired quantity of CO_2 permanently from the atmosphere (Supplementary Methods). The effectiveness of using CDR for reducing future damages from past emissions declines with the time elapsed between emissions and capture (Extended Data Fig. 8): immediate removal eliminates damages, but a 25-year delay results in an approximately 50% reduction in damages through 2100 relative to no removal. Thus, use of CDR as a tool to redress future damages from past or current emissions requires careful attention to the timing of removal.

Discussion

We provide a quantitative framework for linking individual emissions to aggregate and local-level damages, and an empirical estimation that links warming temperatures with country-level aggregate economic output. We find that past—and probably future—damages from observed emissions, and attributable to specific emitters, are economically large. As is common in most climate damage estimation, the precise magnitude of our L&D estimates remain uncertain. Overall uncertainty stems from three main sources: (1) sampling uncertainty, or the combined effect of econometric and climate model uncertainty, which is contained in our reported confidence intervals and quantitatively decomposed; (2) model choice uncertainty, including how to model GDP impacts or incorporate potential adaptation; and (3) policy uncertainty, including choices over discounting, damage horizon and emissions attribution. Accumulating data and further scientific advances hold promise for making progress on the first two sources; the third source will necessarily be guided by legal, ethical and practical concerns that are not provided by our framework. It is possible that the scientific standards of evidence we adopt, including reported 95% confidence intervals, are more stringent than 'more likely than not' standards employed in many legal settings[34]. We also note that our estimates do not account for the existence or efficacy of any emissions-offsetting behaviour on the part of emitting entities.

Multiple avenues exist for addressing damages that have already occurred (HD-CO_2), including lump sum payments through the international system, or debt-for-climate swaps[35]. Challenges in these aggregated approaches include whether those who have been harmed—including individuals and households—would receive meaningful compensation. Well-developed opportunities for transfer payments also exist outside the international system, such as bilateral, low-cost transfer payments to the mobile phones of low-income households in developing countries[36]. Our results, however, do not speak to who within countries is deserving of—or entitled to—such transfers, although higher-resolution impact estimates could in principle guide such allocations. Our results also highlight that although relative damages tend to be largest in low-income settings (Fig. 2c,d), absolute damages are largest in the world's largest economies (Fig. 4 and Extended Data Fig. 6), a result of smaller percentage damages acting on much larger economies. Calculated absolute damages again do not necessarily indicate what is owed to these economies by other emitters. For example, we compute that the damages experienced by the US from global emissions since 1990 are greater than the global damages caused by the US by its own emissions over that period, but this need not imply that a framework for responsibility would necessarily assign the US to be a net recipient of transfers. Our calculations can, and probably should, be overlaid with ethical and normative frameworks that take into account other information, such as the ability or need for individuals and countries to make or receive payments.

For FD-CO_2, a suite of options could in principle be used beyond direct compensation, including CDR, solar radiation management (SRM) or investments in adaptation. All face substantial challenges. Carbon dioxide removal could have advantages in the setting in which direct compensation is difficult, yet even if it were cost-effective and feasible at scale, using CDR to remove past emissions only eliminates a fraction of ongoing damages. The benefits and costs of possible SRM approaches remain poorly understood, with important sectors unlikely to benefit from some proposed approaches[37,38], and SRM deployment remains highly controversial. Credible use of these alternate strategies to compensate future harm from past or current emissions will require stronger evidence.

Investments in adaptation could also limit future damages, yet we lack quantitative evidence identifying specific investments that reduce risk and limit damages at scale[39], and there is limited evidence that society has been broadly successful in reducing damages in recent decades[29] (Extended Data Fig. 2b and Extended Data Fig. 3d). Adaptation funding has lagged both promises and needs[40], and if L&D payments are tied to damages net of adaptation, as we propose, countries may under-invest in adaptation to maximize compensation—highlighting the need for incentive-compatible system design.

Our approach also focuses on the (typically negative) externality that emissions create for other entities through warming and associated damages, but we do not consider the potential for related externalities, both positive and negative, that could occur as a result of the economic activity in the emitting entity that generated the emissions. We know of no empirical work that addresses the relevant bilateral magnitudes of these additional externalities.

Our quantitative estimates capture an important aggregate channel (GDP), through which climate damages have occurred. Other channels that are poorly captured in GDP data—including damages to health[41], ecosystem function[42] and loss of cultural homeland[43]—will not be reflected in our current estimates, nor will impacts not highly correlated with interannual variation in country level temperatures, including sea level rise[44], tropical cyclones[45] or other climate extremes[46]. As a result, our damage estimates will understate the total damages associated with historical and future emissions, perhaps substantially. Nevertheless, our estimates of the SC-CO_2, the quantity most easily comparable to other studies, are at least five-times larger than recent estimates using 'bottom-up' cross-sectoral approaches to damage estimation[19,47], although they are very similar to a recent global econometric estimate[25]. The estimates we present here are large, in part, because these effects scale with the size of economies, because we find that the effect of a given amount of warming has persistent economic impacts, and because these GDP growth effects compound.

More broadly, our framework for computing loss and damage should be applicable in any setting with the following ingredients: accurate baseline measurements of some outcome of interest (GDP, health and so on), a credible damage function linking that outcome to a measured climate variable, a modelling approach able to estimate local changes in that climate variable as a function of emissions perturbations, and accurate estimates of emissions from an emitting entity of interest. Given rapid scientific progress on damage estimation, climate attribution[48] and emissions measurement[49], opportunities for a substantially expanded quantitative understanding of loss and damage appear close at hand.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41586-026-10272-6.

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Methods

Here we provide a methods overview, including of our accounting framework for loss and damage, how that framework is estimated, the data used, and important ethical decisions that must be made. Full details are provided in the Supplementary Information.

Framework overview

We treat CO_2 emissions as generating a flow of future damages for populations around the world. Total L&D is decomposed into three components: HD-CO_2, FD-CO_2 and SC-CO_2 (Supplementary Section 1). This framework aligns L&D estimation with existing approaches for computing the social cost of carbon[7,20]. As CO_2 remains in the atmosphere for decades to centuries[50,51], emissions generate damages that extend far into the future, with impacts distributed unequally across countries[27].

Climate modelling

We use FaIR (v.2)[52] to translate emissions perturbations into changes in GMST. Local temperature changes are then derived through pattern scaling using the CMIP6 ensemble of global climate models[21], following the methodology from IPCC Sixth Assessment Report[53] (Supplementary Information, sections 2.1 and 2.2). Uncertainty in the mapping of global to local temperature change is characterized using estimates from regional climate projections[54]. Population-weighted local temperatures are calculated using gridded population data[55].

Country-level emissions data come from the Global Carbon Budget 2022[56]. Carbon major emissions data (1988–2015) are from the Carbon Disclosure Project[32,57], and we consider both production- and consumption-based emissions accounting approaches[58,59] (Supplementary Information, section 3). Individual behaviour emissions estimates come from published life cycle analyses[30,31], and celebrity emissions data from public flight tracking records. To estimate when to begin counting emissions, we set our baseline ‘year of knowledge’ as 1990, or a year after the establishment of the IPCC. This is perhaps conservative: using text-based analysis of United Nations documents, other analyses set the date a decade earlier[60], and internal company documents reveal that some major emitters were aware of climate risks beginning around 1980[61] (Supplementary Information, section 1.5).

Economic damage function

We estimate the relationship between temperature and economic output using panel fixed effects regression of GDP growth on temperature, with data from 1961–2019 using ERA5-Land climate data[62] and GDP data from the World Bank[63]. Our baseline model includes five lags of temperature, supported by both distributed lag models and local projections analysis[64] (Supplementary Information, section 2.3 and Supplementary Figs. 8–10). We find evidence of persistent growth effects of temperature on output, with marginal effects stabilizing after 3–7 years using breakpoint detection methods[65] (Extended Data Fig. 4). Multiple past studies support non-linear temperature–growth relationships[22–24,66–68], and we test robustness to alternate specifications following recent debates in the literature[69]. Standard econometric guidance[70] suggests including sufficient lags to capture persistent effects. For projecting future growth absent climate change, we use estimates from recent econometric models of long-run growth dynamics[71].

Discounting and ethical considerations

We present results across a range of discount rates (1–5% fixed, plus Ramsey discounting) and responsibility start dates. The choice of discount rate for climate policy has been extensively debated[26,72–74], with arguments for lower rates on ethical grounds[75] and higher rates reflecting market interest rates[76]. We note that discounting affects past and future damages in opposite directions: higher discount rates reduce future damage values but increase past damage values (Supplementary Information, sections 1.2 and 1.5).

Sensitivity and robustness

We test sensitivity to discount rates, time horizons (2100 versus 2300), econometric model specifications, baseline growth assumptions and potential adaptation scenarios[29]. We use estimates from recent damage function studies[47,77] to benchmark our results. We also consider the asymmetry in climate-carbon cycle responses to emissions versus removals[78] when evaluating carbon dioxide removal scenarios (Supplementary Information, section 2.5 and Supplementary Figs. 11–15). Uncertainty estimates account for both econometric and climate model uncertainty (Extended Data Fig. 5).

Data availability

Data needed to replicate all results are available on Zenodo at https://doi.org/10.5281/zenodo.18158445 (ref. 79).

Code availability

The R and python code needed to replicate all results are available on Zenodo at https://doi.org/10.5281/zenodo.18158445 (ref. 79).

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Author contributions M.B., N.S.D. and S.H. designed the study. M.Z. led the statistical analysis with input from M.B. N.S.D. processed climate data. All authors contributed to interpretation of results. M.B. and S.H. led the drafting of the manuscript, with input from all authors.

Competing interests The authors declare no competing interests.

Additional information

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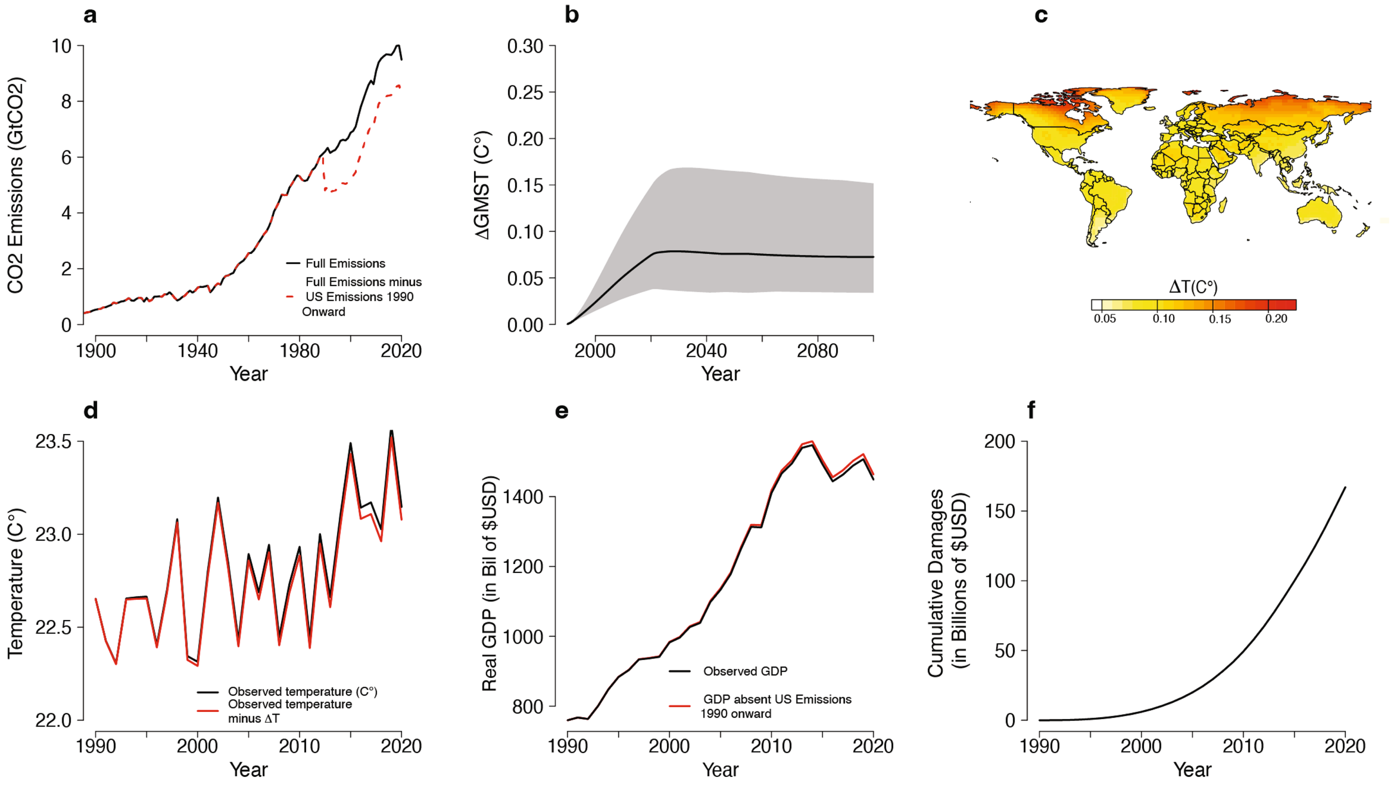
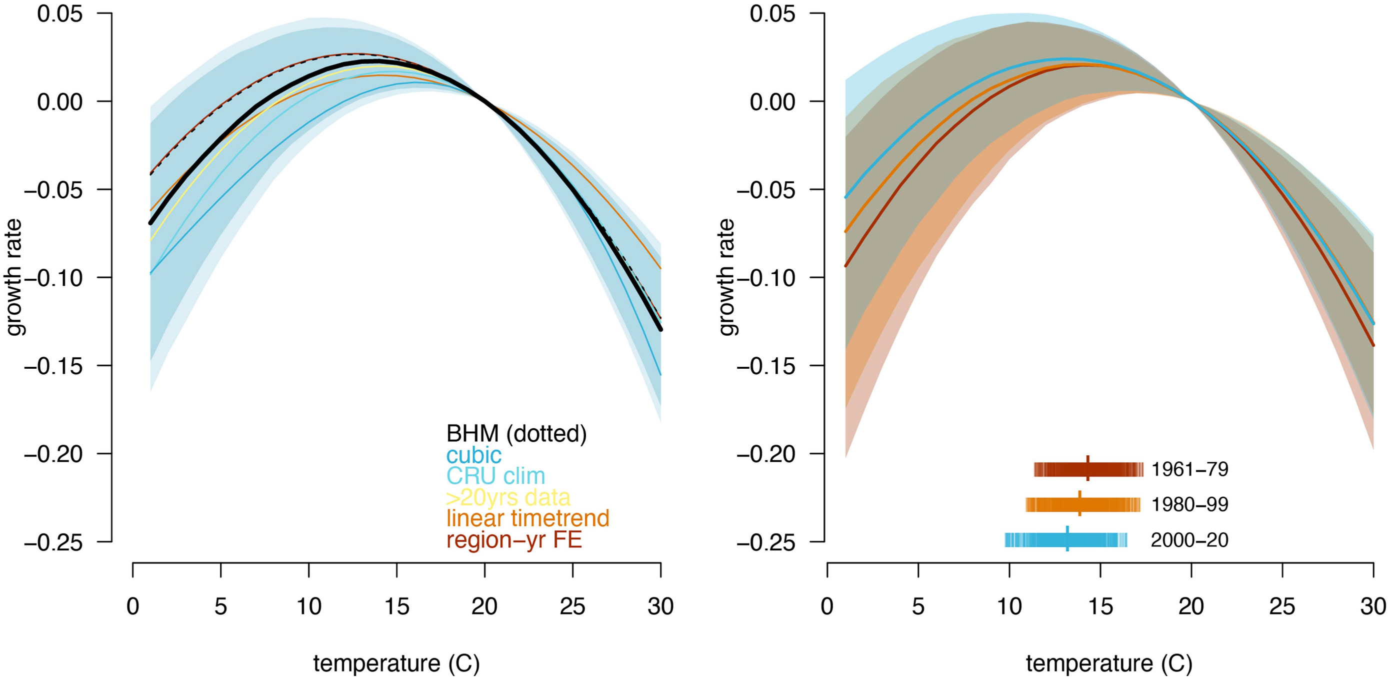
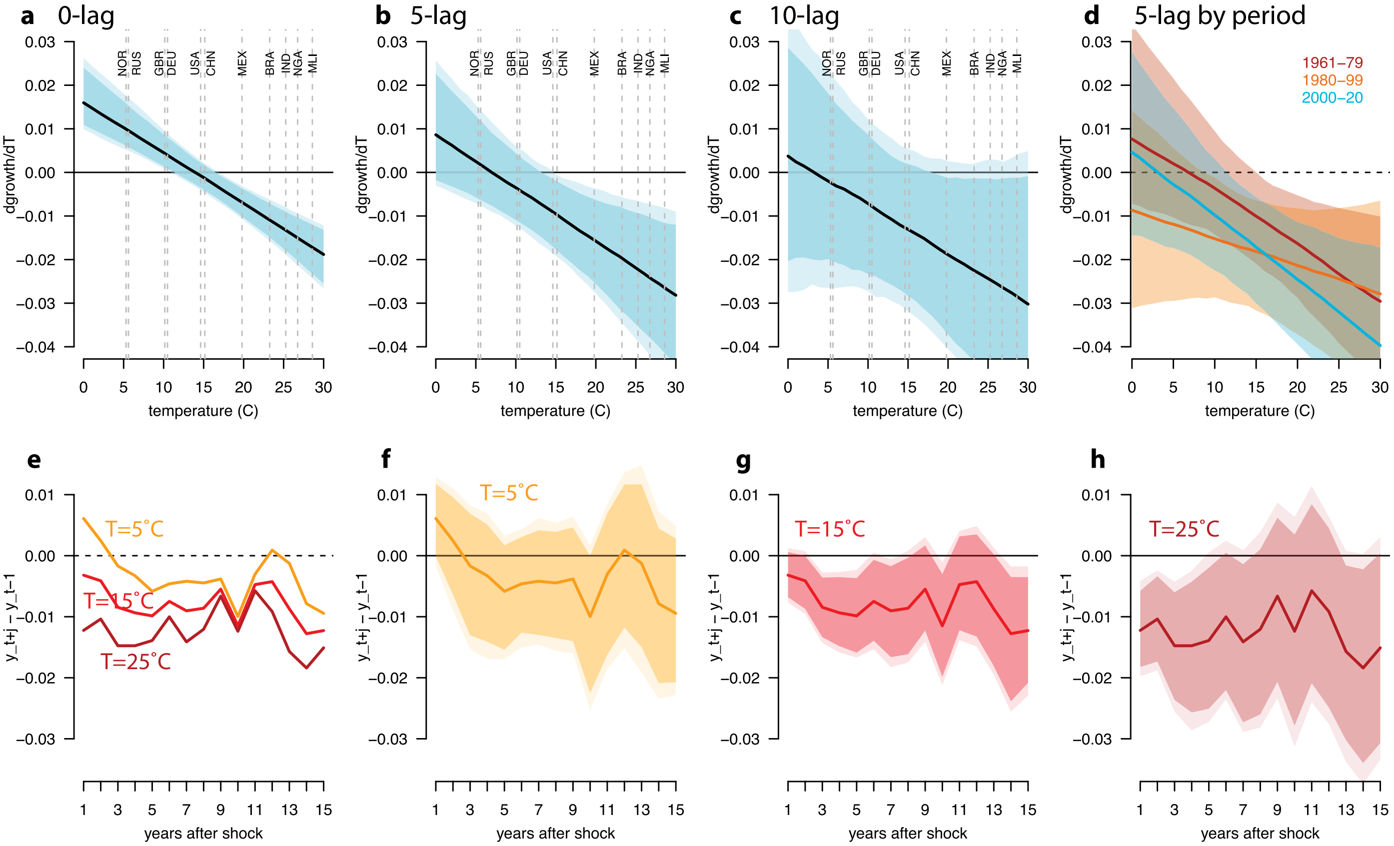


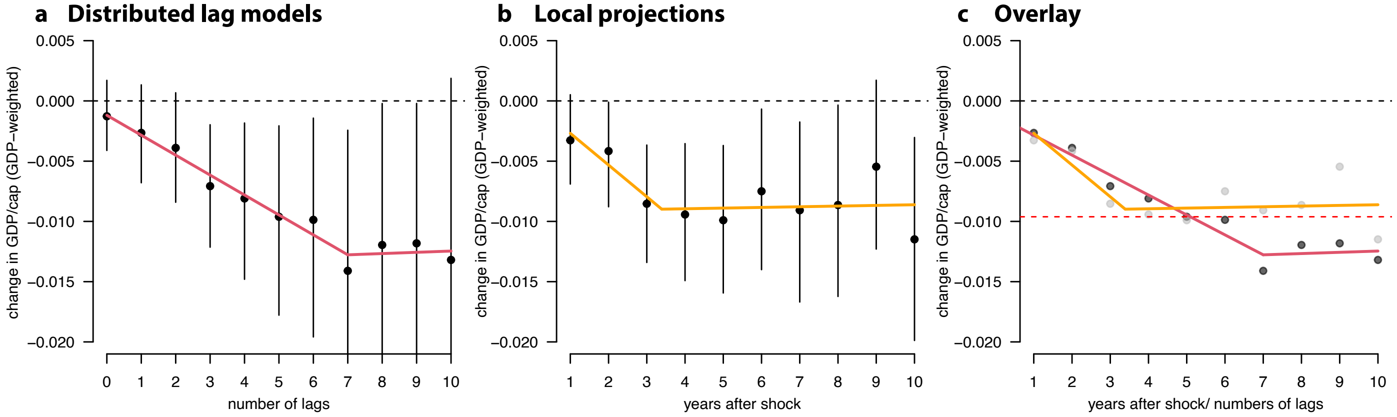
Extended Data Fig. 1 | Multi-step approach for attributing damages to emissions. Damages to the Brazilian economy from US emissions since 1990 are used as an example. **a** Total CO_2 emissions from 1900 to 2020 before and after shutting off USA's emissions starting in 1990, **b** Global mean surface temperature response from USA emissions (1990-2020), calculated using FaIR. Black line is median response. Grey interval is temperature response under varying parameters in FaIR. **c** change in temperature in 2020 as a result of US emissions, median estimate from "pattern scaling" the global temperature increase using 30 global climate models. **d** Observed Brazil population-average temperature time series (black) and baseline temperature absent USA emissions (red), **e** Observed Brazil real GDP 1990-2020 (black) and estimated counterfactual GDP absent USA emissions, calculated using empirical temperature-GDP damage function, **f** cumulative damages owed by USA to Brazil (1990-2020).



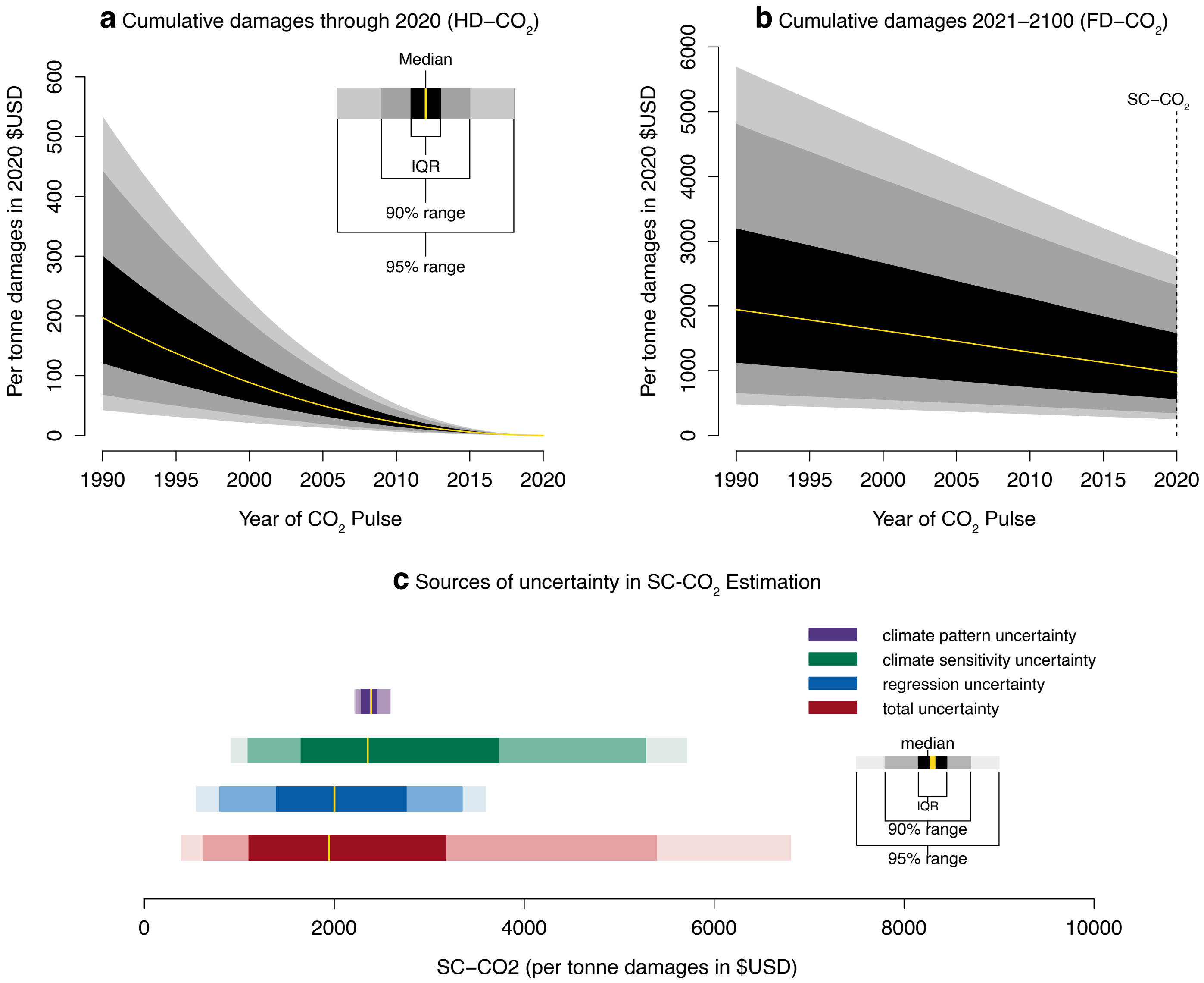
Extended Data Fig. 2 | Nonlinear response of growth in GDP/capita to temperature is robust to alternate specifications and data, and is stable over time. a Solid black line and blue shaded area are point estimate and 95% bootstrapped confidence interval of relationship between growth in GDP/capita and annual average temperature, using ERA5-Land climate data (n = 8895 country-year observations). Other lines are estimates under alternate climate data (CRU instead of ERA), alternate time fixed effects (region-year instead of year), alternate time trends (linear instead of quadratic), or functional forms for the temperature-growth relationship (cubic instead of quadratic), as described by the labels. Dotted black line is original pooled estimate from ref. 22. **b** Global temperature response function has not changed since 1960, despite average per capita incomes nearly tripling during this period. Colors represent period-specific response functions for 1961-1979 (red), 1980-1999 (orange), 2000-2020 (blue). Shaded regions are bootstrapped 95% confidence intervals (1000 bootstraps). Rug plots at bottom show estimated temperature optima for each period and bootstrap.



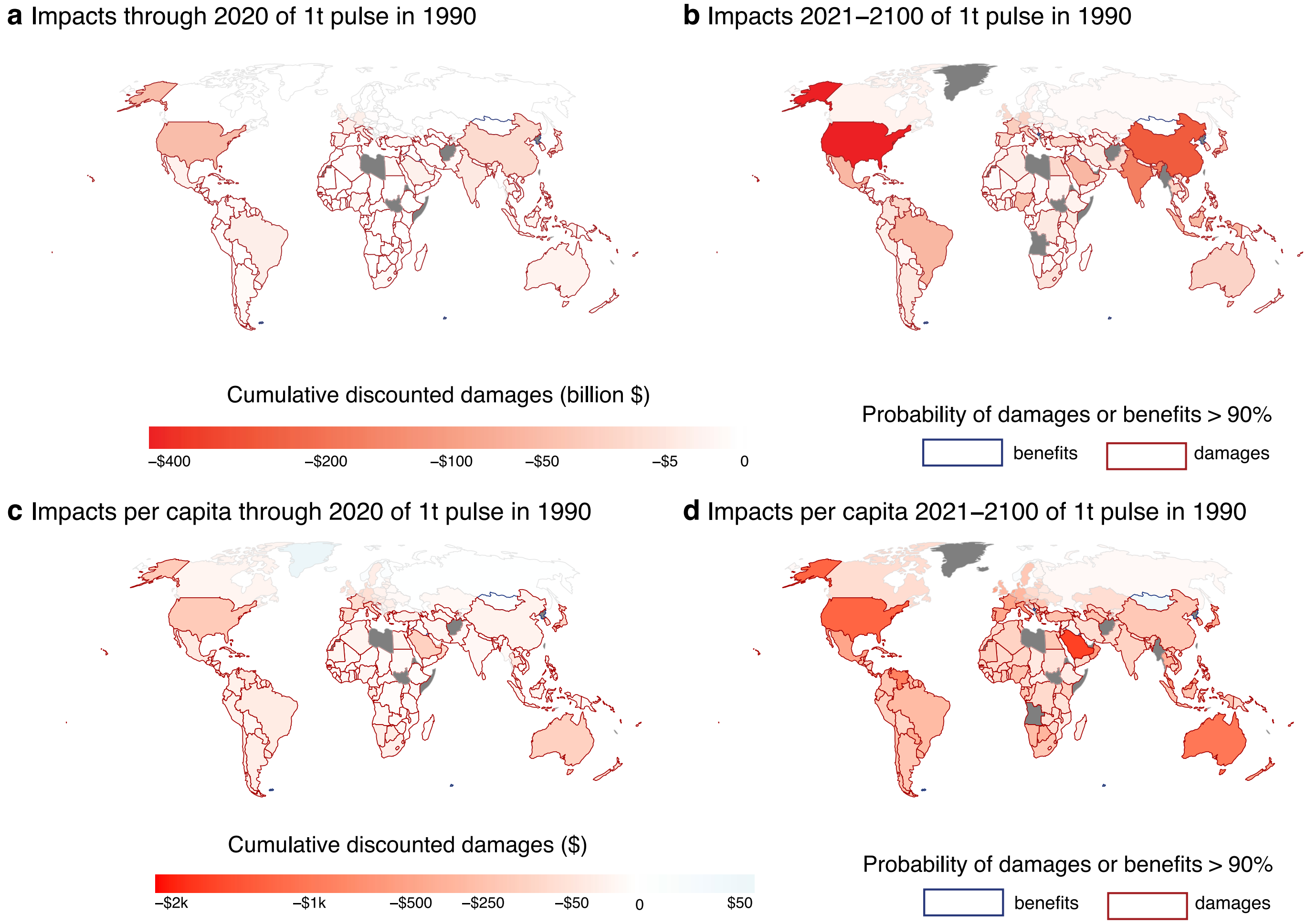
Extended Data Fig. 3 | Both distributed lag models and local projections show evidence of growth effects. a–**c**. Each panel shows estimated marginal effects (∂growth/∂Temp) from a global pooled regression of growth in GDP/capita on temperature, with 0, 5, or 10 lags of temperature. Light shaded regions are bootstrapped 95% confidence intervals, darker regions are 90% CI (1000 bootstraps). Dotted vertical lines show average temperatures at end of the sample (2016-2020) for select economies globally. Marginal effects are noisier but more negative with increasing numbers of lags, consistent with temperature affecting the growth rate of GDP. **d** Marginal effects for 5-lag model estimated separately in three 20-year periods are not statistically different from each other and have not flattened over time; point estimates are more negative in later periods. **e**–**f** Estimates from local projections model plot the impact on growth in the 15 years following a temperature shock in year $j = 0$, for economies with average temperatures at 5, 15, and 25 °C; point estimates shown for each economy in **e** and confidence intervals in **f**–**h**. Consistent with distributed lag models, a one year temperature shock has a persistent negative effect on output for economies with average temperatures above around 15 °C, although estimates are somewhat noisier at longer time lags.



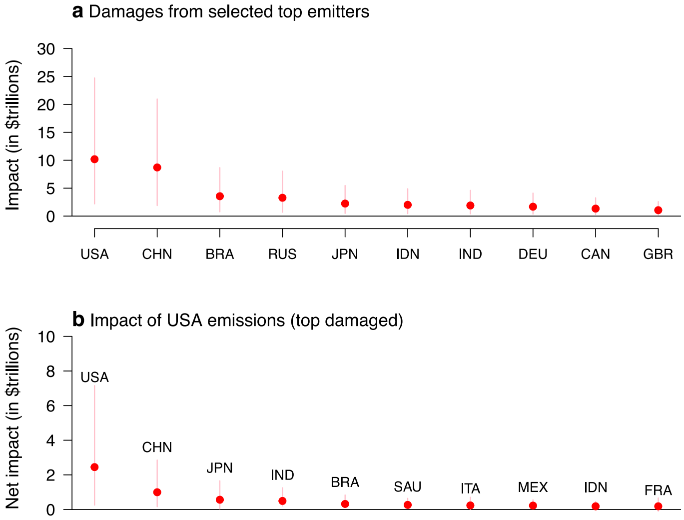
Extended Data Fig. 4 | Marginal effects of temperature on growth stabilize after 3–7 years. Using distributed lag models with between 0-10 years of lags, or local projections models with responses measured through 10 years after a 1-year shock, we test whether marginal effects stabilize after a certain number of years by calculating the GDP-weighted marginal effect at each lag and testing for trend breaks in the estimates using a breakpoint algorithm; see Supplementary Methods. **a** GDP-weighted marginal effects for distributed lag models stabilize around seven lags. Estimated trend breaks shown in red. **b** GDP-weighted estimates from local projections model stabilize after around three lags; estimated trend breaks shown in orange. **c** Overlay of distributed lag and local projection estimates. Estimates are equal at 5 lags, our chosen baseline model. Dotted red line shows the cumulative 5-year effect used in all projections in the paper.



Extended Data Fig. 5 | Uncertainty in estimates of HD-CO$_2$, FD-CO$_2$, and SC-CO$_2$, accounting for both econometric and climate uncertainty. a,b As in Fig. 2a,b, showing total global per ton damages from 1Gt pulse of CO$_2$ emitted in different years, beginning in 1990, cumulated using a 2% discount rate. Confidence bands account for both econometric uncertainty (regression uncertainty in estimated temperature-GDP relationship) and climate uncertainty (including uncertainty in the response of global temperature to emissions, and uncertainty in how global temperature change translates to local temperature change). **c.** Influence of different estimation components on uncertainty in estimates of SC-CO$_2$, fixing other components at their median. Estimates are based on 5-lag temperature-growth relationship, assuming no growth impacts after 2100.



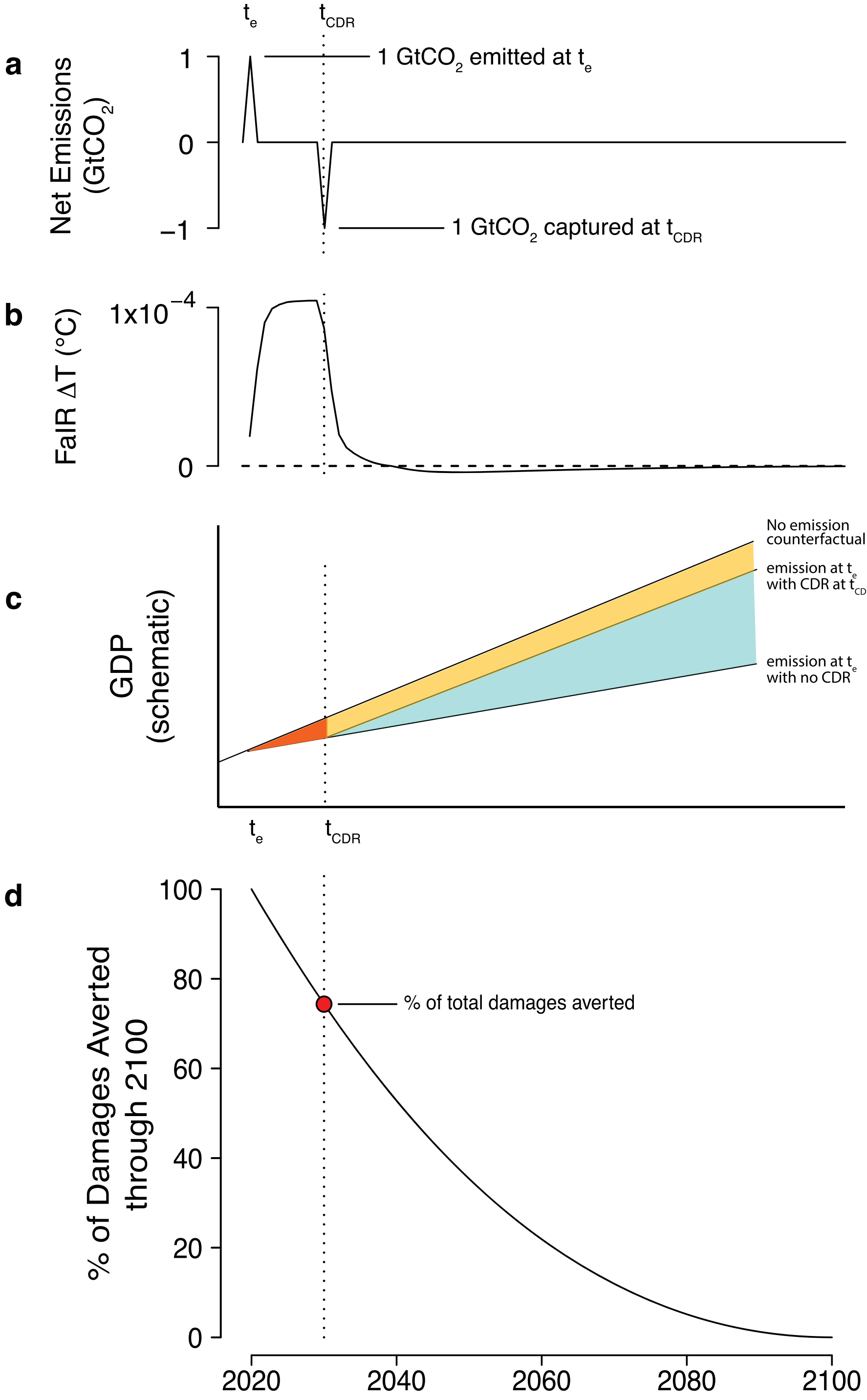
Extended Data Fig. 6 | Spatial distribution of HD-CO$_2$ and FD-CO$_2$. Colors depict cumulative impact of a 1t CO$_2$ emission in 1990, expressed either in total cumulative damages or benefits (in $; top plots) or damages per capita (bottom plots). Blue shading indicates cumulative benefits, red indicates cumulative damages, countries in grey have no data. Country borders are outlined if probability of damages or benefits exceeds 90%, accounting for both climate and econometric uncertainty. Left plots shows damages through 2020 (HD-CO$_2$), right plots damages 2021-2100 (FD-CO$_2$).



a Damages from selected top emitters

b Impact of USA emissions (top damaged)

Extended Data Fig. 7 | Uncertainty in attribution of historical climate damages or benefits through 2020 to specific emitters, for emissions 1990-2020. a Uncertainty in historical damages or benefits from emissions from the top 10 historical emitters. Point estimates correspond to estimates shown in Fig. 4, error bars to 95% confidence interval accounting for both climate and econometric uncertainty. **b.** Uncertainty of impact of USA emissions over the same period on top "receiving" countries. Values are in trillions USD.



Extended Data Fig. 8 | Effectiveness of carbon removal for reducing damages declines as a function of time between emissions and capture. **a**. Example of pulse experiment, where 1Gt pulse of CO_2 is emitted in $t_e = 2020$ and 1Gt removed with CDR in future year t_{CDR} (here, 2030). **b**. FaIR estimate of warming as a result of this pulse and subsequent capture. **c**. Schematic of impact on GDP in a hypothetical economy. Warming from initial pulse makes the economy grow more slowly, driving a wedge between GDP without the emission and GDP with the emission, up through time of removal. Damage between t_e and t_{CDR} is represented by orange triangle. If a ton is removed at time t_{CDR}, the economy resumes growing at its original pace but from a lower initial value in t_{CDR}, and the wedge is sustained into the future, creating the damage in the yellow polygon. Put simply, damage continues to occur after removal, due to the wedge that was created before removal. If the ton was never removed, the additional damages is in blue. The SC-CO_2 is the sum of the colored triangles (discounted annually back to 2020). Increasing delay between t_e and t_{CDR} increases both the orange and yellow triangles. Drawing is schematic and for visual clarity, polygon sizes are not to scale. **d.** Quantitative estimates of the percent of damage averted through 2100, for a 2020 emissions year and a $t_{CDR} > 2020$, assuming all damages end in 2100. Removal in 2030 reduces damages by 80%. Removal in 2050 reduces damages by roughly half.

Extended Data Table 1 | Total global per ton damages from 1Gt pulse of CO_2 emitted in different years, beginning in 1990

	DAMAGES ACCUMULATED THROUGH 2020 (IN BILLIONS OF $USD)					DAMAGES ACCUMULATED 2021-2100 (IN BILLIONS OF $USD)				
	1.5%	2%	3%	5%	7%	1.5%	2%	3%	5%	7%
1990	176	184	202	248	308	2284	1840	1239	649	399
1991	164	172	188	229	282	2251	1812	1219	637	391
1992	153	160	175	211	258	2220	1785	1200	625	383
1993	143	149	162	194	236	2188	1759	1181	614	375
1994	132	138	150	178	215	2156	1732	1161	602	367
1995	123	128	138	163	195	2125	1706	1142	590	359
1996	113	118	127	149	177	2094	1680	1123	579	351
1997	104	108	116	136	159	2062	1653	1103	567	342
1998	95	98	106	122	143	2029	1625	1083	554	334
1999	86	89	95	110	127	1996	1598	1063	542	325
2000	78	80	86	98	113	1963	1571	1043	530	317
2001	70	72	77	87	100	1931	1543	1023	518	309
2002	63	64	68	77	87	1898	1516	1003	506	300
2003	55	57	60	68	76	1866	1488	983	494	292
2004	49	50	53	59	66	1833	1461	963	482	284
2005	43	44	46	51	56	1801	1434	943	470	275
2006	37	38	39	43	48	1768	1406	923	457	267
2007	31	32	33	36	40	1735	1379	903	445	258
2008	26	27	28	30	33	1702	1351	882	433	250
2009	22	22	23	25	27	1669	1323	862	420	241
2010	18	18	19	20	21	1636	1296	842	408	233
2011	14	14	15	16	17	1603	1268	822	396	224
2012	10.8	11	11.3	11.9	12.6	1570	1240	801	383	216
2013	8.1	8.2	8.4	8.8	9.3	1536	1212	781	371	207
2014	5.7	5.8	5.9	6.2	6.4	1503	1184	761	359	199
2015	3.7	3.8	3.8	4	4.2	1469	1156	740	346	190
2016	2.2	2.2	2.2	2.3	2.4	1435	1127	719	333	181
2017	1.1	1.1	1.1	1.1	1.2	1401	1099	698	321	172
2018	0.39	0.4	0.4	0.41	0.42	1367	1070	677	308	164
2019	0.07	0.07	0.08	0.08	0.08	1333	1041	656	296	155
2020	0	0	0	0	0	1298	1013	636	283	147

Numbers correspond to estimates in Fig. 2a,b. Left columns show damage accumulated through 2020 under different fixed discount rates, right columns show damage from that same emission between 2021-2100.

Extended Data Table 2 | SC-CO_2 under different discounting schemes, baseline growth scenarios, regression models, and time horizons

	DISCOUNT RATE						
SCENARIO	DISCOUNT RATE AT 1%	DISCOUNT RATE AT 2%	DISCOUNT RATE AT 3%	RAMSEY DISCOUNT (0.2%,1.24)	TIME HORIZON	POST-2100 GROWTH	REGRESSION MODEL
5lag + No impacts > 2100	$1,682	$1,013	$636	$1,381	through 2100		5-lag model
5lag + No growth effects > 2100 + Growth at 2100	$8,314	$2,383	$1,006	$4,671	through 2300	SSP 2100 rates	5-lag model
5lag + Growth at 2100	$15,804	$3,448	$1,203	$7,822	through 2300	SSP 2100 rates	5-lag model
5lag + adaptation	$1,108	$690	$448	$923	through 2100		5-lag model
5lag + adaptation + Growth at 2100	$4,397	$1,369	$631	$2,554	through 2300	SSP 2100 rates	5-lag model
5lag + No impacts > 2100 + 5-year rebound	$436	$290	$201	$373	through 2100		levels model, 5-year rebound
5lag + No impacts > 2100 + 10-year rebound	$527	$348	$239	$450	through 2100		levels model, 10-year rebound
5lag + No impacts > 2100 + 20-year rebound	$696	$452	$306	$590	through 2100		levels model, 20-year rebound

Scenarios with “Growth at 2100 rate” use SSP3 estimates of country-year-level growth through 2100 as the baseline growth rate, extending the estimates in 2100 through 2300 to estimate impacts during that time period. “No impacts > 2100” assumes impacts stop in 2100, and “No growth effects > 2100” assumes that temperature does not impact the growth rate after 2100 but that the accumulated wedge by 2100 in the perturbed versus baseline GDP level is sustained. See Fig S1 for a schematic. Ramsey discounting uses values calibrated to a 2% near term rate, following ref. 47. The column “post-2100 growth” indicates the counterfactual growth rate assumed for economies after 2100. Reported SC-CO_2 estimates in this table do not precisely match those in Fig. 2e, as Fig. 2e estimates are median estimates from a distribution that considers full climate and regression (damage function) uncertainty. For computational tractability, the values reported here combine median estimates from the climate model ensemble with regression point estimates. See Supplemental Methods for additional scenario detail.