Response to Request for Information Development of a Climate Superfund Cost Recovery Program for the State of Vermont

Respondent:

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1. Describe a stepwise process to identify responsible parties, determine their applicable share of covered greenhouse gas emissions, and determine the cost recovery demand amount as described in Act 122. In doing so, please identify the datasets (publicly available) and describe the methodology and research the approach is based on. Provide an evaluation of the comprehensiveness and accuracy of those data sets. If appropriate, evaluate the utility of using additional information not publicly available to determine cost recovery demands.

The State has several options available for (1) identifying responsible parties, (2) determining their applicable share, and (3) determining the cost recovery demand amount, as described in Act 122, briefly outlined here and more fully detailed below.

1. To identify responsible parties:
    a. A first approach is to use existing, peer-reviewed and/or publicly available emissions data of company-level fossil fuel production, assessing the companies that exceed the emissions threshold in the law.
    b. A second approach could have the State ask major fossil fuel companies to furnish documentation of their emissions over the covered period.
    c. A third approach could be a mix of (a) and (b), taking existing firm-level emissions data as given, and providing companies with an opportunity to update those numbers.
2. Determining the applicable share of covered emissions requires dividing a company's emissions by peer-reviewed, consensus-based, scientific estimates of total covered emissions, meaning fossil fuel emissions from January 1, 1995 through December 31, 2024.
3. Determining the cost recovery demand amount is detailed in response to Question 2, below, a function of how much damage is attributable to each party's applicable share of covered emissions.

1. Identifying responsible parties:

Per the law, a responsible party is an "entity or successor in interest to an entity that during any part of the covered period was engaged in the trade or business of extracting fossil fuel or refining crude oil and is determined by the Agency attributable to for more than one billion metric tons of covered greenhouse gas emissions during the covered period. The term responsible party does not include any person who lacks sufficient connection with the State to satisfy the nexus requirements of the U.S. Constitution."

There are three elements to this definition that I see: (1) responsible parties generate emissions through the production and sale of fossil fuels; (2) they have a threshold of emissions of 1 billion tonnes; (3) they have sufficient nexus with the State, presumably based on commerce and sales tax laws. I cannot speak to (3), but discuss (1) and (2) below.

a. Using publicly available emissions data: There are at least two publicly available datasets, one of which is peer-reviewed (Heede 2014), that compile the historical greenhouse gas (GHG) emissions of major fossil fuel firms associated with the production and sale of their products. The State can simply use these data as estimates of emissions contributions over the covered period, removing entities that do not meet the 1 billion tonne threshold in the law.

- The **Carbon Majors Database (CMD)**[1] uses firms' self-reported production data (e.g., annual reports, Securities and Exchange Commission filings) as well as reputable third-party sources (e.g., the U.S. Energy Information Administration) to estimate annual-scale Scope 1 (direction operational) and Scope 3 (combustion of marketed products) emissions from 122 of the world's largest oil, gas, coal, and cement producers traceable to the total volume or mass of fossil fuel (e.g., barrels of oil or tonnes of coal) extracted by each firm. The database spans back to 1854, covering 72% of anthropogenic carbon dioxide (CO_2) and methane (CH_4) emissions since the start of the Industrial Revolution. The emissions from these fuels are calculated using widely-accepted "emissions factors" from the Intergovernmental Panel on Climate Change (IPCC)[2], which estimate the amount of CO_2 and CH_4 released when those fuels are combusted. The Carbon Majors process also accounts for additional sources of direct production emissions, such as the flaring of CO_2 or CH_4 at oil and gas facilities and fugitive methane emissions from extraction sites, and adjusts for non-energy uses of fossil fuels, such as the production of petrochemicals.

- The **Columbia Center on Sustainable Investment (CCSI)**, a joint center of Columbia Law School and Columbia Climate School, takes a complete supply chain approach to estimate the historical carbon footprint of 6 oil "supermajors" – BP, Chevron, Eni, ExxonMobil, Shell, and TotalEnergies – from 1980 to 2019[3]. Rather than the extraction-based analysis of the Carbon Majors Database, the CCSI method uses a mix of quantitative models and reported data on global oil refinery outputs and sales volumes to estimate the entire life cycle of fossil fuel emissions, from initial exploration and drilling to processing to transport to final combustion. Unlike the CMD, which provides both CO_2 and CH_4 emissions, the CCSI database reports only carbon dioxide equivalent (CO_2-e), which standardizes various greenhouse gasses by their global warming potential, typically until 2100. Additionally, CCSI reports only emissions from oil production and sales, and therefore does not include emissions from gas, coal, or cement by the 6 firms or their subsidiaries.

b. Solicit emissions data from firms: A second approach could see the State directly solicit emissions numbers directly from the entities themselves. Compiling a list of entities would be relatively straightforward given publicly available information on investor-owned companies. From that list, which could be ordered by their current stock price, which would be reflective in part, of historical production and sale of fossil fuels, one would have a triaged list of companies to contact to ask for compliance with the law.

c. Combine a. and b.: A third approach to determining responsible parties could see combining approaches a. and b., detailed above. One can use, for example, the CMD data as a basis, and provide companies the opportunity to update those emissions numbers, or solicit emissions numbers for the most recent years, which are not yet reflected in data like those from CMD. As an aside, it is widely understood that the emissions reported in both of the above databases, or that solicited directly from firms, are likely underestimations of firms' real-world emissions.

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[1] https://carbonmajors.org/

[2] https://www.ipcc-nggip.iges.or.jp/EFDB/main.php

[3] https://ccsi.columbia.edu/content/oil-supermajors-carbon-footprint-refining-sales-climate-change

2. Determining their applicable share:
Knowing what percentage of emissions over the covered period that is attributable to each of these firms is a means to estimating their applicable share. Irrespective of the approach taken above, a., b., c., or some other approach, the denominator against which each firm's emissions are relativized (i.e., turned into percentages) remains the same: total covered emissions, meaning total fossil fuel emissions between January 1, 1995 and December 31, 2024.

Estimates of total covered emissions can come from peer-reviewed consensus-based data, such as those generated by teams of scientists around the world and widely used in the scientific community such as in the United Nations Intergovernmental Panel on Climate Change (IPCC) Assessments and the United States National Climate Assessment (USNCA).

Briefly, fossil fuel contributions to total emissions are generally calculated by combining measurements of atmospheric CO_2 concentrations, the land and ocean carbon sinks, land-use change, and energy statistics to estimate anthropogenic emissions and then divvy them up among major sectors. The Community Emissions Data System (Hoesly et al., 2018), which was used as input data to the historical global climate model simulations for the most recent IPCC assessment report, contains annual estimates of total emissions of CO_2, CH_4, and other GHGs. Other widely used datasets include the Global Carbon Budget (Friedlingstein et al., 2023), which is an annual, peer-reviewed report that employs the methods described above to estimate total anthropogenic carbon emissions from fossil fuels and land-use change.

3. Determining the cost recovery demand amount:
Determination of the cost recovery amount requires an attribution of the damages associated with the covered emissions.

The law notes that "the cost recovery demand shall be equal to an amount that bears the same ratio to the cost to the State of Vermont and its residents, as calculated by the State Treasurer pursuant to section 599c of this title, from the emission of covered greenhouse gases during the covered period as the responsible party's applicable share of covered greenhouse gas emissions bears to the aggregate applicable shares of covered greenhouse gas emissions resulting from the use of fossil fuels extracted or refined during the covered period."

My interpretation of this section is that the Act suggests the possibility of using a linear apportioning of damages to responsible parties. This means that if a responsible party's applicable share equals 1% of covered emissions, then that party's cost recovery demand amount is equal to 1% of total damages attributable to he covered emissions. This is a straightforward accounting with a rational basis, though I think there is more than one way to do this that would be consistent with the law.

In particular, the cost recovery amount could be calculated in at least three ways, though there are likely more. All three I outline below share the same principle: the idea is to compare the world as it is, with all emissions and climate harms and damages, to a simulated world where a particular set of emissions is removed (**Figure 1**). Scientists call this approach a "leave-one-out" simulation. Such simulations are performed with climate models, as detailed more fully in answer to Question 2, below.

The first approach to determine the cost recovery amount is straightforward, involving the comparison of two worlds: the world as it has been in terms of climate hazards and damages including the covered emissions, and the world as it would have been if those emissions had never occurred. Relying on a Treasurer's damage estimate to the State over the covered period from all covered emissions, the State could then simply assign responsibility proportionally according to each party's relative contributions to those total emissions over the covered period.

A second approach to determine the cost recovery amount could directly use the firm-level data from CMD or CCSI after a determination of the list of responsible parties. This approach would then compare the world as it has been with all emissions, to a simulated world without each responsible party. The difference between the world as it has been and the world absent one responsible party's emissions is an estimate of the damages attributable to that responsible party over the covered period.

A third approach to determine the cost recovery amount would be to use a simulation framework that is instead agnostic about any one emitter. Instead it would use a simulation technique as above, assessing the damages to the State associated with different levels of different applicable shares of covered emissions (e.g., 0.5%, 0.75%, 1%, 2%, 3% and so on). This analysis would provide the State with a simple look-up table of the cost recovery demand amount corresponding to any conceivable applicable share of covered emissions. It would allow the State the ability to assign the cost recovery amount based on the State's determination of each responsible party's applicable share. This approach immediately provides a damage estimate associated with any relative percentage of covered emissions, allowing for straightforward association between the applicable share and the cost recovery demand amount.

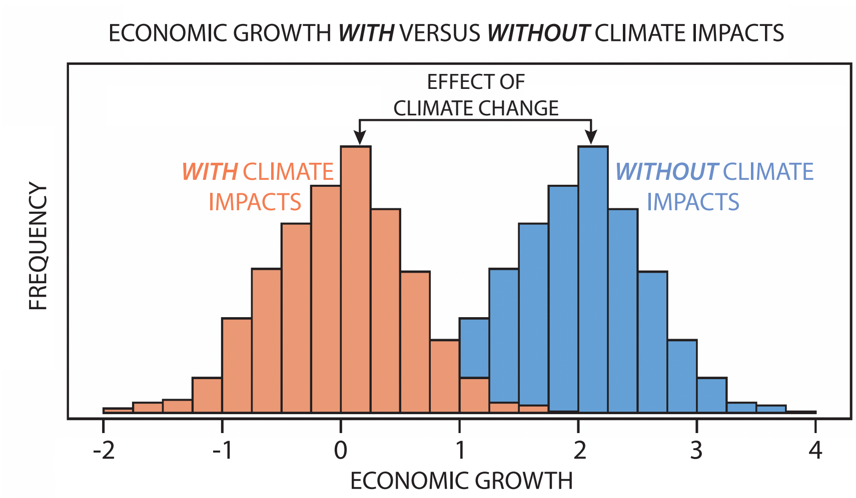

Figure 1 | Schematic illustration of the comparison being made to assess the costs of climate impacts. The orange bars represent the distribution of, for example, economic growth, that has been witnessed in the real-world. The blue bars represent the possible distribution of economic growth in a world where some set of emissions are removed, like those associate with a particular responsible party, or all covered emissions. The difference between these two distributions is the effect of climate impacts traceable back to the removed emissions, on some damage estimate, like economic growth. Note that the blue "counterfactual" distribution is created using model simulations of the relationship between emissions, warming, climate hazards, and damage.

2. Describe a stepwise process to develop the cost to Vermont of the covered greenhouse gas emissions. In doing so, identify the data sets available and describe the methodology and research approach to develop:

(1) a summary of the various cost-driving effects of covered greenhouse gas emissions on the State of Vermont including effects on public health, natural resources, biodiversity, agriculture, economic development, flood preparedness and safety, housing, and any other effects that may be relevant;

Briefly, there are (1) bottom-up or (2) top-down approaches to estimating the cost-driving effects of covered emissions on the State.

Bottom-up methods focus on the sectoral costs of emissions-driven climate hazards and then aggregate upward. Hazards such as heatwaves and extreme precipitation have well-documented impacts on a wide variety of systems, including public health, agriculture, labor productivity, and ecosystem services. A potentially tractable bottom-up approach is to consider state level damage estimates that are provided as part of the FEMA disaster declaration response, or to use re-insurance agency estimates of insured and uninsured losses for particular disasters in the State over the covered period. The State would then would likely need to furnish, through, for example, a traditional climate attribution, that the event was made possible or worse by covered emissions. Such an analysis would tie disasters individually back to particular covered emissions and potentially, responsible parties. For example, an analysis could consider the insured losses associated with the 2023 summertime floods in the State, or the loss estimate provided by the Governor in order to issue a FEMA disaster declaration. These losses could be aggregated across sectors to provide an estimate of the total insured losses or total damages from the floods. Then a separate extreme event attribution could assess how much worse the floods were owing to the covered emissions by comparing the precipitation totals in the world as it was relative to a world with the covered emissions removed. Then the State could apportion cost recovery demand amounts proportionally based on that event. A key question for the State to consider in a bottom-up accounting of the costs from emissions is what sets of extreme events should be considered, what sectors to consider, how damages should be counted (insured versus uninsured losses, for example) and how to most appropriately aggregate costs across sectoral impacts to estimate the full damages from emissions-driven climate change.

Top-down methods that use macroeconomic indicators, such as per capita gross domestic product (GDPpc) and GDPpc changes in response to climate hazards also represents a tractable approach. This approach is used by many peer-reviewed studies and is presented in consensus-based scientific assessments, such as the IPCC's 6th Assessment Report (AR6) and the USNCA; it is also the approach with which I am most familiar. The approach, rather than estimating individual losses in particular economic sectors, instead focuses instead on estimating the economic growth changes attributable to emissions-driven climate change and its hazards, like floods, or a particular flood. This approach, rather than aggregating local costs upward and tracing the applicable share back to individual parties, instead estimates how much economic growth was depressed or amplified by the climate hazards under consideration. Essentially, it positions one to answer questions of the following nature: how much more would Vermont's economy have grown in dollars in 2023 and beyond, were it not for the historic flooding that shuttered businesses, damaged homes and infrastructure, destroyed crops, and created public health risks? In the absence of flooding, the public and private capital that was poured into disaster recovery and adaptation could have been instead put towards productive growth (e.g., expanding Vermont's housing stock or investments in new businesses), rather than attempting to restore the economy to its status quo before the floods (e.g., repairing flood-damaged housing and washed-out roads). That foregone economic growth is a measure of the costs of the hazard that subsumes the direct damages from the hazard, the costs of repairs, and the productivity foregone. Because the method is top-down, one can use a single attribution of how different levels of emissions shape a the magnitude of the hazard (e.g., floods) and a single "damage function" (discussed below) that relates the hazard to economic damages (e.g., GDPpc growth). As such it provides a straightforward and integrated way to trace the costs of all floods or heatwaves or droughts back to a particular set of emissions, such as those originating from a responsible party. As with a bottom-up approach, a top-down approach is likely a conservative lower bound on the true costs, given non-market considerations such as ecosystem services.

This top-down approach relies on identifying a highly generalizable shared macroeconomic response to a hazard, often using national- or global-scale datasets[4], which are less limiting than state-level sectoral data. This generalizable macroeconomic response is called a "damage function." It is often presented in terms of marginal effects, meaning a damage function can tell one, for example, how much marginal economic loss is attributable to a 1% increase in extreme precipitation or a 1°C increase in the five hottest days of the year. The power of the damage function is its generalizability, and thus is can then be applied to many contexts, such as estimating the aggregate economic impacts on Vermont during the covered period of 1995 to 2024, or the costs of a specific event, such as the Summer 2023 floods.

There are several publicly-available datasets of indicators that could be used in this analysis. Important work on the economic costs of heatwaves (Callahan & Mankin, 2022) and extreme precipitation (Kotz et al., 2022, 2024) has leveraged global GDP data at the subnational (e.g., states in the United States or provinces in Canada) scale, with the ability to parse out impacts on the agricultural, manufacturing, and services sectors (Wenz et al., 2023). For the United States, the Bureau of Economic Analysis provides state-level GDP data with a high level of sectoral detail[5], potentially allowing for a more detailed analysis of where the costs of climate change are borne.

Alternatively, the empirical methods detailed below can also be used to assess more targeted damages from responsible parties' covered emissions. For instance, agroeconomic data from the U.S. Department of Agriculture[6] can be used to quantify the agricultural costs of changing climate risks (Diffenbaugh et al., 2021) and data on insured and uninsured flood losses can be used to understand the increase in flood damages attributable to precipitation change (Davenport et al., 2021). This means that the top-down approach could also provide sectoral-based estimates of losses traceable back to particular sets of emissions, as detailed in response to the next question.

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[4] See, for example, subnational GDP data here: https://zenodo.org/records/7017229
[5] https://united-states.reaproject.org/data-tables/
[6] https://www.nass.usda.gov/

(2) a categorized calculation of the costs that have been incurred and are projected to be incurred in the future within the State of Vermont of each of the effects identified under subdivision (1) of this section; and

The State has a number of options here, including using the Social Cost of Carbon (Climate Analytics, 2023; Burke et al., 2023). I would point the State to those resources for details on those kinds of approaches, which I believe are entirely rational for this effort.

Below, I detail the recent methodological advances have made it possible to perform an "end-to-end" attribution of historical climate damages. This approach can also be extended to consider future climate damages associated with historical covered emissions.

Briefly this approach identifies the economic costs arising from the climate change associated with individual parties' emissions or identifying the relative emissions over a particular period necessary to manifest climate damages (see Callahan & Mankin, attached). This process requires three fundamental mappings: (1) the first links particular emissions to a warming response; (2) the second links this warming response to a climate hazard response, like floods or heatwaves; and (3) the third links the climate hazards to economic damages (**Figure 2**).

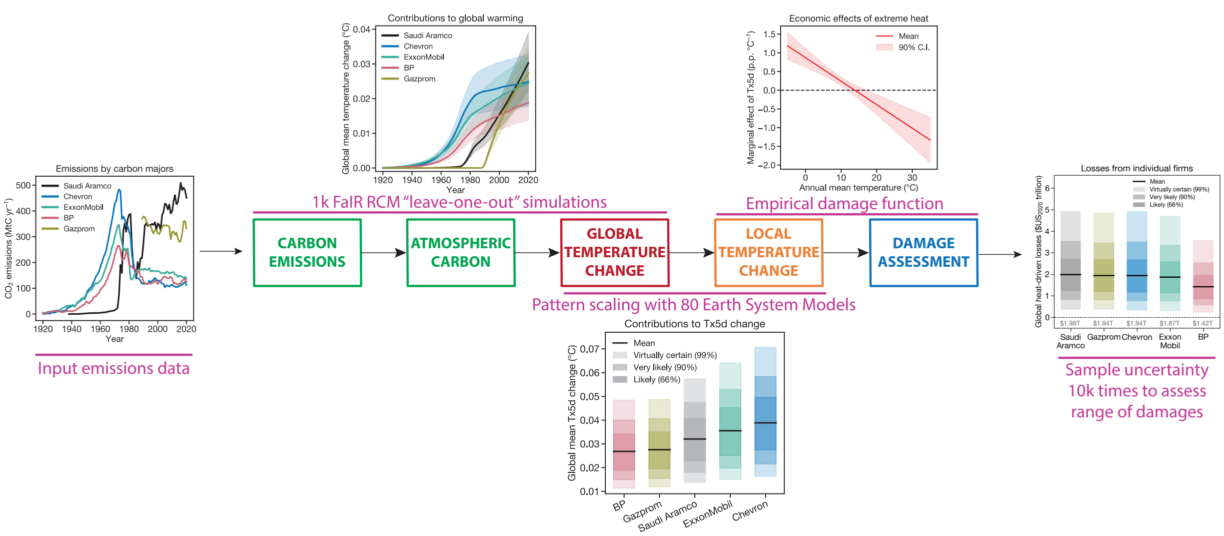

Figure 2 | Diagram illustrating the method to assess the costs of extreme heat traceable back to specific emissions (adapted from Callahan & Mankin, in press, 2024). The first step simulates temperature changes in world with all emissions included; this control simulation becomes the basis for evaluating the change in warming when one emitter or a set of emissions are removed (in a "leave-one-out" simulation). The approach can then use annually-resolved emissions data (like those from CMD, discussed in response to Question 1, above), and perform a number of simulations where one emitter is removed. These two steps are shown for the top five emitters in the CMD database using a climate model called the Finite Amplitude Impulse Response Model (FaIR), a Reduced Complexity Model (RCM) used in the IPCC. With the global temperature change attributable to particular emissions, one can estimate how such warming affects the magnitude of the hazard, here the five hottest days of the year (Tx5d), or "local temperature change". One can then use a "damage function" that relates economic productivity changes to such extreme heat to assess the local-scale economic changes due to particular emissions, performing the "damage assessment."

1. **Emissions to warming**
   Determining emitters' contributions to global warming requires a means of estimating the counterfactual: "what might global temperatures have been absent a party's emissions?" Reduced complexity climate models, which simulate the global temperature response to GHG emissions and other climate forcings,, provide a means of estimating these counterfactuals. They can be run a) with all historical emissions and b) with all historical emissions *minus those of a particular emitter over a particular time period* (using the emissions datasets described above). The difference between these two scenarios represents the contribution of that party's emissions to global temperature change. In the "emitter-agnostic" framework, different percentages of GHG emissions can be subtracted to estimate the warming caused by, say, a party responsible for 5% of global emissions over the covered period. Uncertainties in the emissions-temperature relationship can be systematically sampled using established protocols and propagated through subsequent steps of the analysis.

2. **Warming to hazards**
   A change in global temperature does not produce the same climate response everywhere. The next step in the process, therefore, is to determine the local change in the risk of climate hazards resulting from an increase in global temperature. This can be accomplished using a technique known as pattern scaling, in which fully-coupled global climate models are used to estimate the spatially-explicit pattern of changes in a hazard, such as heatwaves or extreme precipitation, in response to an increase in global temperature. Combining steps 1 and 2 provides an answer to the question: "How has the warming resulting from the emissions of a particular party affected the local risk of climate hazards?" As with the previous step, uncertainty in the relationship between global temperature and local changes in hazard can be systematically sampled and propagated. For Vermont, a particular focus would be on how extreme precipitation and floods have been shaped by emissions, meaning a hazard model that links warming to extreme precipitation would be developed.

3. **Hazards to damages**
   The final step is to map climate hazards onto their economic consequences by constructing what is commonly referred to as a "damage function". This function can be estimated using peer-reviewed econometrics techniques such as fixed effects panel regression, fit to observed historical climate and economic data. Such functions have already been constructed to estimate the effects of extreme heat (Callahan & Mankin, 2022) and precipitation (Kotz et al., 2022, 2024) on economic growth. As mentioned previously, it is necessary to construct these functions using available national or global data[7] to identify the generalizable response, which can then be applied to specific cases. One can then combine these statistical models fit to observed data with the counterfactual scenarios of climate hazards generated in steps 1 and 2 to estimate what growth would have been absent the changes in climate hazards arising from the global warming caused by a party's emissions. The difference between these historical and counterfactual estimates of economic growth represents the economic damages attributable to that party's emissions, thus completing the chain.

[7] See, for example, subnational GDP data here: https://zenodo.org/records/7017229

This general framework can be applied to a number of state- or county-level economic indicators – from whole-economy GDP to specific sectors to flood damages to crop yields – and climate hazards to determine attributable damages either over a specific period, such as 1995-2024, or for a particular event, such as the 2023 flooding in Vermont. The approach would be to select a few emissions-driven hazards that have impacted the State, like floods, heatwaves, and droughts, and provide attributions of how emissions have impacted their magnitude in Vermont and then aggregate across hazards.

I note that climate models already provide an approach to physically connect warning and a hazard like extreme precipitation (IPCC, 2021). There too are damage functions that link extreme precipitation to changes in economic productivity (Kotz et al. 2022) and there are approaches to aggregate damages across hazards (Kotz et al. 2024). The extension here would be to apply these techniques in a singular framework (outlined in **Figure 2**) to estimate how the covered emissions have impacted Vermont's economy.

Within this approach, there is also the possibility to provide an "emitter-agnostic" estimate of cost recovery demand amounts. This approach would calculate the damages to Vermont associated with particular levels of emissions (e.g., 0.5% or 1% of covered emissions beyond the 1 billion tonne threshold in the law). One can then use the publicly available data from the CMD, CCSI, or solicit data directly from firms directly to identify the set of firms exceeding this threshold as responsible parties. As part of the required registration process under Section 599a, the State can require responsible parties to provide emissions data.

It is worth emphasizing that the outlined approach yields only estimates of *historical* damages from *historical* emissions. Yet the long-lived nature of carbon dioxide in the atmosphere means emissions during the covered period will continue to warm the planet and cause further economic damages in the future. It is possible to combine the econometric modeling described above with plausible scenarios of future economic growth trajectories and trade-offs to estimate future damages resulting from the committed warming of these past emissions (Burke et al., 2023; Callahan & Mankin, 2023).

One approach to doing so is to use economic projections of GDP growth changes in the future as a baseline against which to calculate damages from historical emissions. These data are part of the Intergovernmental Panel on Climate Change scenario generation process, called Shared Socioeconomic Pathways (Riahi et al., 2017). This approach has been successfully applied in the literature to assess the future economic costs of El Niño, a climate oscillation that generates extreme weather (Callahan & Mankin, 2023) and could be applied here.

(3) a categorized calculation of the costs that have been incurred and are projected to be incurred in the future within the State of Vermont to abate the effects of covered greenhouse gas emissions from between January 1, 1995 and December 31, 2024 on the State of Vermont and its residents. Provide an evaluation of the comprehensiveness and accuracy of available data sets, methodology, and research to develop the cost to Vermont of the covered greenhouse gas emissions.

The costs of adaptation are not something I have expertise in. With adaptation costs in hand, and estimates of how they alter the marginal damage associated with a hazard, one can update future damage estimates using the adaptation-adjusted damage function.

3. Please provide any other materials, suggestions, cost, and discussion you deem appropriate.

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Carbon majors and the scientific case for climate liability

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Will it ever be possible to sue anyone for damaging the climate? Twenty years after this question was first posed, we argue that the scientific case for climate liability is closed. Here we detail the scientific and legal implications of an "end-to-end" attribution that links fossil fuel producers to specific damages from warming. Using Scope 1 and 3 emissions data from major fossil fuel firms, peer-reviewed attribution methods, and advances in empirical climate economics, we illustrate the trillions in economic losses attributable to the extreme heat caused by emissions from individual firms. Emissions linked to Chevron, the highest-emitting investor-owned firm in our data, for example, very likely caused between $791 billion and $3.6 trillion in heat-related losses over 1991-2020, disproportionately harming the tropical regions least culpable for warming. More broadly, we outline a transparent, reproducible, and flexible framework that formalizes how end-to-end attribution could inform litigation by assessing whose emissions are responsible and for which harms. Drawing quantitative linkages between individual emitters and particularized harms is now feasible, making science no longer an obstacle to the justiciability of climate liability claims.

Once climate attribution emerged as a field of inquiry, scholars both scientific[1] and legal[2] raised questions about whether climate liability claims could be pursued via common law[3]. Extreme weather events—floods, droughts, extreme heat, and more—upend lives, undermine livelihoods, and damage property. If such extremes could be tied to climate change, the logic goes, injured parties could seek monetary or injunctive relief through courts[1]. Over the last two decades, science and law have been engaging a set of challenges that take climate liability from a thought experiment into a realistic practice.

Scientifically, the focus has been on developing standardized methods to codify a scientific consensus on the role climate change plays in amplifying extreme events, as reflected in the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC)[4]. Such "consensus" methods are widely accepted and used in the scientific community, having been applied in peer-reviewed publications to a variety of events[5–7] from heat waves[8,9] to droughts[10,11], floods[12], hurricanes[13,14], and wildfires[15]. This science has advanced such that events are now attributed in near-real-time[16,17] or in advance using forecast models[18]. As courts rely on scientific syntheses from organizations like the IPCC[19], the consensus developed around event attribution methods[20] suggests they could meet legal standards for admissibility[21]. By revealing the human fingerprint on events previously thought to be "acts of God," attribution science has helped make climate change legally legible[22–24].

Legally, a focus has been on assessing whether climate attribution is compatible with existing causation and standing frameworks. Over 100 climate-related lawsuits have been filed annually since 2017; many more will come. The legal theories undergirding these cases vary widely, shaping who is liable and for what conduct[25]. For example, some cases seek to accelerate climate policy under the theory that people have the right to climate stability[26]. Others use agreements like the Energy Charter Treaty to stymie climate action[27]. Some cases center on the disinformation and climate denialism fomented by fossil fuel firms[28], while others contend that firms have failed to adequately disclose climate risks to investors[29]. Other climate-related cases fall outside these categories and novel legal theories will continue to emerge.

Here we focus on the theory that people can hold emitters liable for the damage wrought by warming[1,30]. Such cases mirror efforts to hold industries like tobacco[31] and pharmaceuticals[32] liable under legal standards like the duty of care, public nuisance, failure to warn, or strict liability. Because of the broad financial, legal, and climatic implications of these suits[33], assessing the scientific support for their claims is critical. While these cases—like disinformation-focused cases—use evidence that fossil fuel firms have long been aware of climate change, they specifically attempt to tie these firms to the human costs of their emissions. For example, an Oregon county has sued several fossil fuel firms for amplifying the 2021 Pacific Northwest heat wave and its resulting economic and health costs[34]. New York City and Rhode Island have brought similar claims[35,36]. Firms like ExxonMobil are a frequent target, with plaintiffs ranging from residents of flooded Alaskan villages to Puerto Rican municipalities damaged by Hurricanes Irma and Maria[37,38]. While attribution science is relevant to wider climate policy, accountability, and justice, it is particularly helpful to this theory of liability, as both initial standing questions and the merit stages of cases may require plaintiffs to show causal linkages between emitters and particularized injuries.

The fate of climate liability cases remains uncertain: success, failures, and appeals abound. In 2015, the nonprofit Urgenda won a key ruling that the Dutch government breached its constitutional duty of care by not reducing emissions[39]; more recently, a court ruled that Montana's efforts to deregulate emissions violated its residents' right to a healthy environment[40]. In contrast, New York's case against five fossil fuel companies was dismissed in 2018 on the grounds that judges should not make climate policy. As cases laboriously wind their way through courts around the world, litigation shows no signs of slowing[25]. And as extreme events intensify and losses accumulate—and as political action on climate change lags the urgency of the crisis—more people are turning to the legal system for relief[25]. There is talk of a "coming wave of climate legal action" for which courts are woefully unprepared[41].

Here we illustrate how climate attribution that goes from emissions to impact at the corporate scale is now possible, addressing a major hurdle to climate liability. Using peer-reviewed methods, we estimate the economic losses suffered due to the extreme heat caused by emissions from major fossil fuel firms ("carbon majors") over 1991 to 2020. We present two actionable approaches for the end-to-end attribution framework: one considering the accumulated harms from a hazard, like heat waves over 1991-2020, and another considering the harms from a specific event, such as the 2003 European heat wave. The cumulative and event-specific approaches can be applied to myriad scales of emitters and claimants, and extended to different classes of hazards, from heat waves as here, to floods, droughts, sea level rise, and more. We also show how each approach can be applied in a way that is agnostic about any particular emitter, allowing communities to assess responsibility for losses rather than naming parties prima facie. We argue that while this type of end-to-end attribution will provide clarity in some respects, the ultimate question of whether climate liability is justiciable will be resolved in courts. More widely, we advocate for the creation of a transparent and objective science-based initiative to provide peer-reviewed and reproducible attributions and expert testimony to ensure courts can evaluate these emerging legal claims.

Attribution science and causation

To sue over an injury, a litigant typically must demonstrate a causal connection between the action of the defendant and the plaintiff's injury, sometimes via meeting a "but for" standard: "but for the actions of the defendant, the plaintiff would not have been injured"[2]. Demonstrating "but for" causality in the context of climate impacts is difficult[2]: Atmospheric carbon dioxide is well-mixed and many parties have emitted; emissions and impacts are dislocated in space and time[42]; the causal chain from emissions to impacts is nonlinear[43]; and uncertainties compound from emissions, to warming, to hazards, to impacts[44]. Such causal ambiguity is not unique to the climate. It is a feature of assessing liability for environmental hazards more widely, which has led to a tiered legal strategy of establishing both "general" and "specific" causation[45]. General causation assesses whether a hazard could cause a type of harm, such as the way asbestos increases cancer risk. It is often held to a high standard of scientific certainty[46]. Specific causation, on the other hand, considers whether a defendant's actions caused the particular injury to the litigant: whether a specific worker's cancer was caused by asbestos in their workplace, for example. In some jurisdictions, specific causation is held to a less-strict "more likely than not" standard[45].

Resolving causality in climate liability could take many forms beyond establishing "but for" causation. One can, for example, assign liability proportionally according to emitters' contributions to total emissions[47,48], using deductive storyline-type approaches about how emissions-driven warming has shaped particular types of climate impacts[49], or based on the social cost of carbon[50,51]. These approaches alleviate the need to show that the injury would not have occurred without a specific emitter's contribution and is generally consistent with the original formulation of climate liability: if global warming has tripled the risk of a flood, then warming is responsible for two-thirds of its risk, making contributors proportionally liable for two-thirds of its harm[1]. Such a philosophy accords with the extreme climate event attribution field, which links the risk or magnitude of an event to global warming. Yet proportional contributions to global warming may not translate into equivalent contributions to particularized injuries. Nonlinearities among warming, climate extremes, and people imply that the same emissions can have different effects at different times[52], and cascading uncertainties mean that the signal of an individual emitter may not rise above the noise in a complex climate system[53]. Furthermore, some jurisdictions have limited the application of market-share liability theories[54] and courts may be reluctant to accept this approach in place of more traditional "but for" causation standards[2].

Such realities clarify the need to scientifically demonstrate "but for" causation, specifically the linkage between an individual emitter and a particular injury. The lack of end-to-end attributions has been cited as a barrier to climate litigation[2,22,55,56] and has been used by fossil fuel firms to argue that plaintiffs lack standing to sue over climate damages[57]. As a result, despite the important role for existing attribution science in informing approaches such as proportional liability, scientific approaches that demonstrate causal linkages from emitters to impacts have been termed the "Holy Grail" of climate litigation[56].

Advances enabling "end-to-end" attribution

Despite these challenges, two recent advances make end-to-end climate attribution possible. Firstly, physical science can more confidently connect individual emitters to local climate change. Secondly, social science can more confidently connect local climate change to socioeconomic outcomes.

On the first, "source attribution" research[58] has linked emissions from countries[59–61] and carbon majors[62] to increases in global mean surface temperature[63] (GMST), sea level rise[63], ocean acidification[64], and local extreme climate events[65–67]. Source attribution often uses an emissions-driven climate model to simulate historical and counterfactual climates, where the latter is the same as the historical save for the removal of one emitter's time-varying emissions (i.e., a "leave-one-out" experiment). The difference between the two simulations represents the contribution of the removed emitter, providing a test of "but for" causation[2]: *but for the emissions of this actor, the climate would have been thus*. One could perform these simulations with a coupled Earth system model[68], but such models are opaque and computationally expensive. A computationally tractable approach is to use reduced-complexity climate models (RCMs) that accurately simulate the behavior of the Earth system using a smaller number of equations.

RCMs[69–72] have long been part of the consensus methods used in IPCC assessment reports[73] for purposes like simulating mitigation pathways[74]. More recently, RCMs have been applied to source attribution for tasks such as simulating country-level contributions to global mean temperature change[50,53]. RCMs are zero-dimensional, lacking spatial information. But peer-reviewed methods like pattern scaling[75–77] provide robust statistical relationships between global and local climates that allow scientists to estimate local temperature change based on RCM output[78]. Together, RCMs and pattern scaling link the contributions of individual emitters to local temperature changes in an efficient, transparent, and reproducible manner[50,53,67].

Yet local climate changes do not inevitably imply particularized injuries. To connect individual emitters to impacts, researchers must quantify the human consequences of local climate changes. Enter the second major advance: more robust quantifications of the socioeconomic impacts of climate change[79]. Recent peer-reviewed work has used econometrics to infer causal relationships between climate hazards and outcomes like income loss[79], reduced agricultural yields[80], increased human mortality[81,82], and depressed economic growth[83–85]. In the attribution context, these causal relationships have been applied to quantify the historical costs of flooding[86], crop losses[87], and reduced economic output from increases in average[88] and extreme[89] temperatures. These methods are also consensus-based, reflected in synthesis reports like the fifth U.S. National Climate Assessment[90].

While the "fraction of attributable risk" (FAR) metric is another consensus-based attribution approach applied widely to extreme events and their impacts[91–95], it is not necessarily suitable for quantifying the influence of climate change on people, which are often nonlinear and can depend on event intensity rather than probability[43,96–98]. Approaches that better-resolve hazards and costs are helpful to directly connect GHG emissions to socioeconomic losses. For example, Strauss et al.[99] relied on hydrodynamic modeling and property damage estimates to quantify the anthropogenic contribution to damages from Hurricane Sandy in New York, an approach more tailored and nuanced than the FAR. Our more generalized framework uses econometric dose-response functions that parameterize relationships between climate hazards and human outcomes, but it could easily be adapted to other settings such as flooding from a particular storm.

Here we show that emissions traceable to carbon majors have increased heat wave intensity globally, causing quantifiable income losses for people in subnational regions around the world. Our analysis uses reductions in GDP per capita growth to represent particularized injuries, consistent with recent suits in Oregon[34] and several Puerto Rican municipalities[37]. Both of these cases cite the severe economic burden associated with extreme climate events, so scientific attribution of that claim is potentially valuable, even if it does not fully resolve the precise damages in those cases. Yet the power of the attribution framework we present is that it is flexible, transparent, and modular, meaning that other damages (e.g., adaptation costs based on alternative damage functions), other hazards (e.g., tropical cyclones), and other time periods (whether for emissions or damage accounting) can be included to support particular attribution questions as the scientific, legal, and climatic landscapes develop.

An end-to-end attribution framework

The oil, coal, and gas extracted by fossil fuel firms have produced substantial emissions of carbon dioxide and methane over the last 100 years (Fig. 1a). Between 1920 and 2020, Saudi Aramco, Chevron, and ExxonMobil produced a cumulative total of 16.6, 14.2, and 13.2 GtC in CO_2 emissions, respectively. Emissions data are drawn from the publicly available Carbon Majors database[62,100], which leverages public production information from sources such as company regulatory filings as well as standard emissions factors. These data include both Scope 1 and Scope 3 emissions, which includes emissions from the production and combustion of the fossil fuels sold by these companies. We note these emissions ledgers are likely conservative: they do not include Scope 2 emissions or leaks and spills, and are subject to under-reporting, especially early in the 20th century[62]. While we only illustrate emissions since 1920 in Fig. 1, our analysis uses all available firm-level data (Table S1).

To link these firms to specific impacts from their emissions, we leverage a three-step peer-reviewed end-to-end attribution framework[53] (Methods). The goal of this framework is to construct a “counterfactual” world in which an emitter’s contribution to local extreme heat is isolated and removed. We first use the FaIR RCM[72] to translate firms’ emissions into GMST changes (Fig. 1b); next, we apply pattern scaling[77] to calculate resulting subnational changes in extreme heat, defined here as the temperature of the five hottest days in each year, or “Tx5d” (Fig. 1c); lastly, we apply an empirical damage function to calculate income impacts of these extreme heat changes[89] (Fig. 1d). We compare heat-driven economic damages between the historical and counterfactual worlds, with their difference being the firm’s contribution to damages. Non-climate factors, such as changes in the global oil trade, are held constant. Our analysis centers only the temperature effects of the emissions produced by carbon majors.

We first simulate historical GMST change using total emissions with FaIR v2.1.0 over 1000 times, sampling parametric uncertainty using IPCC-based parameter combinations[101]. In our counterfactual simulations, we re-simulate GMST change after subtracting each firm’s CO_2 and CH_4 emissions from global emissions. The difference between the observed and each firm’s counterfactual simulation represents the GMST change attributable to that firm (Fig. 1b), revealing that, for example, Chevron is responsible for ~0.025 °C of the >1°C warming in 2020. We then translate these FaIR-based GMST change time series into spatiotemporal patterns of Tx5d change using pattern scaling coefficients estimated from 80 Earth system model simulations, showing that, for example, ExxonMobil is responsible for a 0.036 °C increase in average Tx5d values over 1991-2020 globally (Fig. 1c).

Finally, we use an empirically derived damage function that generalizes the relationship between extreme heat intensity and economic growth[89] to estimate the impacts of firm-caused Tx5d changes (Fig. 1d). This relationship varies as a function of regional average temperature: tropical regions lose more than 1 percentage point (p.p.) in growth for each 1°C increase in the intensity of the hottest five days in each year, whereas temperate regions experience modest effects[89] (Fig. 1d). While other factors such as sectoral composition and adaptive capacity may affect regional sensitivity to extreme heat, average temperature has been found to predict that sensitivity more effectively than average income, consistent with other work[84,102].

We calculate losses in the historical and leave-one-out simulations 10,000 times for each region using a Monte Carlo approach (Methods), taking their difference to calculate losses attributable to the emissions from each firm. Because changes in annual mean temperature shape the impacts of extreme heat, we also pattern-scale regional annual mean temperature. Our final calculations incorporate both changes in Tx5d itself as well as changes in the average temperatures that moderate the effect of Tx5d[89]. As a result, emissions increase both the intensity of extreme heat and its marginal damage by raising underlying average temperatures. The interaction between mean and extreme temperature explains why the pattern of heat-driven losses does not simply mirror that of the marginal effect of extreme heat, which shows benefits in high-latitude regions[89]. We also account for the economic rebound shown in previous work[89], whereby the effect of extreme heat is recovered after 2-3 years, meaning we do not assume permanent growth impacts of extreme heat.

In this analysis, we focus on the costs due to extreme heat as represented by Tx5d, rather than combining the total costs across myriad hazards[103,104], such as rainfall extremes[105] or sea level rise[99]. The first reason for this choice is legal: to date, litigation has often been motivated by a single hazard or high-impact event, such as an Oregon county's suit over the 2021 Pacific Northwest heat wave, likely due to the legal imperative to demonstrate specific causality. While combining damages from many hazards would better capture the overall costs of warming[103,104], it is inconsistent with the specificity that has motivated legal claims to date. As legal efforts evolve to consider multiple hazards or a more complete accounting of damages, so too could the attribution framework we present here. The second reason is physical: extreme heat is robustly linked to global warming[78] and has large and direct economic costs[89,106].

Heat wave damage from carbon majors

The global economy would be $28 trillion richer (90% [very likely] range: 12 – 49, in 2020 $US) were it not for the extreme heat caused by the emissions from the 111 carbon majors considered here (Fig. 2). Saudi Aramco is responsible for $2.05 trillion (90% range: 0.85 – 3.6) in global economic losses from intensifying extreme heat, and Gazprom is responsible for ~$2T (90% range: 0.83 – 3.6). The contributions from these two state-owned enterprises are due to their recent and rapid emissions (Fig. 1a), despite not making large contributions earlier in the 20th century. Chevron, ExxonMobil, and BP have caused \$1.98 trillion (0.79 – 3.6), \$1.91 trillion (0.77 – 3.4), and \$1.45 trillion (0.59 – 2.6) in losses, respectively (Fig. 2a). Investor-owned companies (e.g., Chevron, ExxonMobil) and state-owned enterprises (e.g., Saudi Aramco, Gazprom) are each collectively responsible for ~\$14T in losses (Fig. 2b). Ranges in these damage estimates arise from carbon cycle and climate uncertainties in the FaIR simulations and the parametric uncertainties from the pattern scaling and damage function. Yet the 99% range for each of the top five firms does not include zero (Fig. 2a), making it virtually certain that each has contributed to global heat-driven losses.

Losses can also be assessed at finer, more legally relevant regional scale, revealing inequities in the causes and consequences of global warming (Fig. 2c). Together, extreme heat from the five highest-emitting firms (Fig. 2a) has driven annual GDP per capita reductions exceeding 1% across South America, Africa, and Southeast Asia. In contrast, the United States and Europe—where Gazprom, Chevron, ExxonMobil, and BP are headquartered—have experienced milder costs from extreme heat. Owing to the dependence of Tx5d damages on mean temperatures, mid-latitude regions experience greater heat-driven losses as their average temperatures rise; the same holds for higher latitudes, but the losses are smaller. If we hold mean temperatures at their observed values and instead estimate damages from changes in Tx5d intensity alone, the pattern of damages becomes heterogeneous, with mild benefits in high-latitude regions rather than mild losses, reflecting the pattern of Tx5d marginal effects (cf. Fig. 2c, Fig. ED1). The gradient of losses increases equatorward irrespective of whether we allow mean temperatures to change (Fig. 2c, Fig. ED1), emphasizing the global inequity in extreme heat impacts and their spatial dislocation from the emissions that produced them.

We foreground a cumulative framing of end-to-end attribution, noting that an emitter's impact can encompass multiple events and years. However, much of climate attribution and liability is focused on exceptional singular events, like the 2021 Pacific Northwest heat wave[107]. A flexible end-to-end attribution framework should be able to account for individual extreme events in addition to cumulative exposure. Our approach does this, showing the contributions of carbon majors to four historic heat waves: India in 1998 (Fig. 3a, e), France in 2003 (Fig. 3b, f), Russia in 2010 (Fig. 3c, g), and the continental U.S. in 2012 (Fig. 3d, h). While each heat wave has been studied extensively (e.g., refs.[8,9,87,108,109]), the contributions of carbon majors have not yet been quantified.

Together, the top five firms increased the intensity of the five hottest days corresponding to those events by 0.08 °C, 0.11 °C, 0.27 °C, and 0.09 °C, respectively (Fig. 3a-d), and thus can be tied to losses from those events (Fig. 3e-h). For example, Chevron's emissions are responsible for \$1.9B (0.31 – 4.7), \$3B (0.05 – 7), \$2.8B (gains of 0.99 – losses of 7.7), and \$28.8B (4 – 61) in losses from the 1998 Indian, 2003 French, 2010 Russian, and 2012 American events, respectively. We perform these attributions by applying the observation-based generalized damage function to specific regions and years, a practice consistent with work that estimates how individual extreme events affect economic output[106] and the wider usage of deduction in climate attribution[49]. While any individual region or year will modestly deviate from the generalized response we estimate, the approach mathematically approximates their responses on average.

Collectively, these results provide the first estimate of the global economic toll that individual fossil fuel firms have produced due to the extreme heat caused by their emissions of carbon dioxide and methane. The veil of plausible deniability that carbon majors have hid behind for decades is threadbare.

Clarifying who is responsible

How could end-to-end attribution analyses like ours be used? Each case will differ and depend on the motivation of the litigants and their climate context. As presented in Figures 2 and 3, science can clarify "but for" causation at various scales across a class of hazards, like heat waves, or for a particular event, like the 1998 Indian heat wave. But it is also essential to clarify who is potentially liable. There are many emitters, and affected communities may want to know who is most liable for impacts they endure—whom do they name as defendant? A nation? A firm? A collective? A sector? This, too, science can help clarify.

To date, attorneys and litigants have often named defendants as part of the initial legal process, under the assumption that knowing a defendant's emissions is sufficient to make a claim. Our analysis makes clear, however, that what matters is not simply the magnitude of the emissions, but also the timescale over which they were released and the impact under consideration. Nonlinearities at each step from emissions to impacts imply that proportional contributions to global warming are not necessarily equivalent to proportional contributions to impacts. And yet calculating the contributions of all possible emitters could be costly. Legal work is expensive and time-consuming, and the need to retain experts could be a crucial barrier to the low-income or under-resourced communities who have the greatest claims for restitution.

Science can help claimants assess potential defendants in a transparent and low-cost way. As an example, we present a strategy for assessing who is responsible for cumulative losses from extreme heat (Fig. 4). Here, the analysis asks: "how much extreme heat damage is attributable to a given percentage of global emissions?" Our approach is straightforward: we repeat our leave-one-out simulations using idealized percent contributions to total 1850-2020 CO_2 and CH_4 emissions, rather than the emissions of any particular firm. Such an approach is actor- and scale-agnostic, meaning it simply presents the impacts associated with a given contribution to global emissions made over a given time period.

Global losses from extreme heat scale quasi-linearly with emissions contributions (Fig. 4a). Each additional percentage point contribution to total 1850-2020 CO_2 and CH_4 emissions generates an additional $834 billion in global economic losses from extreme heat in 1991-2020. Our generalized approach enables litigants to consider emitters at various scales quickly: any individual or group of emitters can be placed in this contribution-damages space to rapidly assess their attributable impacts. For example, the general relationship between contributions and heat wave damages can be used to link the top five firms (Fig. 4a, orange) or all firms (Fig. 4a, blue) to losses, based on collective emissions. Nations, economic sectors, or industries could equally be placed in this space to assess contributions to heat-driven losses.

Crucially, these losses depend on the time period over which the emissions are counted (Fig. 4b), demonstrating key choices that must be made by policymakers, litigants, and courts. If one's accounting begins in 1990, around the development of the scientific consensus on climate change[60], heat wave losses attributable to an actor contributing 5% of global emissions tally $2.5 trillion (90% range: 1.05 – 4.5), contrasting with the $4.2 trillion (1.7 – 7.5) when counting from 1850. Yet fossil fuel firms have accurately predicted climate change since the 1970s[110] and have since used their power and profit to cast doubt on the relationship between fossil fuels and warming[111]. If we use the 1977 date of the first reported successful projection of global warming by ExxonMobil[110], heat wave losses attributable to an actor contributing 5% of global emissions come to $3.3 trillion (1.4 – 5.8). These losses are all large, with 99% ranges that do not include zero, but can vary by >50% across start dates.

Remaining work and ways forward

By clarifying "what" damages and "who" is responsible, our attribution frameworks have flexibility and applicability to many contexts. Extreme heat is one of myriad climate impacts and the costs we assess are large. As science advances and new hazard models, damage functions, and climate impacts estimates are developed, such as extreme rainfall[105] or El Niño[112], these costs could be incorporated into a fuller accounting of climate damages attributable to emitters. Given the flexible, open-source nature of RCMs and the maintenance of preexisting pattern scaling libraries[75], such damage estimates can be easily ported into our framework to provide a more complete documentation of the costs attributable to particular emitters. On the other hand, some injuries motivating suits, such as the adaptation costs incurred by a municipality for local sea level rise, could require cost assessment approaches that are not only reliant on globally derived damage functions. In those cases, our emitter-based attribution framework can potentially provide quantitative estimates of how the hazard has been altered by particular emitters, but other mixed-methods approaches could be used to connect those estimates to the specific choices facing local decision-makers. The framework we advance here is flexible and its potential applications are broad.

Performing coordinated near-real-time end-to-end attribution following events would allow communities to understand the contributions of individual actors to the losses they suffer. Scientific enterprises like the World Weather Attribution[16] could be extended to include end-to-end attribution in their workflow, or could be a model for a new scientific body centered on assessing causation in climate impacts. Recent calls to operationalize extreme event attribution for loss and damage debates have been motivated by the consensus methods that have been developed for event attribution[20]. And just as event attribution has moved from a scientific thought experiment to the mainstream over the last twenty years, the same could be true of end-to-end attribution. A standing scientific body would be an essential resource for courts and citizens, providing tailored end-to-end attribution analyses, translation, and potentially expert testimony, responsibly informing the coming wave of litigation to ensure claims use the best available science.

A key area for future collaboration among attribution and legal scholars concerns shared evidentiary standards. Frequentist statistical practices common in scientific studies (e.g., "$p < 0.05$") may not be appropriate for climate liability cases for a number of reasons. First, they set the bar for evidence higher than legal standards such as "more likely than not."[113] Moreover, significance testing can be abused and misinterpreted[114], its thresholds are generally arbitrary[115], and such testing provides a poor characterization of uncertainty[116]. Here, we have chosen to present the range of outcomes and damage estimates possible given uncertainties in the causal chain from emissions to impact.

Other scientific approaches in attribution science, such as "storylines," could help reconcile epistemic differences between the legal and attribution communities and reduce the need for end-to-end attribution to specific harms in each case. Storylines are a narrative-driven attribution approach using conditional assumptions, often about the dynamics underpinning an extreme event, to assess the thermodynamic contributions of global warming. Storylines foreground deterministic rather than probabilistic characterizations of causality[117] and thus complement the application of our end-to-end attributions of individual events, such as floods or tropical cyclones—an area for future work. Our present analysis reflects the primacy of "but for" causation in existing legal frameworks, but as climate impacts grow and cases advance, the evolution of legal approaches to causation could allow other attribution approaches to become sufficient for legal standing[118]. Complementary and simultaneous development of multiple approaches is the most effective way for the scientific and legal communities to evaluate the growing evidence for climate liability[49].

The validity of the scientific case for climate liability does not mean that claims will succeed in court. Essential questions remain, such as the period over which emissions should be counted. That fossil fuel firms have predicted climate change and its consequences for decades implies a potential "duty of care" violation, meaning that those firms could be liable for emissions occurring before the consensus on climate change emerged[119]. Research using archival methods[120], computational frame analysis[121], and interviews[122] has documented the disconnect between the internal and public communications of fossil fuel firms. Advances in this area could add credibility to climate liability cases. Ultimately, however, accounting and framing choices reside beyond the scope of science—they must be made by legal teams and decided by judges and juries. Other legal barriers include legislation like the United States Clean Air Act, which may displace federal common-law claims[123], or courts' perception that these cases inappropriately intervene in policymaking[124].

Moreover, despite the harm arising from extreme heat, fossil fuels have also produced immense prosperity. We do not assess the economic benefits from fossil-fueled energy, for which these firms have already been handsomely paid. Courts may need to consider how the benefits of energy use are balanced against its externalities and the potential duty of care these firms have to the public[119]. Recent alternatives to litigation, like "polluter pays" bills drawing on superfund and loss and damage logic, are advancing in state legislatures around the United States. The first one passed in Vermont[125] suggests that some lawmakers see a clear distinction between the benefits and harms of fossil fuels and can evaluate them individually. Climate damages are a negative externality from fossil fuels not reflected in the current value of these firms. This disconnect is particularly strong given that these externalities have fallen most severely on the poorest people across the globe—those who have benefited least from fossil fuels or have been exploited for its extraction[126]. More broadly, just as the benefits of a medication do not absolve a manufacturer who fails to warn its customers about side effects, it is clear that the benefits of fossil fuel use should not absolve carbon majors of liability for these devastating externalities[2], particularly when they have misled the public about the dangers of their products[120].

As climate disasters accumulate, courts will see more and more climate cases. Formalizing communication and education between the scientific and judicial communities is vital, ensuring that science is useful and that courts recognize its limits. Alongside these efforts, new legal theories and the urgent press of climate disaster could spur courts to embrace climate liability claims[118]. The next twenty years will bring greater clarity on these remaining questions. Here we provide an essential start: the development of a rigorous, flexible, transparent, and widely applicable end-to-end attribution framework.

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Figure Captions

Fig. 1 | Carbon majors have individually contributed to extreme heat intensification. A) CO_2 emissions in megatons of carbon (MtC) per year from the five top-emitting fossil fuel firms ("carbon majors"). B) Changes in global mean temperature caused by the cumulative emissions of each carbon major. Vertical axis denotes the magnitude of global warming due to each firm in each year. Solid line shows the mean from 1001 FaIR simulations, each run with a different calibrated parameter set; shading shows the 90% range across the FaIR ensemble. C) Changes in 1991-2020 global average subnational Tx5d (temperature of the five hottest days in each year) from each carbon major, estimated by combining the FaIR simulations with CMIP6-based pattern scaling. Solid line shows the mean and shading shows the IPCC uncertainty ranges arising from interacting FaIR and pattern scaling uncertainties. D) Marginal economic effect of increases in Tx5d on economic growth in percentage points per degree Celsius (p.p. $°C^{-1}$) across a range of regional annual mean temperature values. Solid line shows the mean estimate and shading shows the 90% range, based on the observed relationship between Tx5d and economic growth. Positive values indicate that cool regions benefit from higher temperatures whereas negative indicate that warm regions suffer from higher temperatures.

Fig. 2 | Carbon majors have caused cumulative economic losses from extreme heat. A) Cumulative global heat-driven economic losses linked to the five top-emitting fossil fuel firms over 1991-2020. Black line shows the mean across 10,000 simulations convolving all sources of uncertainty and gray shading denotes the IPCC likely (66%), very likely (90%), and virtually certain (99%) ranges. B) Heat-driven economic losses linked to groups of carbon majors: all, investor-owned companies (IOCs), state-owned enterprises (SOEs), and the top five shown in A. In A and B, bottom inset text denotes the average losses linked to each actor or group. C) Average annual GDP per capita (GDPpc) change in subnational regions due to heat extremes driven by the combined emissions of the top five firms shown in A. White regions are those for which we do not have continuous GDPpc data over 1991-2020. Map was generated using cartopy v0.17.0 and regional borders come from the Database of Global Administrative Areas.

Fig. 3 | Carbon majors have caused losses from individual extreme heat events. A-D) Average change in regional Tx5d values due to the emissions of the five top-emitting carbon majors in 1998 (A), 2003 (B), 2010 (C), and 2012 (D). Note that C uses a distinct color scale from A, B, and D. E-H) Economic losses due to Tx5d intensification in India in 1998 (E), France in 2003 (F), Russia in 2010 (G), and the continental U.S. in 2012 (H) due to the emissions of carbon majors. In E through H, dot shows the average estimate and lines span the 90% (very likely) range. Maps were generated using cartopy v0.17.0 and regional borders come from the Database of Global Administrative Areas.

Fig. 4 | Damages attributable to any actor depend on their emissions and the time period considered. A) Attributable global heat-driven economic losses over 1991-2020 as a function of the percent contribution to global CO_2 and CH_4 emissions over the 1850-2020 period. B) Losses attributable to a 5% contribution to global emissions, when that contribution is assessed starting in 1850 (as in A), 1997, or 1990, and ending in 2020 in all cases.

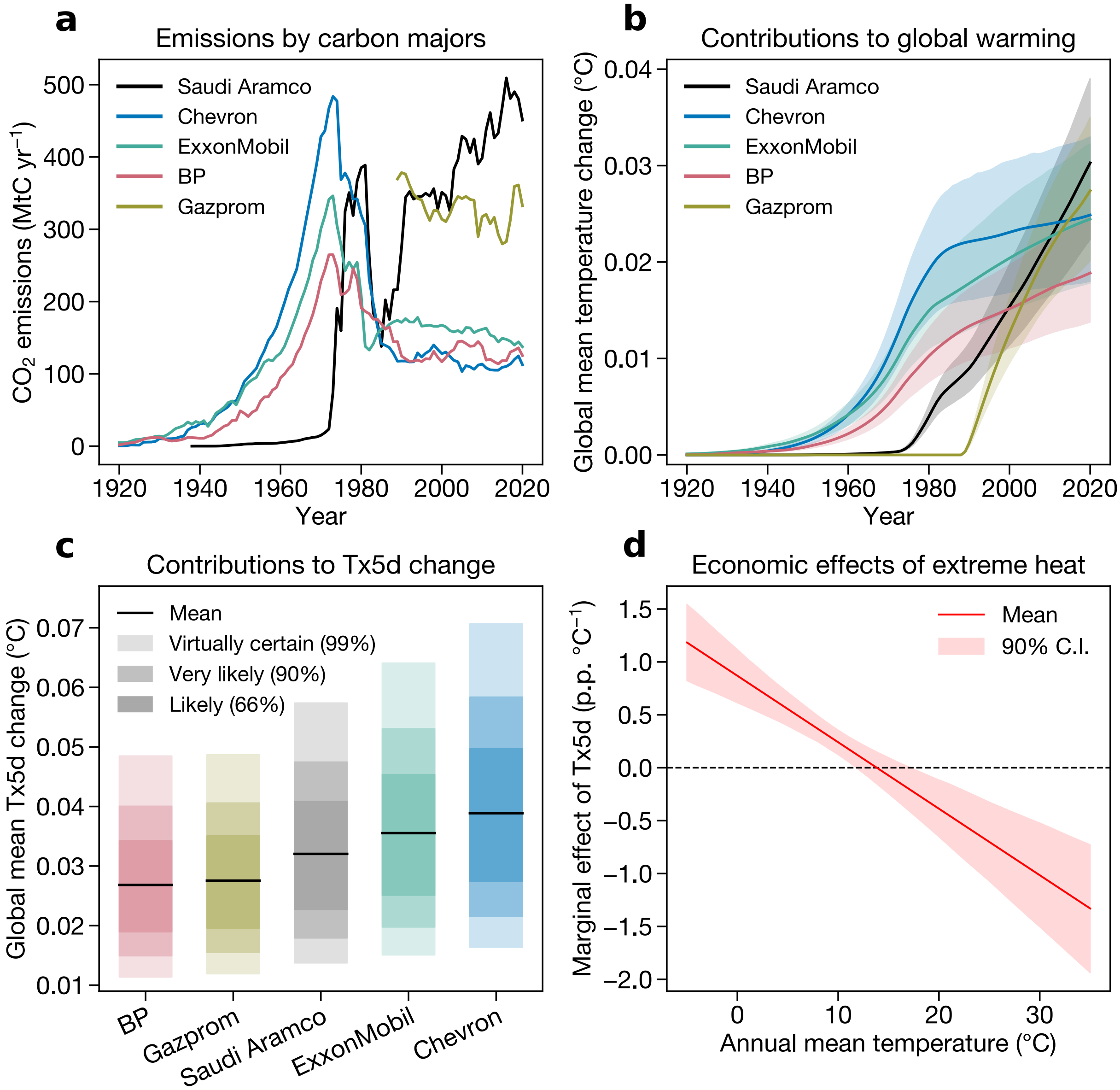

a
Emissions by carbon majors
CO_2 emissions (MtC yr^{-1})
Year
Saudi Aramco
Chevron
ExxonMobil
BP
Gazprom
b
Contributions to global warming
Global mean temperature change (°C)
Year
Saudi Aramco
Chevron
ExxonMobil
BP
Gazprom
c
Contributions to Tx5d change
Global mean Tx5d change (°C)
Mean
Virtually certain (99%)
Very likely (90%)
Likely (66%)
BP
Gazprom
Saudi Aramco
ExxonMobil
Chevron
d
Economic effects of extreme heat
Marginal effect of Tx5d (p.p. °C^{-1})
Annual mean temperature (°C)
Mean
90% C.I.

Figure 1

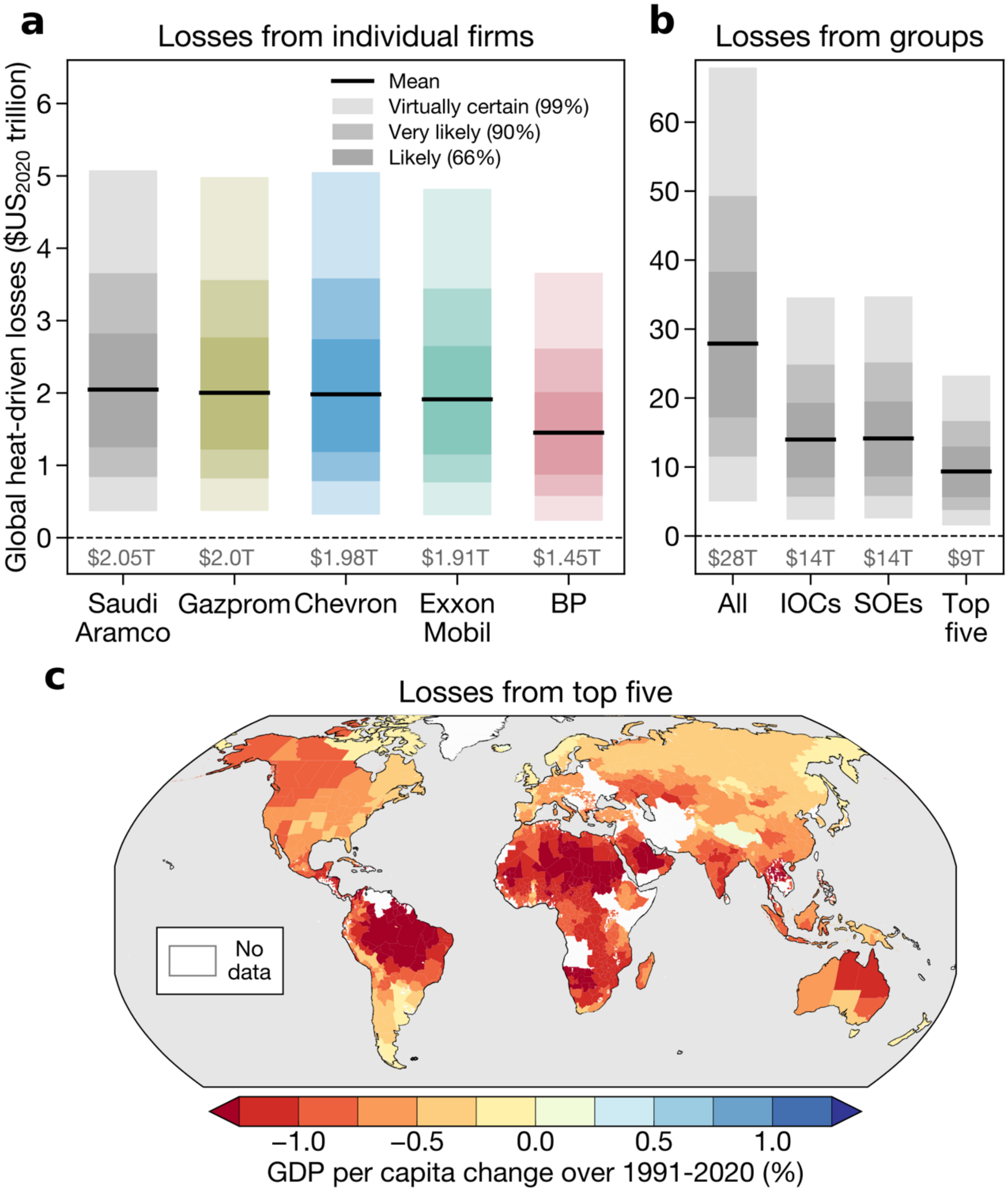

a
Losses from individual firms
Global heat-driven losses ($US2020 trillion)
Mean
Virtually certain (99%)
Very likely (90%)
Likely (66%)
0
1
2
3
4
5
6
$2.05T
$2.0T
$1.98T
$1.91T
$1.45T
Saudi Aramco
Gazprom
Chevron
Exxon Mobil
BP
b
Losses from groups
0
10
20
30
40
50
60
$28T
$14T
$14T
$9T
All
IOCs
SOEs
Top five
c
Losses from top five
No data
−1.0
−0.5
0.0
0.5
1.0
GDP per capita change over 1991-2020 (%)

Figure 2

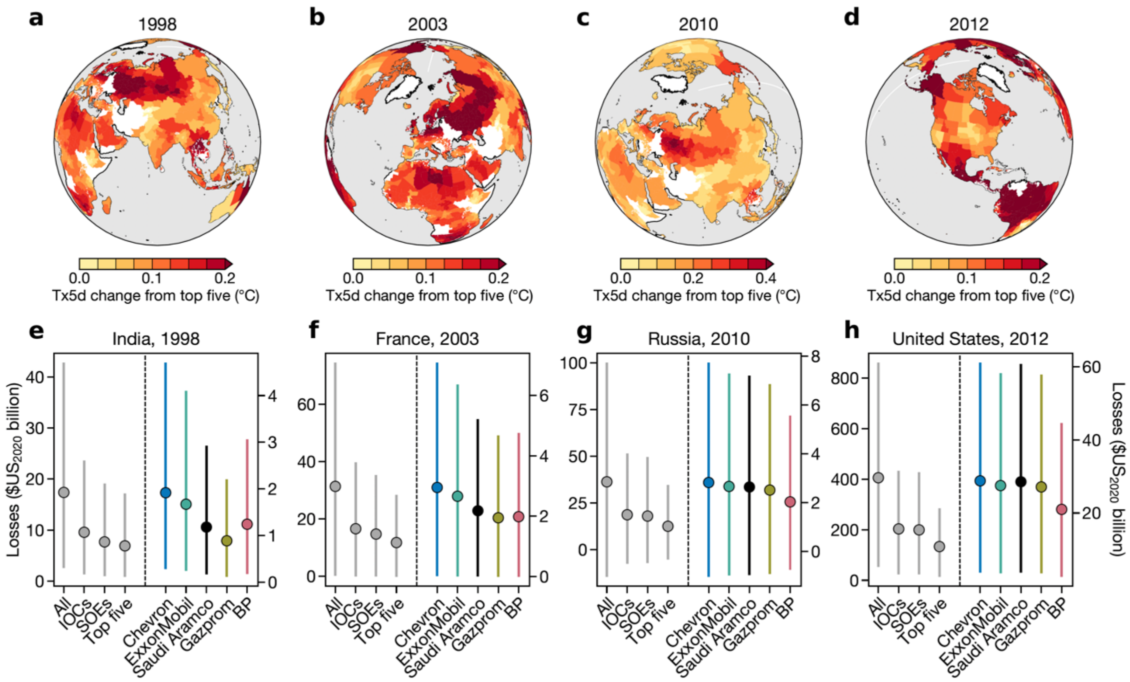
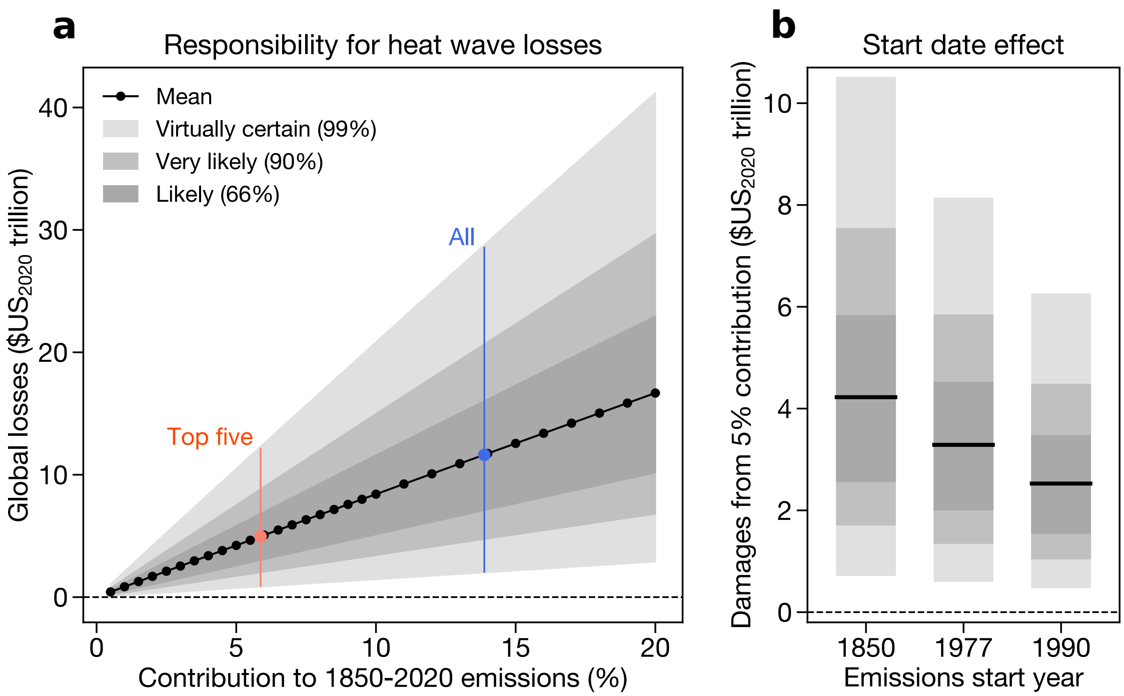
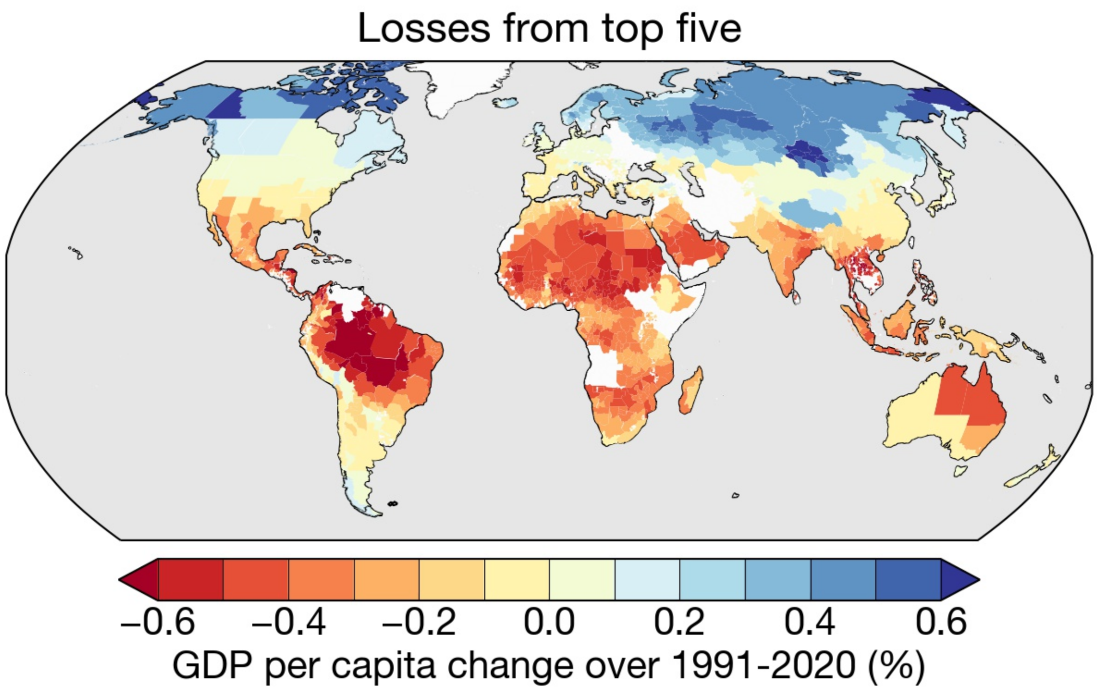

a
1998
0.0
0.1
0.2
Tx5d change from top five (°C)
b
2003
0.0
0.1
0.2
Tx5d change from top five (°C)
c
2010
0.0
0.2
0.4
Tx5d change from top five (°C)
d
2012
0.0
0.1
0.2
Tx5d change from top five (°C)
e
India, 1998
f
France, 2003
g
Russia, 2010
h
United States, 2012
Losses ($US2020 billion)
All
IOCs
SOEs
Top five
Chevron
ExxonMobil
Saudi Aramco
Gazprom
BP

Figure 3.



a
Responsibility for heat wave losses
Mean
Virtually certain (99%)
Very likely (90%)
Likely (66%)
All
Top five
Global losses ($US2020 trillion)
Contribution to 1850-2020 emissions (%)
b
Start date effect
Damages from 5% contribution ($US2020 trillion)
Emissions start year
1850
1977
1990

Figure 4.



Extended Data Figure 1.

Methods

Our end-to-end attribution integrates model experiments with three steps: (1) emissions to warming; (2) warming to hazards; and (3) hazards to damages. For the first step, we use a reduced-complexity climate model (RCM), which translates emissions into global temperature change, reconciling the carbon cycle and climate response uncertainty (see *Step 1: FaIR simulations*). For the second step, we use a statistical model that translates global temperature change into local changes in the hottest five days of the year (see *Step 2: Pattern scaling*). For the last step, we use an empirical model that estimates the marginal economic damage of the five hottest days of the year (see *Step 3: Damage function*). Different sets of emissions data could be included in Step 1, other hazard models could be ported in at Step 2, and other damage models could be used in Step 3, suggesting the flexibility of the framework.

Step 1: FaIR simulations

We use the Finite amplitude Impulse Response (FaIR) emissions-driven RCM to quantify the contributions of individual emitters to global mean surface temperature change. FaIR takes input time series of greenhouse gas emissions and natural climate forcings, simulates the carbon cycle and radiative forcing response, and calculates resulting warming, providing an output time series of global mean surface air temperature (GMST). All FaIR simulations are run from 1750 to 2020.

For each firm, our analysis requires comparing three experiments: in the first experiment, we run FaIR in a "natural" scenario, with only naturally occurring historical forcings, like solar variations and volcanic eruptions, preserved. This experiment calculates the time series of GMST in a counterfactual world with no human GHG emissions. In the second experiment, we run FaIR in a "historical" scenario, inputting both total historical human-caused emissions as well as the natural forcings to calculate the GMST we have experienced from observed historical forcing. The difference between the "historical" and "natural" FaIR simulations provides a time series of the change in GMST attributable to historical human-caused emissions and allows us to validate the skill of our simulations. Our simulations are skillful, reproducing the experimental results from the Detection and Attribution Model Intercomparison Project[127] (DAMIP) run with the fully coupled Earth System Models participating in the sixth phase of the Coupled Model Intercomparison Project[128] (CMIP6). The IPCC best estimate of human-induced warming over 2010-2019 relative to 1850-1900 is 1.07 °C, with a likely (66%) range of 0.8 °C – 1.3 °C (ref.[128]). The results from our FaIR simulations are consistent with this estimate, with an average warming in 2010-2019 relative to 1850-1900 of 1.05 °C and a 66% range of 0.89 °C – 1.23 °C.

Our third experiment is performed for each emitter separately. This experiment has the same protocol as the "historical" experiment, but this time we remove the emissions from a single firm from total emissions. This "leave-one-out" experiment provides the counterfactual time series of GMST where the chosen firm did not emit. The difference between the time series of "historical" and "leave-one-out" GMST provides a time series of the change in GMST attributable to a single emitter.

A "leave-one-out" experimental design does not consider socioeconomic consequences of counterfactual emissions, only thermodynamic ones. As such, our counterfactual approach is agnostic about whether a "leave-one-out" framing implies that the fossil fuel production itself never took place (with opaque and unpredictable market and production implications), or whether it is analogous to a scenario where a firm instead took steps to mitigate or remove the emissions associated with their fossil fuel production.

Each firm's emissions are time series of carbon dioxide and methane emissions—representing Scope 1 and Scope 3 emissions from fossil fuel production—drawn from data from the Carbon Majors database[100]; we use all available years of emissions data for each firm. We exclude actors from the database that are listed as nation states, using only investor-owned companies or state-owned enterprises. Not all firms have data spanning the same number of years as companies were incorporated at different times, but we use all available emissions data to avoid artificially constraining our analysis. Table ED1 shows the years over which emissions data are available for the five top-emitting firms in our data. Similarly, for the experiments for all 111 firms in our data or the groups of investor-owned/state-owned firms, we use all available data for each firm regardless of start date.

To sample carbon cycle and radiative forcing uncertainties, we perform each of the above FaIR experiments 1001 times, providing a large perturbed-parameter ensemble for each experiment. The 1001 parameter combinations were developed as part of the IPCC sixth assessment report[101]. Our 1001-member FaIR parameters are a subset of a larger parameter set of 1.5 million, which was then constrained to be consistent with fully coupled CMIP6 Earth System Models. We therefore run 1001 simulations for the "natural," "historical," and each "leave-one-out" experiment, sampling each parameter set for each firm. These simulations provide a distribution of GMST changes attributable to each firm for each year, where the range in values is attributable to uncertainties in the carbon cycle and the response of warming to forcing. These parameter sets were downloaded on September 13, 2023, with further information available at the following URL:
https://docs.fairmodel.net/en/latest/examples/calibrated_constrained_ensemble.html

Step 2: Pattern scaling

The scale of our damages analysis is the subnational region, equivalent to states in the United States or provinces in Canada. This is the scale at which heat waves have been found to affect economic growth[89] (in contrast to the country-level approach of previous studies[83,84], a finer spatial scale is necessary to account for the effect of heat waves). Following previous work, heat waves are defined here as the five hottest days in each year (denoted "Tx5d"), though other heat metrics could be used.

In order to quantify the effects of carbon majors' emissions on local extreme heat, it is necessary to link changes in GMST provided by the FaIR simulations to regional changes in Tx5d. Motivated by the strong linear relationship between GMST change and local extreme heat[78], we use pattern scaling to calculate changes in Tx5d in each region as a linear function of GMST change. To do this, we leverage the "hist" and "hist-nat" experiments conducted as part of the DAMIP protocol for CMIP6, which are the fully coupled analogues to our "historical" and "natural" FaIR experiments. For each participating model and each experiment, we calculate regional Tx5d. Next, we take the difference between the "hist" and "hist-nat" experiments in both GMST and regional Tx5d over the 1991-2020 period to calculate anthropogenic changes in those quantities. We then linearly regress the time series of anthropogenic Tx5d change onto the time series of anthropogenic GMST change for each region to yield a pattern scaling coefficient that represents the sensitivity of local Tx5d change to GMST change in units of "degree of regional Tx5d change per degree of GMST change." Multiplying these coefficients with the firm-level sets of FaIR simulations that provide the GMST change attributable to each emitter yields the Tx5d change due to each carbon major in each subnational region (Fig. 1c). We use 1991-2020 as the time period of this analysis to match the time period of the damages analysis.

We perform this local pattern scaling regression separately for each of 80 CMIP6 climate model simulations, specifically those which have hist and hist-nat simulations available for daily high surface air temperature ("tasmax") and monthly mean air temperature ("tas"). For the CMIP6, 8 distinct models are available, but we use as many ensemble members for each model as possible. This choice allows us to sample uncertainty from both model structure (i.e., uncertainty across models) and internal climate variability (i.e., uncertainty across realizations within an initial-condition ensemble of each model). Previous work showed that internal climate variability can form an important component of uncertainty in local attributable damages[53], and we explicitly incorporate this uncertainty in the pattern scaling step of our analysis.

The choice to use many ensemble members from a single model means that some models are overrepresented in this ensemble but ensures that we are sampling pattern scaling uncertainty due to both model structure and internal climate variability. When we perform our final Monte Carlo uncertainty assessment (see *Uncertainty quantification*), we adjust the model sampling probabilities so that models with fewer realizations are equally likely to be sampled as models with more[89].

Step 3: Damage function

We use a damage function that relates changes in local Tx5d to changes in GDP per capita growth ("economic growth") in subnational regions. This function was derived following peer-reviewed methods of ref.[89], using a panel regression of observed Tx5d and observed GDP per capita growth in a global sample of regions over 1979-2016, isolating the causal effect of year-to-year changes in extreme heat from other geographic or time-trending correlates.

Specifically, we use the coefficients from the following regression estimated using Ordinary Least Squares:

$$g_{it} = \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \beta_1 Tx_{it} + \beta_2 Tx_{it}{*}T_{it} + \gamma_1 V_{it} + \gamma_2 V_{it}{*}A_i + \pi P_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

T refers to annual mean temperature, Tx refers to Tx5d, V refers to temperature variability, A refers to annual cycle of temperature, P refers to temperature, μ_i is a region fixed effect that removes all time-invariant regional average characteristics, and δ_t is a year fixed effect that removes all global shocks that are common to a given year. The coefficients of interest are β_1, which denotes the effect of Tx5d when mean temperature is 0, and β_2, which denotes the change in the effect of Tx5d as mean temperature increases. Marginal effects of Tx5d are shown in Fig. 1d in the main text. We include the terms for temperature variability (V) and the annual cycle (A) following Kotz et al.[129]. Specifically, they allow us to distinguish the impacts of temperature extremes from the impacts of within-year temperature variability, which may be independently damaging.

The estimated effects of Tx5d on economic growth are spatially heterogeneous, with negative effects of extreme heat in warm regions (regions with annual mean temperature above ~14 °C), but negligible or positive effects in cool regions. The disproportionate negative effect of marginal changes in Tx5d in warm tropical regions could occur due to both their underlying warmth, which may place them closer to physiological thresholds for human health or agriculture, as well as the lower income in tropical regions, which may make them more economically vulnerable to climate stress. Uncertainty in these subnational damage function coefficients is estimated by bootstrap resampling the regression, producing a distribution of 1000 coefficients that reflects sampling uncertainty in our estimates.

Tx5d is only one of the many ways to measure extreme heat[130]. Other metrics based on the temperature of hot periods include the hottest day[131], hottest seven days[132], or hottest month[6]. In previous work[89], we showed that all of these measures have broadly similar damage functions, but that Tx5d has the clearest economic effect among them, potentially because it is the best geophysical measure of the synoptic time scale of most heat events.

An alternative approach is to define location- or time-specific thresholds, above which heat is termed "extreme" and can be accumulated over time, similar to the "degree day" metrics used in many agricultural applications. In the climate-economic context, an example of this is Miller et al.[106], in which they use cumulative measures of extreme heat above a threshold to examine economic impacts of historical heat waves. Such cumulative metrics have the advantage of incorporating multiple heat events over the course of a year and the varying duration of those events. On the other hand, they require researchers to make several arbitrary choices: what threshold is chosen, whether that threshold is relative to a day of year, month, or season, whether extreme heat has equivalent effects in spring or fall as in summer, and so on. We believe that the simplicity and transparency of our approach has advantages in this emerging legal context. More complex metrics of extreme heat or other events are a fruitful target for future research. Because our framework is flexible and modular, it can accommodate more complex or tailored metrics of heat, other extremes, and other hazards as needed.

To assess heat-driven damage attributable to individual emitters, we integrate the three steps outlined above, calculating economic changes in the "historical" and "leave-one-out" scenarios for each firm, relative to the "natural" scenario which only includes solar and volcanic forcing. We do the following:

1) First, we calculate the change in each region's Tx5d values due to the difference in Tx5d between the pattern-scaled FaIR "historical" (or "leave-one-out") simulation and the pattern-scaled FaIR "natural" simulation. This difference is then subtracted from the observed, real-world time series of Tx5d for each region, providing counterfactual subnational annual-scale time series of Tx5d. This common "delta method" ensures that the Tx5d differences are benchmarked to the observed climate, both to bias-correct the model predictions and to impute realistic timing to interannual variability.
2) The difference between observed and counterfactual Tx5d is then multiplied by the damage function coefficients to calculate a change in each region's economic growth, due to the change in Tx5d between the "natural" and "historical" or "leave-one-out" experiments.
3) We then add this difference in economic growth to observed economic growth. This provides a counterfactual trajectory of economic growth consistent with the included emissions. Higher counterfactual economic growth values than those observed in the real world implies damages from emitter-driven Tx5d changes—i.e., a region *would have* grown faster *but for* the effect of the extreme heat attributable to the included emissions.
4) We then put these economic changes in dollar terms by taking these counterfactual economic growth time series from each emitter and re-integrating each region's GDP per capita time series. Further details on this procedure are available in Callahan and Mankin[89] and Diffenbaugh and Burke[88]. We now have, for each region, a time series of per capita GDP damages in the historical world and a time series of per capita GDP damages in a world with one emitter removed.

5) Finally, we take the difference between the historical damage estimate and the leave-one-out damage estimate to calculate the contributions of individual firms. Further details on this procedure are available in Callahan and Mankin[53].

The effect of extreme heat on economic growth is not permanent. In previous work[89], we observed a rebound effect whereby economic growth accelerates in the years following heat waves—for example, as crops are resown or people return to work. From a distributed lag model based on Eqn. 1, where we add lags of each term to assess their effect over time, we find that this effect appears to last three years. Neglecting such a rebound effect could lead to overestimates of the effect of heat waves on long-term growth. We therefore account for this recovery in our damage estimates, allowing Tx5d changes to affect both contemporary and future economic growth such that no single heat wave has a permanent effect.

Additionally, because changes in annual mean temperature moderate the effect of Tx5d change, we perform a similar pattern scaling analysis with regional annual mean temperature. Following previous work, the final damages calculations incorporate both changes in Tx5d itself as well as changes in the underlying annual mean temperature values that moderate the effect of Tx5d[89].

Predicting regional income

Our analysis requires continuous GDP per capita time series order to integrate counterfactual economic growth and calculate counterfactual income. Many regions around the world, especially those in the poorest and warmest areas of the tropics—those that are most strongly affected by extreme heat—do not have such subnational data available, making it difficult to assess the impacts of climate change in those regions. To fill this gap, we extend the regional GDP per capita prediction procedure outlined in Callahan and Mankin[89] to predict subnational GDP per capita from 1991-2020.

This procedure takes three inputs: country-level GDP per capita (GDPpc) data from the World Bank World Development Indicators, gridded nighttime luminosity data from satellites, and subnational GDPpc (from the regions where such data is available) from the DOSE dataset collected by Wenz et al.[133]. We estimate a multiple regression model where observed regional GDPpc is regressed on the corresponding country's GDPpc, regional average nighttime luminosity, and their interaction[134]. (To perform this procedure over 1991-2020, we linearly extrapolate regional nightlights beyond their original 1992-2013 time boundaries.) This regression model skillfully explains variation in regional GDPpc, with an R^2 of approximately 0.9, and has performed well in out-of-sample cross-validation tests[89]. We then predict regional GDPpc in the regions where it is not available, using the country-level GDPpc and nightlights data in these regions. There are some countries where the relationship between national and regional GDPpc appears abnormal, specifically Uzbekistan and Kenya, so we drop these countries from the final data construction (see Supplementary Fig. 8 of Callahan and Mankin[89]). In other countries, such as Afghanistan, even country-level GDPpc data is not continuously available across the 1991-2020 analysis time period. In both cases, white regions in Fig. 2 show the areas for which GDPpc data is not available in the final analysis.

We use the US GDP deflator to correct for inflation and convert each dollar to 2020-equivalent dollars.

This procedure inherently introduces uncertainty in our final estimates, and we sample this uncertainty in two ways following Callahan and Mankin[89]. First, we bootstrap the multiple regression model 250 times, resampling by country with replacement to account for within-country autocorrelation in growth. Second, in each bootstrap iteration, we add random noise to the predictions with amplitude equal to the standard deviation of the estimation model's residuals. This procedure ensures that the uncertainty from this prediction procedure is reflected in our final damage estimates.

We emphasize that we do not use these GDPpc reconstructions in the original regression estimates that produce the damage function, only in the process of calculating absolute GDPpc losses from changes in economic growth.

Event-specific estimates

To quantify the influence of carbon majors on damages from specific events, we use a similar method as in our main analysis. The key difference is that we only calculate the damages from the change in Tx5d and average temperature in the year of the event. In practice, this means we set the Tx5d and average temperature values in the leave-one-out simulation equal to the observed values in all years, except the year of the event. For example, we calculate damages for India in 1998 by setting the historical and leave-one-out Tx5d and temperature values to be exactly the same as the observed values, except for in 1998. We then repeat our damage calculation, with damages only being produced by the climate change in 1998 and not any other year. We also note that these heat waves happen to coincide with the Tx5d in each case we present. We would not always expect that to be the case, as damaging heat waves may not always include the five hottest days of the year. Indeed, even in the cases we present, five days may not encompass the full duration of the heat wave; for example, the 2010 Russian heat wave occurred over several weeks in July. However, previous analysis showed that extending the time window of the analysis, such as using the hottest 15 days instead of the hottest 5, yields very similar answers[89]. Other heat metrics or approaches may be appropriate for other events that do not occur during the hottest parts of the year.

As described above, heat waves produce an economic rebound in the years following the event. As such, we continue to account for the economic recovery in these single-event estimates by allowing

Tx5d changes to affect growth in the year of the event as well as the two years following it. When we present country-level damage estimates for these individual events, we sum damages across all regions in the chosen country for that year and the 2 years following. For example, for India in 1998, the damage estimates presented in Fig. 3 represent losses in 1998, 1999, and 2000, induced by the 1998 heat wave, before India catches back up to its original economic trajectory in 2001 and damages are zero thereafter. For the United States in 2012, we exclude Hawaii and Alaska from this calculation to only calculate damages for the contiguous U.S.

Uncertainty quantification

Our damage calculations reflect uncertainty from the FaIR simulations, pattern scaling, damage function estimates, and regional income prediction. To propagate these uncertainties into our final estimates, we use a Monte Carlo approach, sampling uncertainty with 10,000 iterations. In each iteration, we sample one of the 1001 FaIR simulations, one of the 80 climate model estimates of the pattern scaling coefficients (keeping all regional coefficients together from a single climate model), one of the 1000 damage functions from the bootstrap estimate, and one of the 250 regional GDPpc predictions.

Data Availability

All data that support the findings of this study are available via IEEE DataPort at doi.org/10.21227/w3fm-w720.

Code Availability

All computer code that support the findings of this study are available via IEEE DataPort at doi.org/10.21227/w3fm-w720.

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Author Contributions

Both authors designed the analysis. C.W.C. performed the analysis. Both authors interpreted the results and wrote the paper.

Competing Interests

The authors declare no competing interests.

Additional Information

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Extended Data Legends

Extended Data Figure 1 | Damages when annual average temperatures are held at their observed values. As in Fig. 2A, but when emissions only affect the intensity of Tx5d values and not the annual average temperatures that moderate the effect of Tx5d. Map was generated using cartopy v0.17.0 and regional borders come from the Database of Global Administrative Areas.

Firm Name	Headquarters	Start Year	End Year
Saudi Aramco	Saudi Arabia	1938	2020
Gazprom	Russia	1989	2020
Chevron	United States	1912	2020
ExxonMobil	United States	1884	2020
BP	United Kingdom	1913	2020

Extended Data Table 1 | Availability of emissions data for top five firms. This table shows the name (first column), country of headquarters (second column), first year of available emissions data (third column), and last year of available emissions data (fourth column) for the five top-emitting firms in our data. Data is from the Carbon Majors database[100], based on work by Heede[62].