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 companies, 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 companies. Emissions linked to Chevron, the highest-emitting investor-owned company in our data, for example, very likely caused between US $791 billion and $3.6 trillion in heat-related losses over the period 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 through common law[3]. Extreme weather events—floods, droughts, extreme heat and more—upend lives, undermine livelihoods and damage property. If such extremes could be linked to climate change, the logic goes, injured parties could seek monetary or injunctive relief through courts[1]. Over the past 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 heatwaves[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 such as the IPCC[19], the consensus developed around event attribution methods[20] suggests that 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. More than 100 climate-related lawsuits have been filed annually since 2017; many more will come. The legal theories forming the basis for 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 such as the Energy Charter Treaty to stymie climate action[27]. Some cases centre on the disinformation and climate denialism allegedly fomented by fossil fuel companies[28], whereas others contend that companies have failed to adequately disclose climate risks to investors[29]. Other climate-related cases fall outside these categories and new legal theories will continue to emerge.

Here we focus on the theory that people can hold emitters liable for the damage caused by warming[1,30]. Such cases mirror efforts to hold industries such as tobacco[31] and pharmaceuticals[32] liable under legal standards such as 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. Although these cases—similar to disinformation-focused cases—use evidence that fossil fuel companies have long been aware of climate change, they specifically attempt to link these companies to the human costs of their emissions. For example, an Oregon county has sued several fossil fuel companies for amplifying the 2021 Pacific Northwest heatwave and its resulting economic and health costs[34]. New York City and Rhode Island have brought similar claims[35,36]. Companies such as 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]. Although attribution science is relevant to wider climate policy, accountability and justice, it

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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 Foundation 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]. By 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 substantial hurdle to climate liability. Using peer-reviewed methods, we estimate the economic losses resulting from the extreme heat caused by emissions from major fossil fuel companies ('carbon majors') over the period 1991–2020. We present two actionable approaches for the end-to-end attribution framework: one considering the accumulated harms from a hazard, such as heatwaves over 1991–2020, and another considering the harms from a specific event, such as the 2003 European heatwave. The cumulative and event-specific approaches can be applied to myriad scales of emitters and claimants, and extended to different classes of hazards, from heatwaves 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, although 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 that 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 through 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. We 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. However, 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 companies 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. First, physical science can more confidently connect individual emitters to local climate change. Second, social science can more confidently connect local climate change to socioeconomic outcomes.

For 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 climates and counterfactual climates, in which the latter is the same as the former, save for the removal of one emitter's time-varying emissions (that is, 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. We 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 behaviour 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 such as 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 such as pattern scaling[75–77] provide robust statistical relationships between global and local climates that allow scientists to estimate local temperature change on the basis of 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].

However, 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 notable 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 such as 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 such as the US government's Fifth National Climate Assessment[90].

Although the 'fraction of attributable risk' 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 influences 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 greenhouse gas emissions to socioeconomic losses. For example, Strauss et al.[99] relied on hydrodynamic modelling 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 fraction of attributable risk. 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 heatwave intensity globally, causing quantifiable income losses for people in subnational regions around the world. Our analysis uses reductions in gross domestic product per capita (GDPpc) 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. However, the power of the attribution framework we present is that it is flexible, transparent and modular, meaning that other damages (for example, adaptation costs based on alternative damage functions), other hazards (for example, 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 companies have produced substantial emissions of carbon dioxide and methane over the past 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 makes use of 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 that these emissions ledgers are probably conservative: they do not include scope 2 emissions or leaks and spills and are subject to underreporting, especially early in the twentieth century[62]. Although we only illustrate emissions since 1920 in Fig. 1, our analysis uses all available company-level data (Extended Data Table 1).

To link these companies to specific impacts from their emissions, we use 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 Finite amplitude Impulse Response (FaIR) RCM[72] to translate companies' 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). Last, 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 company's contribution to damages. Nonclimate factors, such as changes in the global oil trade, are held constant. Our analysis centres only on 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 1,000 times, sampling parametric uncertainty using IPCC-based parameter combinations[101]. In our counterfactual simulations, we resimulate GMST change after subtracting each company's CO_2 and CH_4 emissions from global emissions. The difference between the observed and each company's counterfactual simulation represents the GMST change attributable to that company (Fig. 1b). According to our analysis, for example, Chevron is responsible for about 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 company-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 five hottest days in each year, whereas temperate regions experience modest effects[89] (Fig. 1d). Although 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 company. 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 (ref. 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 effects of extreme heat, which shows benefits in high-latitude regions[89]. We also account for the economic rebound shown in previous work[89], in which the effect of extreme heat is recovered after 2–3 years, meaning that we do not assume permanent growth impacts of extreme heat.

In this analysis, we focus on the costs resulting from 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: so far, 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 heatwave, probably because of the legal imperative to demonstrate specific causality. Although 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 so far. As legal efforts evolve to consider several 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].

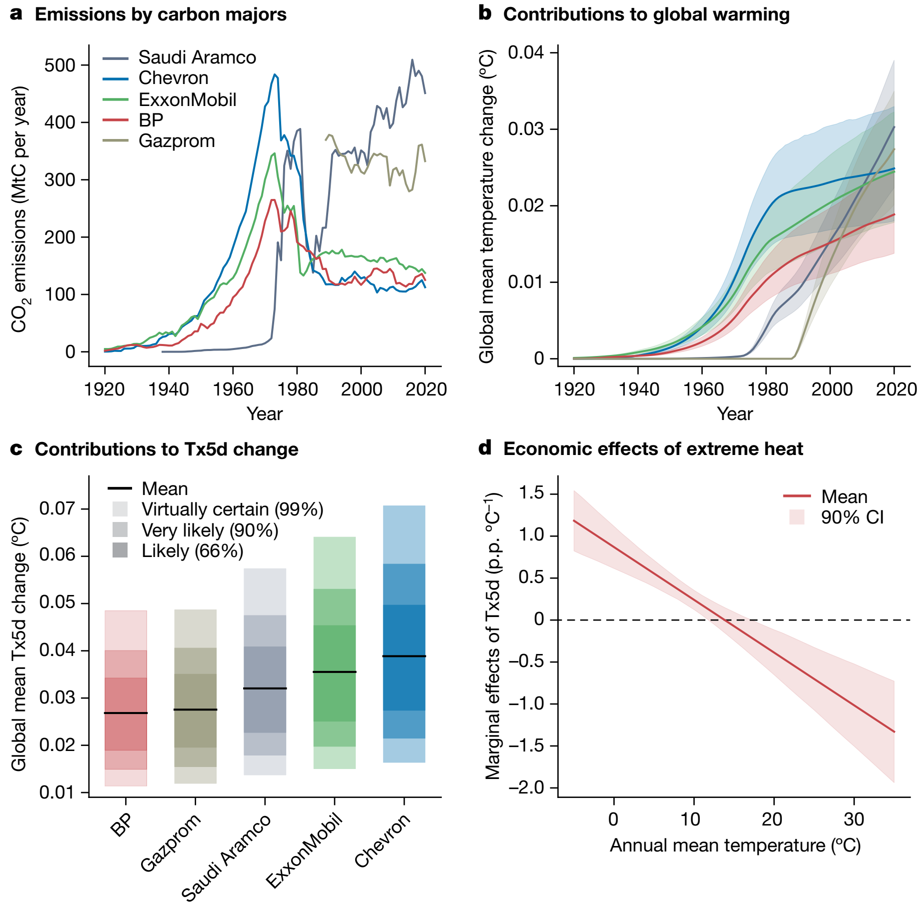

Fig. 1 | Estimated change in global mean temperature and local extreme heat by carbon majors. a, CO_2 emissions in megatonnes of carbon (MtC) per year from the top five emitting fossil fuel companies ('carbon majors'). **b**, Changes in global mean temperature caused by the cumulative emissions of each carbon major. Vertical axis denotes the magnitude of global warming resulting from each company in each year. Solid lines show the mean from 1,001 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% confidence interval (CI) range, based on the observed relationship between Tx5d and economic growth. Positive values indicate that cool regions benefit from higher temperatures, whereas negative values indicate that warm regions suffer from higher temperatures[89].

Heatwave damage from carbon majors

The global economy would be $28 trillion richer (90% (very likely) range: 12–49, in 2020 US dollars) were it not for the extreme heat caused by the emissions from the 111 carbon majors considered here (Fig. 2). To provide examples of this attribution, Fig. 2a shows losses attributable to each of the top five emitting companies in our data. Saudi Aramco is responsible for $2.05 trillion (90% range: 0.85–3.64) in global economic losses from intensifying extreme heat and Gazprom is responsible for about $2 trillion (90% range: 0.83–3.55). The contributions from these two state-owned enterprises are the result of their recent and rapid emissions (Fig. 1a), despite not making large contributions earlier in the twentieth century. Chevron, ExxonMobil and BP have caused $1.98 trillion (0.79–3.57), $1.91 trillion (0.77–3.43) and $1.45 trillion (0.59–2.60) in losses, respectively (Fig. 2a). Investor-owned companies (for example, Chevron, ExxonMobil and BP) and state-owned enterprises (for example, Saudi Aramco and Gazprom) are each collectively responsible for approximately $14 trillion 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. However, the 99% range for each of the top five companies 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 scales, revealing inequities in the causes and consequences of global warming (Fig. 2c). Together, extreme heat from the top five emitting companies (Fig. 2a) has driven annual GDPpc reductions exceeding 1% across South America, Africa and Southeast Asia. By contrast, the USA 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 (see Fig. 2c and Extended Data Fig. 1). The gradient of losses increases equatorward irrespective of whether we allow mean temperatures to change (Fig. 2c and Extended Data Fig. 1), emphasizing the global inequity in extreme heat impacts and their spatial dislocation from the emissions that produced them.

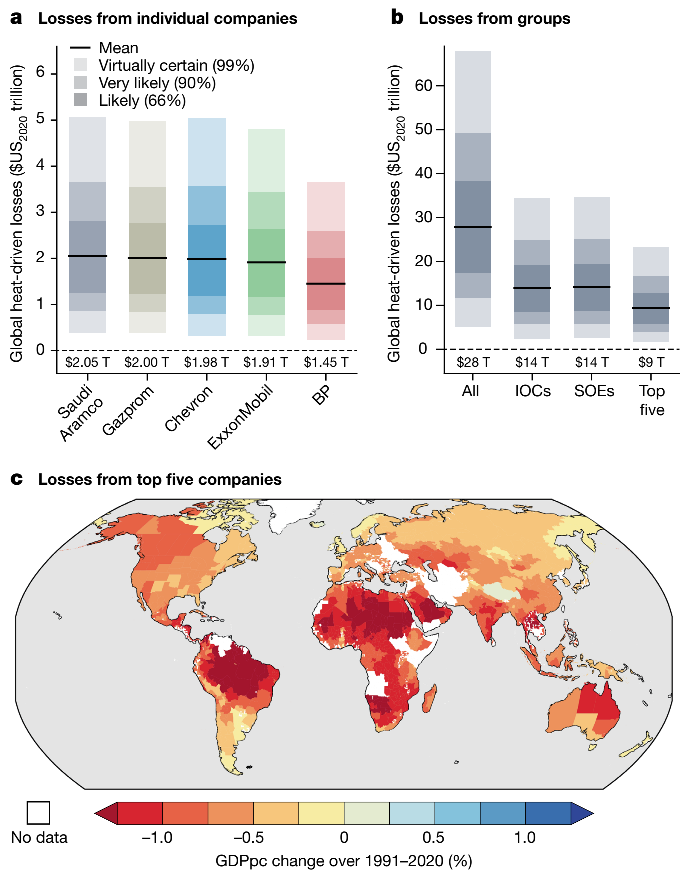

Fig. 2 | Estimated cumulative economic losses from extreme heat by carbon majors. a, Cumulative global heat-driven economic losses linked to the top five emitting fossil fuel companies over 1991–2020, in 2020 US dollars (US_{2020}$). Solid line shows the mean across 10,000 simulations convolving all sources of uncertainty and 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 GDPpc change in subnational regions resulting from heat extremes driven by the combined emissions of the top five companies shown in **a**. White regions are those for which we do not have continuous GDPpc data over 1991–2020. The map was generated using cartopy v0.17.0, and regional borders are from the Database of Global Administrative Areas.

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

Together, the top five companies increased the intensity of the five hottest days corresponding to those events by 0.08, 0.11, 0.27 and 0.09 °C, respectively (Fig. 3a–d), and thus can be associated to losses from those events (Fig. 3e–h). For example, Chevron's emissions are responsible for $1.9 billion (0.31–4.68), $3 billion (0.05–7.05), $2.8 billion (gains of 0.99 to losses of 7.69) and $28.8 billion (4–61) in losses from the 1998 Indian, 2003 French, 2010 Russian and 2012 North 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 use of deduction in climate attribution[49]. Although 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 companies have produced owing to the extreme heat caused by their emissions of carbon dioxide and methane.

Clarifying who is responsible

How could end-to-end attribution analyses such as ours be used? Each case will differ and depend on the motivation of the litigants and their climate context. As presented in Figs. 2 and 3, science can clarify 'but for' causation at various scales across a class of hazards, such as heatwaves, or for a particular event, such as the 1998 Indian heatwave. 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 company? A collective? A sector? This, too, science can help clarify.

So far, 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 underresourced 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 company. Such an approach is actor-agnostic and scale-agnostic, meaning that 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 quasilinearly with emissions contributions (Fig. 4a). Each extra percentage point contribution to total 1850–2020 CO_2 and CH_4 emissions generates a further $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 heatwave damages can be used to link the top five companies (Fig. 4a, orange) or all companies (Fig. 4a, blue) to losses, on the basis of 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 accounting begins in 1990, around the development of the scientific consensus on climate change[60], heatwave losses attributable to an actor contributing 5% of global emissions total $2.5 trillion (90% range: 1.05–4.47), contrasting

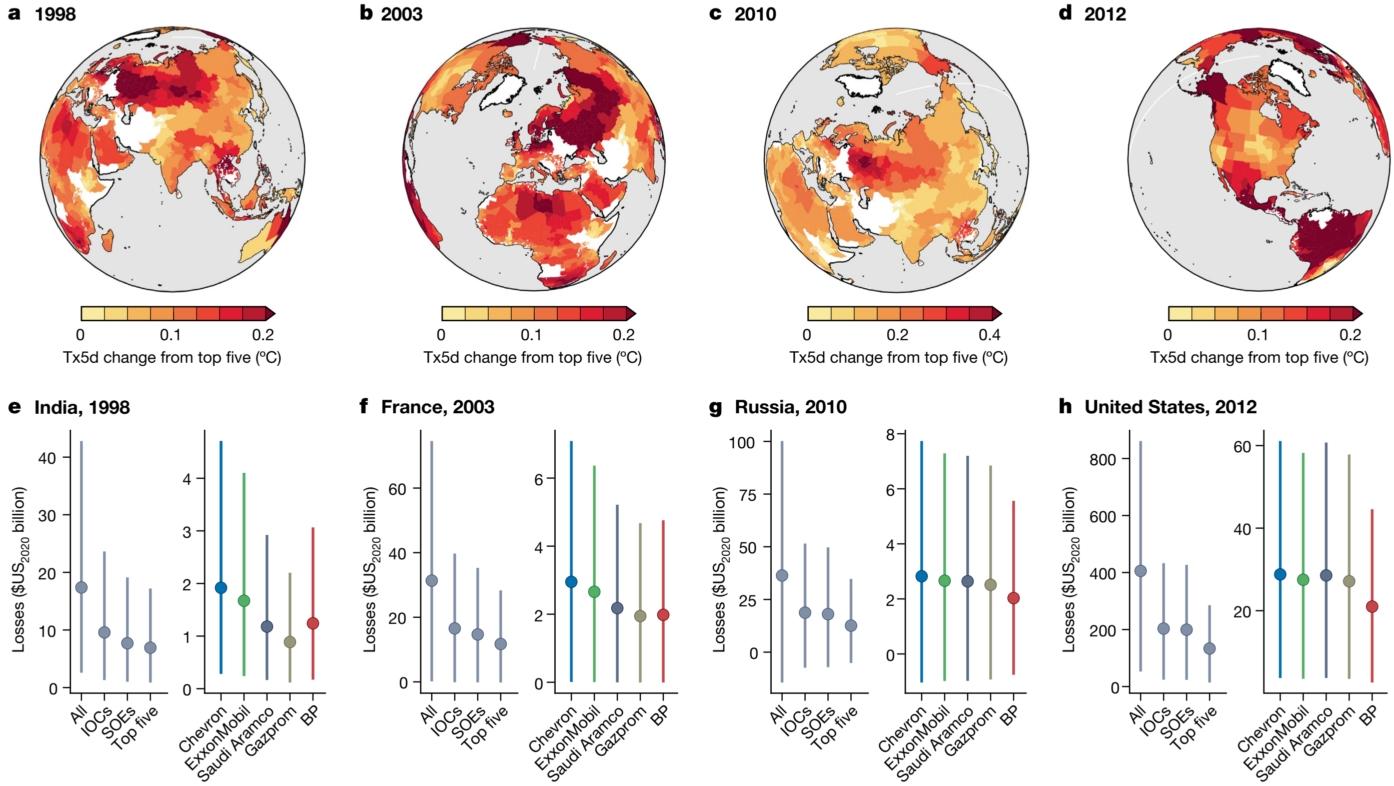

Fig. 3 | Estimated losses from individual extreme heat events by carbon majors. **a**–**d**, Average change in regional Tx5d values owing to the emissions of the top five emitting carbon majors in 1998 (**a**), 2003 (**b**), 2010 (**c**) and 2012 (**d**). Note that **c** uses a colour scale different from that of **a**, **b** and **d**. **e**–**h**, Economic losses owing to Tx5d intensification in India in 1998 (**e**), France in 2003 (**f**), Russia in 2010 (**g**) and the continental USA in 2012 (**h**) owing to the emissions of carbon majors. In **e**–**h**, dots show the average estimate and lines span the 90% (very likely) range. Maps were generated using cartopy v0.17.0, and regional borders are from the Database of Global Administrative Areas. IOCs, investor-owned companies; SOEs, state-owned enterprises.

with the $4.2 trillion (1.7–7.5) when counting from 1850. However, fossil fuel companies 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], heatwave losses attributable to an actor contributing 5% of global emissions total $3.3 trillion (1.4–5.8). These losses are all large, with 99% ranges that do not include zero, but they 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 pre-existing 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 such as 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 centred 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 past 20 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 (for example, '$P < 0.05$') may not be appropriate for climate liability cases for several 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

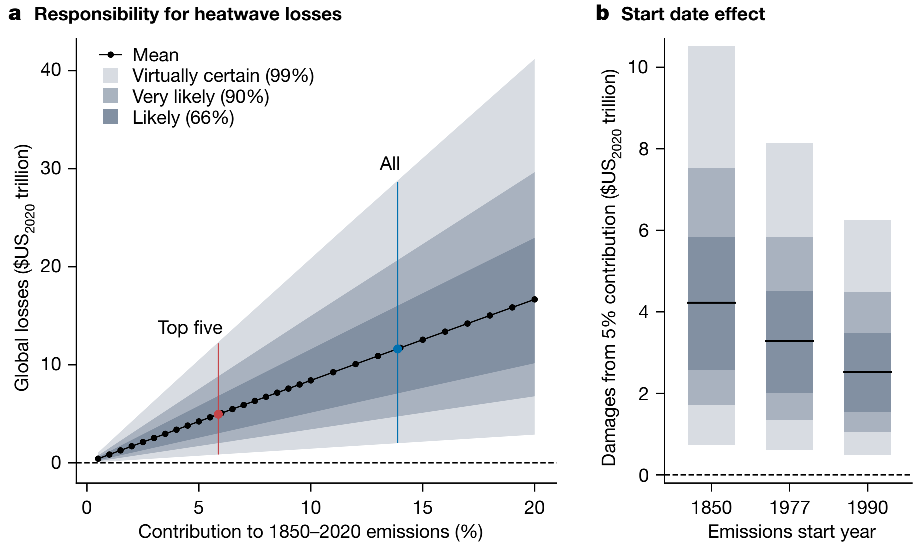

Fig. 4 | Attributable damages depend on emissions and the time period considered. a, Attributable global heat-driven economic losses over 1991–2020, in 2020 US dollars, as a function of the percent contribution to global CO_2 and CH_4 emissions over the 1850–2020 period. **b**, Losses attributable to a 5% contribution to global emissions, when that contribution is assessed starting in 1850 (as in **a**), 1977 or 1990 and ending in 2020 in all cases. Shading shows IPCC uncertainty ranges across 10,000 simulations, as in Figs. 1 and 2.

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 emphasize 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 several 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 companies have predicted climate change and its consequences for decades implies a potential 'duty of care' violation, meaning that those companies 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 companies. 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 such as the US 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-fuelled energy, for which these companies 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 companies have to the public[119]. Recent alternatives to litigation, such as 'polluter pays' bills that draw on superfund and loss and damage logic, are advancing in state legislatures around the USA. 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 companies. 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].

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 20 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.

Online content

Any methods, including any statements of data availability and Nature Research reporting summaries, along with any additional references and source data files, are available in the online version of the paper at https://doi.org/10.1038/s41586-025-08751-3.

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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 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 FaIR emissions-driven RCM to quantify the contributions of individual emitters to GMST 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 GMST. All FaIR simulations are run from 1750 to 2020.

For each company, our analysis requires comparing three experiments: in the first experiment, we run FaIR in a 'natural' scenario, with only naturally occurring historical forcings, such as solar variations and volcanic eruptions, preserved. This experiment calculates the time series of GMST in a counterfactual world with no human greenhouse gas 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 skilful, 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 0.8–1.3 °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 0.89–1.23 °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 company from total emissions. This 'leave-one-out' experiment provides the counterfactual time series of GMST in which the chosen company 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. Thus, 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 in which a company instead took steps to mitigate or remove the emissions associated with their fossil fuel production.

Each company'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 company. We exclude actors from the database that are listed as nation states, using only investor-owned companies or state-owned enterprises. Not all companies 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. Extended Data Table 1 shows the years over which emissions data are available for the top five emitting companies in our data. Similarly, for the experiments for all 111 companies in our data or the groups of investor-owned/state-owned companies, we use all available data for each company regardless of start date.

To sample carbon cycle and radiative forcing uncertainties, we perform each of the above FaIR experiments 1,001 times, providing a large, perturbed-parameter ensemble for each experiment. The 1,001 parameter combinations were developed as part of the IPCC Sixth Assessment Report[101]. Our 1,001-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 1,001 simulations for the 'natural', 'historical' and each 'leave-one-out' experiment, sampling each parameter set for each company. These simulations provide a distribution of GMST changes attributable to each company for each year, in which 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 13 September 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 USA or provinces in Canada. This is the scale at which heatwaves 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 heatwaves). Following previous work, heatwaves are defined here as the five hottest days in each year (denoted 'Tx5d'), although other heat metrics could be used.

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 use 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 company-level sets of FaIR simulations that provide the GMST change attributable to each emitter yields the Tx5d change owing 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 that have hist and hist-nat simulations available for daily high surface air temperature ('tasmax') and monthly mean air temperature ('tas'). For CMIP6, eight 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 (that is, uncertainty across models) and internal climate variability (that is, 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 owing 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 GDPpc 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 GDPpc 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:

$$\begin{aligned} g_{it} = {} & \alpha_1 T_{it} + \alpha_2 T_{it}{}^2 + \beta_1 \mathrm{Tx}_{it} + (\beta_2 \mathrm{Tx}_{it} \times T_{it}) + \gamma_1 V_{it} + (\gamma_2 V_{it} \times A_i) \\ & + \pi P_{it} + \mu_i + \delta_t + \varepsilon_{it} \end{aligned} \quad (1)$$

where g refers to economic growth in region i and year t, 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 the mean temperature is 0, and β_2, which denotes the change in the effect of Tx5d as the mean temperature increases. Marginal effects of Tx5d are shown in Fig. 1d. We include the terms for temperature variability (V) and the annual cycle (A) following ref. 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 about 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 as a result of 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 1,000 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 timescale of most heat events.

An alternative approach is to define location-specific 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 ref. 106, in which the authors use cumulative measures of extreme heat above a threshold to examine economic impacts of historical heatwaves. Such cumulative metrics have the advantage of incorporating several 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 company, relative to the 'natural' scenario, which only includes solar and volcanic forcing. We perform the following:

1. First, we calculate the change in each region's Tx5d values owing 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, owing 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—that is, 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 reintegrating each region's GDPpc time series. Further details on this procedure are available in refs. 88,89. 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 companies. Further details on this procedure are available in ref. 53.

The effect of extreme heat on economic growth is not permanent. In previous work[89], we observed a rebound effect in which economic growth accelerates in the years following heatwaves—for example, as crops are resown or people return to work. From a distributed lag model based on equation (1), in which we add lags of each term to assess their effect over time, we find that this effect seems to last 3 years. Neglecting such a rebound effect could lead to overestimates of the effect of heatwaves 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 heatwave has a permanent effect.

Furthermore, 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 (ref. 89).

Predicting regional income

Our analysis requires continuous GDPpc 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 GDPpc prediction procedure outlined in ref. 89 to predict subnational GDPpc from the period 1991–2020.

This procedure takes three inputs: country-level GDPpc data from the World Bank World Development Indicators, gridded nighttime luminosity data from satellites and subnational GDPpc (from the regions in which such data are available) from the MCC-PIK Database Of Sub-national Economic Output (DOSE) dataset collected by Wenz et al.[133]. We estimate a multiple regression model in which observed regional GDPpc is regressed on the corresponding country's GDPpc, regional average nighttime luminosity and their interaction[134]. (To perform this procedure over the period 1991–2020, we linearly extrapolate regional nightlights beyond their original 1992–2013 time boundaries). This regression model skilfully 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 in which it is not available, using the country-level GDPpc and nightlights data in these regions. There are some countries for which the relationship between national and regional GDPpc seems abnormal, specifically Uzbekistan and Kenya, so we drop these countries from the final data construction (see Supplementary Fig. 8 of ref. 89). In other countries, such as Afghanistan, even country-level GDPpc data are 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 are 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 ref. 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 that 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 heatwaves happen to coincide with the Tx5d in each case we present. We would not always expect that to be the case, as damaging heatwaves 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 heatwave; for example, the 2010 Russian heatwave 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 five, 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, heatwaves produce an economic rebound in the years following the event. Thus, 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 2 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 heatwave, before India catches back up to its original economic trajectory in 2001 and damages are zero thereafter. For the USA in 2012, we exclude Hawaii and Alaska from this calculation, to calculate damages only for the contiguous states of the USA.

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 1,001 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 1,000 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 through IEEE DataPort at https://doi.org/10.21227/w3fm-w720.

Code availability

All computer code that supports the findings of this study are available through IEEE DataPort at https://doi.org/10.21227/w3fm-w720.

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Additional information

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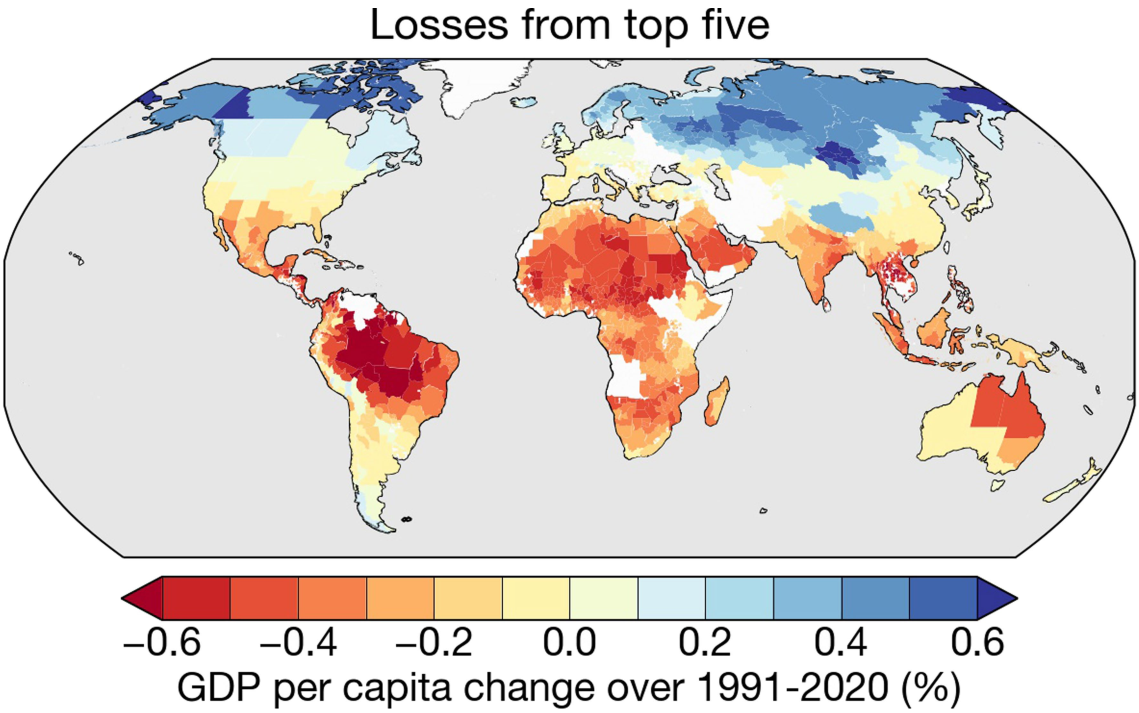

Extended Data Fig. 1 | Damages when annual average temperatures are held at their observed values. As in Fig. 2a but when emissions only affect the intensity of Tx5d values and not the annual average temperatures that moderate the effect of Tx5d. Map was generated using cartopy v0.17.0 and regional borders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

Extended Data Table 1 | Availability of emissions data for the top five companies

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

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 top five emitting companies in our data. Data are from the Carbon Majors database[100], based on work in ref. 62.