Carbon majors and the scientific case for climate liability

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Writing in these pages in 2003, Myles Allen considered the limits of climate science and posed an essential question: "Will it ever be possible to sue anyone for damaging the climate?" Twenty years later, 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 corporate emitters to specific damages from warming. Using 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. Chevron, the highest-emitting investor-owned firm in our data, for example, caused between $479 billion and $1.8 trillion in heat-related losses over 1991-2020, disproportionately harming the tropical regions least culpable for warming. More broadly, we outline transparent, reproducible, and flexible frameworks that formalize how end-to-end attribution could inform litigation by assessing whose emissions are responsible and for which harms. While quantitative linkages between individual emitters and particularized harm were not feasible 20 years ago when Allen first considered the legal implications of attribution science, they are now. Science is 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. To the extent that 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 twenty years, science and law have been engaging a set of challenges that take climate liability from Allen's 2003 thought experiment into a realistic practice.

Scientifically, the focus has been on advances in attribution, specifically the development of standardized methods codifying a scientific consensus on the role climate change plays in amplifying extreme events[4]. Such consensus methods have been applied 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]. The scientific consensus developed around these methods[19] suggests they could meet legal standards for admissibility[20]. By revealing the human fingerprint on events previously thought to be "acts of God," attribution science has helped make climate change legally legible[21–23].

Legally, much of the 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, with many more anticipated. The legal theories undergirding these cases generally fall into one of three categories, shaping who is liable and for what conduct[24]. The first centers on the disinformation campaigns mounted by fossil fuel firms, which claimants argue misled investors to the point of fraud[25]. The second targets governments and their regulatory failures to protect citizens' rights to a stable climate[24].

In this Perspective, we focus on the last of these theories: that emitters are liable for the damage wrought by warming[26]. Such cases mirror efforts to hold other industries like tobacco[27] and pharmaceuticals[28] liable under legal standards like the duty of care, public nuisance, failure to warn, or strict liability. 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, in 2017, the city of Oakland, California sued British Petroleum (BP) and other firms for causing sea level rise along the California coast[29]. New York City and Rhode Island have brought similar claims[30,31]. 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[32,33]. Attribution science is most useful to this theory of liability, as legal standing for plaintiffs requires that they 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[34]; more recently, a court ruled that Montana's efforts to deregulate emissions violated its residents' right to a healthy environment[35]. 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[24]. 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[24]. There is talk of a "coming tsunami of climate litigation" for which courts are woefully unprepared[36].

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 frameworks for end-to-end attribution: 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 impacts, from heat waves as here, to floods, sea level rise, and more. We also show how each framework can be applied in a way that is agnostic about any particular emitter, instead attributing the emissions contribution required to confidently detect damage. Such a flexible approach helps communities assess responsibility for losses, rather than naming parties prima facie. We argue that while this type of end-to-end attribution will provide legal 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 enterprise to provide peer-reviewed and reproducible attributions and expert testimony to ensure courts have the scientific support to buffer the billowing wave of climate liability.

Attribution science and causation

The scientific and legal enterprises share many characteristics: they are consumed with establishing facts, proving causation, building theories, leveraging frameworks, and exercising prudence. But there are crucial differences: The burden of proof is generally higher in science than in law[37], as science works to falsify hypotheses and jettison theories[38], while many legal judgements, such as in U.S. civil law, seek only to prove that something is more likely than not. In the context of climate liability, advances on the scientific side (e.g., attribution) do not necessarily resolve questions on the legal side (e.g., causation, standing). They are different enterprises with different goals. Yet there is reason to believe that advances in attribution can help clarify legal paths to liability, in part by better articulating "but for" causation[2].

To sue over an injury, a litigant typically must demonstrate "but for" causation: without the actions of the defendant, the plaintiff would not have been injured[2]. This task is often straightforward, like for car accidents, workplace negligence, and others. But in the context of climate liability, it is more difficult, as a plaintiff must provide both "general" and "specific" causation. General causation is concerned with whether something causes a type of harm, such as the way asbestos exposure increases cancer risk. It is held to a high standard of certainty, akin to the 95% statistical significance level adopted in many scientific studies[39]. 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. Specific causation is often held to a "more likely than not" standard. In his Perspective, Allen hypothesized how attribution science might meet these standards: If global warming has tripled the risk of a flood, then such warming is responsible for two-thirds of its risk, making contributors liable for two-thirds of its harm[1]. This argument provides elements of general, but not specific, causation—would the event have occurred "but for" an emitter's particular contribution? The role of an individual contributor must be isolated[22,40], and changes in physical events do not necessarily imply the particularized harms that provide standing.

Hurricane Maria, which motivated a suit by Puerto Rican municipalities[32], provides an example. Peer-reviewed research has shown that global warming intensified rainfall from the hurricane[13]. While valuable, such analysis does not resolve "but for" causation[41]; it is not clear, for example, how much any one emitter contributed to such rainfall intensification. Moreover, it is unknown how the amount of rainfall translated into socioeconomic injury from the hurricane. Such gaps have been cited as a significant barrier to climate litigation[2,21,42,43] and have been used by fossil fuel firms to argue that plaintiffs lack standing to sue over climate damages[44].

Scientific advances that resolve this barrier must directly quantify the harm caused by a specific actor's emissions. This is not a trivial task. The causal chain from emissions to impacts is nonlinear[45] and uncertainties compound from emissions, to atmospheric GHG concentrations, to warming, and finally to socioeconomic impacts[46]. Moreover, emissions and impacts are dislocated in space and time—a flood could occur on the other side of the Earth from the source of emissions, months, years, or decades after such carbon was pulsed to the atmosphere[47]. As a result, scientific approaches that illustrate clear causal linkages from emitters to impacts have been termed the "Holy Grail" of climate litigation[43].

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[40] has linked emissions from countries[48–50] and carbon majors[51] to increases in global mean surface temperature[52] (GMST), sea level rise[52], and ocean acidification[53]. Recent efforts have also linked countries' emissions to extreme climate events[54–57], though not the human impacts of those events. Source attribution typically 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 left-out emitter, providing a test of “but for” causation[2]: *but for the emissions of said actor, the climate would have been thus*. One could perform these simulations with a coupled Earth system model[58], but such models are opaque and computationally expensive. A computationally tractable approach is to use reduced-complexity climate models (RCMs) that simulate behavior of the Earth system using a smaller number of equations.

RCMs like MAGICC[59] and FaIR[60,61] have long been part of the consensus methods used in Intergovernmental Panel on Climate Change (IPCC) assessment reports[62] for purposes like simulating mitigation pathways[63]. More recently, RCMs have been applied to source attribution, for tasks such as simulating country-level contributions to global mean temperature change[64,65]. RCMs are zero-dimensional, lacking spatial information. But peer-reviewed methods like pattern scaling[66–68] can address this shortcoming, providing robust statistical relationships between global and local climates that allow scientists to draw maps of local temperature change based on RCM output[69]. Together, RCMs and pattern scaling link the contributions of individual emitters to local temperature changes in an efficient, transparent, and reproducible manner[57,64,65].

Yet local climate changes do not inevitably imply particularized injuries. To connect individual emitters to impacts, researchers must quantify the economic or social effects of local climate changes. Enter the second major advance: more robust quantifications of the socioeconomic impacts of climate change[70]. Metrics like the “fraction of attributable risk” that Allen posited are not always suitable for quantifying the influence of climate change on human impacts[45,71–73], though they have been applied to impacts like rainfall losses[74]. Nonlinearities associated with the impacts of extreme events mean that more complex and tailored approaches are necessary to connect GHG emissions to socioeconomic losses. For example, Strauss et al.[75] use hydrodynamic modeling combined with property damage estimates to quantify the anthropogenic contribution to damages from Hurricane Sandy in New York, an example of an emerging field of research that combines event attribution results with damage estimates. To enable a more generalizable framework, we draw on recent peer-reviewed work that uses econometrics to infer causal relationships between climate hazards and human outcomes like income loss[70]. For example, researchers have used empirical methods to show that climate extremes reduce agricultural yields[76], increase human mortality[77,78], and depress economic growth[79–81]. In the attribution context, these causal relationships have been applied to quantify the historical costs of climate-driven flooding[82], crop losses[83], and reduced global economic output from increases in average[84] and extreme[85] temperatures.

Here we show that emissions directly traceable to carbon majors have increased heat wave intensity globally, and that such additional heat wave intensity has caused quantifiable income losses for people in subnational regions around the world.

Heat wave damage from carbon majors

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 an average of 200, 138, and 131 MtC yr^{-1} in CO_2 emissions, respectively[51]. Fig. 1a illustrates data since 1920 for comparison, but 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 method[64] centered on extreme heat (Supplementary Material). The goal of this framework is to construct a "counterfactual" world in which a firm's contribution to local extreme heat change is isolated and removed. We first use the FaIR RCM[86] to translate firms' emissions into GMST changes (Fig. 1b); next, we apply pattern scaling[68] 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 changes due to these extreme heat changes[85] (Fig. 1d). We compare heat-driven economic damages between the historical and counterfactual worlds, with the difference between them corresponding to the firm's contribution to damages. At all stages, we propagate uncertainties to ensure our findings are robust. We also hold constant non-climate factors in our counterfactuals; for example, we do not consider how removing firms' emissions could have changed the global trade in oil. 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 FaIR's parametric uncertainty, providing a distribution against which we compare our counterfactual leave-one-out simulations. For the latter, we re-simulate GMST change, 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 ~0.024 °C of the more than 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 (Fig. 1c).

Finally, we use an empirically derived damage function that generalizes the relationship between extreme heat intensity and economic growth[85] to estimate the consequences of firm-driven Tx5d changes (Fig. 1d). This relationship varies as a function of regional average temperature: warm tropical regions lose more than 1 percentage point (p.p.) in economic growth for each 1 °C increase in the intensity of the hottest five days in each year, whereas temperate regions do not experience large effects[85] (Fig. 1d).

We calculate losses in both the historical and leave-one-out simulations 10,000 times for each region using a Monte Carlo approach (Supplementary Material), taking their difference to provide losses attributable to the emissions from each carbon major. If this difference is statistically significant ($p < 0.05$) given the uncertainty from the FaIR simulations, pattern scaling, and damage function estimates, the firm has made significant and quantifiable "but for" contributions to economic losses (Supplementary Material). 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[85]. We also account for the economic rebound shown in previous work[85], whereby the effect of extreme heat is recovered after 2-3 years, meaning we do not assume permanent growth impacts of extreme heat.

The global economy would be $27 trillion richer were it not for the extreme heat caused by the emissions from the 100 carbon majors considered here (Fig. 2). Gazprom is responsible for more than $1 trillion in global economic losses from intensifying extreme heat (2020-equivalent $US), and Saudi Aramco is responsible for more than $900 billion. The contributions from these two state-owned enterprises are due to their recent and rapid contributions to emissions (Fig. 1a), even though they did not make large contributions to temperature change earlier in the 20th century. Chevron, ExxonMobil, and BP have caused $479 billion, $364 billion, and $28 billion in losses, respectively (Fig. 2a). Investor-owned companies (e.g., Chevron, ExxonMobil) are collectively responsible for $13.7T in losses, while state-owned enterprises (e.g., Saudi Aramco, Gazprom) are responsible for $13.2T. Ranges in damage estimates can be large, due to the convolution of carbon cycle and climate uncertainties in the FaIR simulations and parametric uncertainties in the pattern scaling and damage function. Yet in all cases, the 99% range for each of the five main firms does not include zero (Fig. 2a), making it virtually certain that each has contributed to large global heat-driven losses.

We use a Kolmogorov-Smirnov test to assess the statistical significance of each firm's effects in each region and year[64] (Supplementary Material). Consistent with scientific practice, we use an alpha threshold of 0.05 (i.e., the conventional significance standard of 95%, or $p < 0.05$). This test explains why Saudi Aramco's total damages are lower than Gazprom's, despite its greater emissions: its contributions to GMST change are more uncertain (Fig. 1b) and therefore fewer of its regional damages are statistically significant. Yet the significance threshold of 95% is more restrictive than the "more likely than not" threshold for evidence in civil cases, which corresponds to an alpha of 0.5[37]. To align our analysis with this legal standard, we re-calculate attributable losses with significance defined as $p < 0.5$ (red lines in Fig. 2a). A "more likely than not" threshold raises the contributions of all firms. Most strikingly, it raises the damages from BP's emissions by two orders of magnitude, from $27B to $1.1T. On the other hand, it does not change results for groups of emitters (Fig. 2b), as collective contributions are large enough to be significant even under a restrictive standard. These results demonstrate that evidentiary standards can influence attributed losses and that applying scientific standards may underestimate the damage for which actors could be held liable.

Losses can also be assessed at finer, more legally relevant regional scale, revealing latent 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 much of the tropics, particularly in 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.

Our approach illustrates 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[87]. End-to-end attribution should therefore be able to account for individual extreme events in addition to cumulative exposure. As a proof of concept, we show 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.[6,8,9,83,88]), 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 \$1.2B, \$1.8B, \$1.2B, and \$7.2B in losses from the 1998 Indian, 2003 French, 2010 Russian, and 2012 American events, respectively. Relaxing the statistical significance threshold increases attributable damages for these events by factor of four on average (Fig. 3e-h, red bars). Single-event source attribution also illustrates how firms can be more or less culpable for different events: Chevron and ExxonMobil are linked to losses in India in 1998 at the 95% confidence level due to their high 20th-century emissions, while Saudi Aramco, Gazprom, and BP cannot, unless the threshold is relaxed to the "more likely than not" standard.

Collectively, these results illustrate, for the first time, 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 Figs. 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? Here, too, science can help clarify the legal landscape.

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 claimants could be missing or erroneously including emitters in their claim. And yet indexing through all possible emitters to attribute each of their contributions 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). In this instance, the analysis asks: "what percentage of global emissions must emitters have released to have caused detectable harm from extreme heat?" Our approach here 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 minimum contribution required over some time period and some spatial scale to have made a detectable impact. Global losses from extreme heat scale quasi-linearly with emissions contributions (Fig. 4a). While emissions contributions below 1.5% do not have statistically significant impacts, any contribution above 1.5% can be tied to heat-driven losses at the 95% confidence level. At the more-likely-than-not level, this threshold falls to 0.5% (Fig. 4a, red line). Above 3%, the relationship scales such that each additional percent contribution to total 1850-2020 emissions generates an additional $815 billion in global economic losses from extreme heat.

Such a 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 whether their contributions have caused detectable harm, flexibly considering different significance levels. 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. 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[49], heat wave losses attributable to an actor contributing 5% of global emissions tally $2.1 trillion, contrasting with the $4.1 trillion when counting from 1850. Yet fossil fuel firms have accurately predicted climate change since the 1970s[89] and have since used their power and profit to cast doubt on the relationship between fossil fuels and warming[90]. If we use the 1977 date of the first reported successful projection of global warming by ExxonMobil[89], heat wave losses attributable to an actor contributing 5% of global emissions come to $3 trillion. These losses are all large and statistically significant, but vary by ~50% across start dates.

Our emitter-agnostic approach can be extended to more legally relevant scales (Fig. 4c) or applied to specific heat wave events, providing a basis from which courts can assess the contributions of actors of interest: if an actor has contributed more than the minimum level required for a significant contribution to losses, there is evidence for causal linkages between that actor's emissions and resulting injuries. This number is less than 3% in many tropical regions but exceeds 5% at higher latitudes, reflecting the unequal spatial structure of the causes and effects of extreme heat (Fig. 2c, top). Relaxing the significance threshold lowers the minimum contribution to less than 2% in tropical regions (Fig. 2c, bottom). We can also assess the minimum contribution for detectable harm for the heat events presented in Fig. 3. For example, we find that any actor contributing at least 2%, 2%, 1.5%, and 1.5% of 1850-2020 emissions can be linked to losses from the 1998, 2003, 2010, and 2012 heat waves, respectively.

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 but one climate impact, and so as science develops and new impacts are revealed, such as extreme rainfall[91] or El Niño[92], 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[66], such damage estimates can be easily ported into our framework. For example, Strauss et al.[75] attribute anthropogenic damages from sea level rise using a semi-empirical relationship between GMST change and local sea level rise. Their attribution analyses could therefore be directly linked to our RCM simulations of GMST contributions, demonstrating the modularity of our framework. Finally, performing near-real-time end-to-end attribution in a coordinated fashion 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], which has helped make event attribution a standard practice for science and the public, 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 "but for" 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[19]. And just as event attribution has moved from the fringe to the mainstream over the last twenty years, the same could be true of source attribution. A standing scientific body could be an essential resource for courts and citizens, providing tailored end-to-end attribution analyses and expert testimony, responsibly informing the coming wave of litigation to ensure claims use the best available science.

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[93]. Research using archival methods[94], computational frame analysis[95], and interviews[96] 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 Clean Air Act, which may displace federal common-law claims[97], or courts' perception that these cases inappropriately intervene in policymaking[98].

Moreover, despite the harm arising from extreme heat, fossil fuels have also produced immense prosperity over the last century. Our results do not reflect the benefits to economic growth that fossil-fueled energy has provided and for which these firms have 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[93]. 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[99]. More broadly, just as the benefits of a medication do not absolve a manufacturer who fails to warn its customers about side effects, we do not believe that the benefits of fossil fuel use should absolve carbon majors of liability for these devastating externalities[2], particularly when they have misled the public about the dangers of their products[94].

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[100]. The next twenty years will bring greater clarity on these remaining questions. Here we provide an essential start: the development of rigorous, flexible, transparent, and widely applicable end-to-end attribution frameworks.

In his prescience, Allen posited this moment twenty years ago, considering the extent to which scientific limitations represent an obstacle to climate liability. While legal and policy barriers remain, science is no longer an obstacle to climate liability claims.

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Competing interests

The authors declare no competing interests.

Author contributions

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

Data and code availability

All data and code that support the findings of this study will be made available upon publication at github.com/ccallahan45/CallahanMankin_CarbonMajor_Attribution/ and archived permanently at [link upon publication].

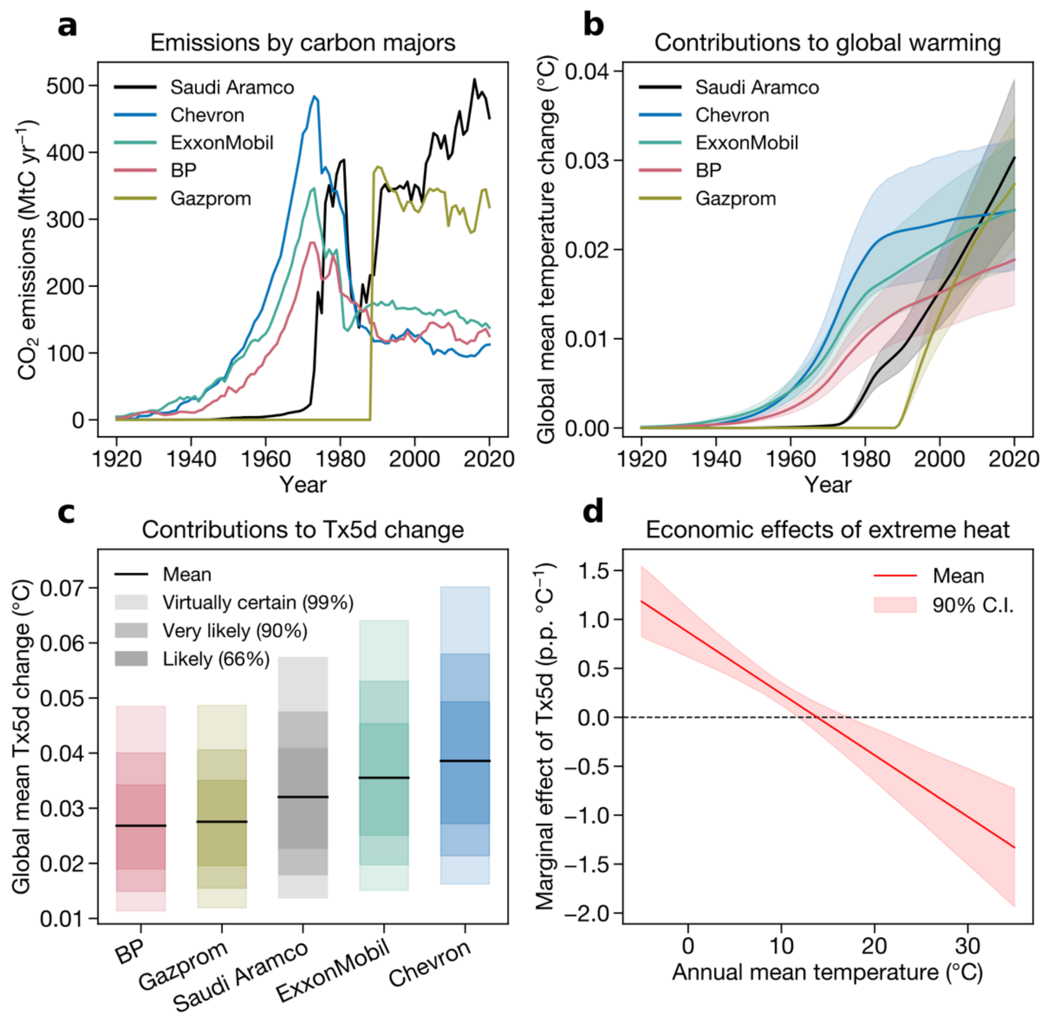

Fig. 1 | Carbon majors have individually contributed to extreme heat intensification. A) CO_2 emissions in megatons of carbon (MtC) per year from the five top-emitting fossil fuel firms (“carbon majors”). B) Changes in global mean temperature caused by the cumulative emissions of each carbon major. Vertical 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 confidence 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, 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.

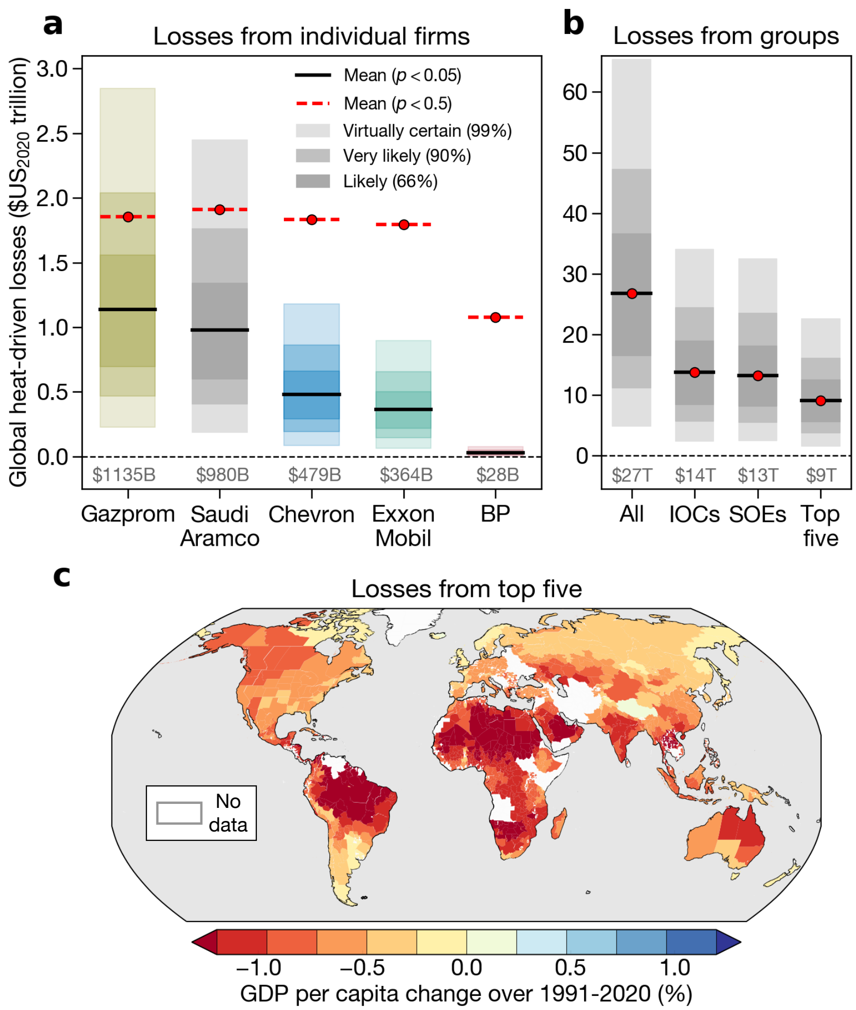

Fig. 2 | Carbon majors have caused cumulative economic losses from extreme heat irrespective of significance standard. A) Cumulative global heat-driven economic losses linked to the five top-emitting fossil fuel firms over 1991-2020. Black line shows the mean across 10,000 Monte Carlo simulations convolving all sources of uncertainty and gray shading denotes the IPCC likely (66%), very likely (90%), and virtually certain (99%) ranges. The main analysis uses a significance threshold of $p < 0.05$; red dots and lines show the average losses for each firm if a threshold of $p < 0.5$ is used, corresponding to a legal standard of "more likely than not." 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. Red dots correspond to a significance threshold of $p < 0.5$. In A and B, bottom inset text denotes the average losses linked to each actor or group using the $p < 0.05$ level. 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, evaluated at the 95% confidence level. 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.

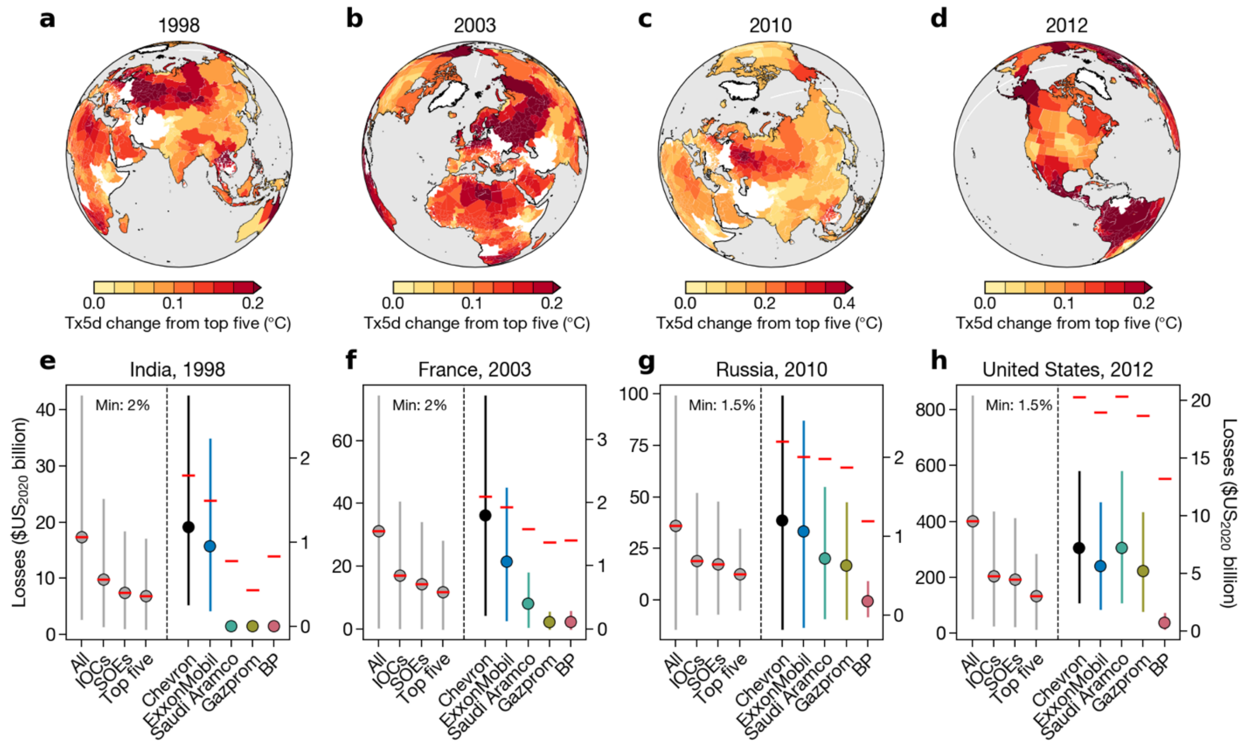

Fig. 3 | Carbon majors have caused losses from individual extreme heat events. A-D) Average change in regional Tx5d values due to the emissions of the five top-emitting carbon majors in 1998 (A), 2003 (B), 2010 (C), and 2012 (D). E-H) Economic losses due to Tx5d intensification in India in 1998 (E), 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, lines span the 90% (very likely) range, and inset text denotes the minimum percent contribution to 1850-2020 emissions that can be statistically tied to losses from each event using a $p < 0.05$ threshold. Red lines in E through H denote the contributions of each carbon major when $p < 0.5$ is used as the significance threshold rather than $p < 0.05$. Maps were generated using cartopy v0.17.0 and regional borders come from the Database of Global Administrative Areas.

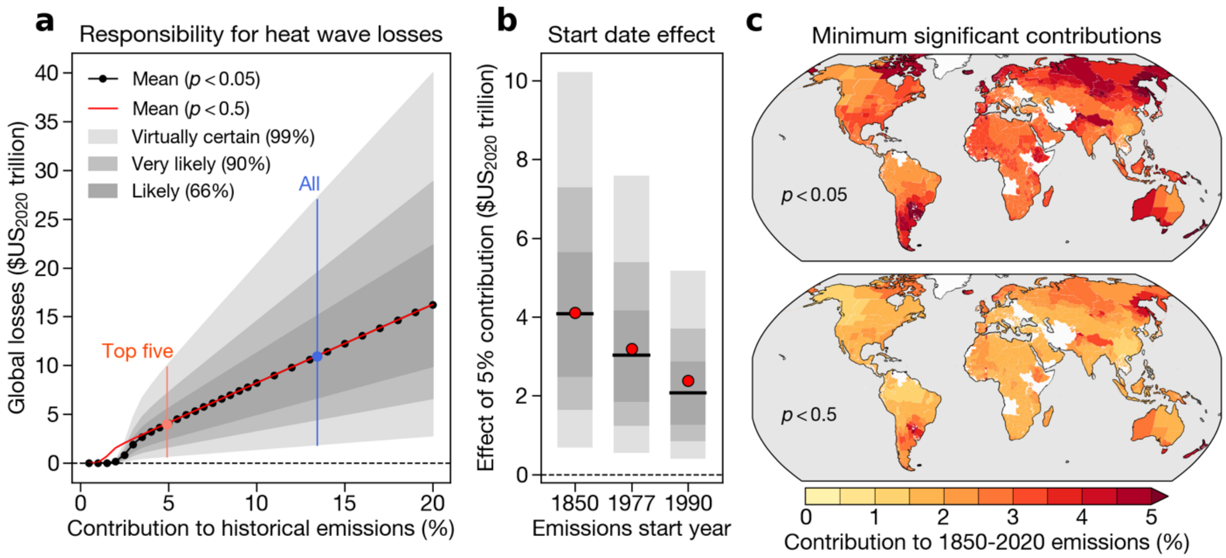

Fig. 4 | The emissions contributions necessary to attribute cumulative economic losses from extreme heat depend on evidentiary standards and the time period considered. A) Attributable global heat-driven economic losses over 1991-2020 as a function of the percent contribution to global CO_2 and CH_4 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), 1977, or 1990, and ending in 2020 in all cases. In (A) and (B), black line, dots, and shading correspond to a $p < 0.05$ threshold whereas red line or dots correspond to a $p < 0.5$ threshold. C) Minimum statistically significant contribution to economic damages in each subnational region corresponding to thresholds of $p < 0.05$ (top) and $p < 0.5$ (bottom). Maps were generated using cartopy v0.17.0 and regional borders come from the Database of Global Administrative Areas.

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SUPPLEMENTARY MATERIAL

Carbon majors and the scientific case for climate liability

Christopher W. Callahan & Justin S. Mankin

Supplementary Methods

Our approach provides an open-source, transparent, rigorous, modular, and extendable end-to-end attribution that isolates and quantifies particular damages from climate hazard(s) that can be traced back to particular emissions, building on our earlier work in this area[1].

Here, we present the damage attributable to enhanced extreme heat due to the emissions of particular actors. We measure this damage as subnational GDP per capita loss. We emphasize that this is not the only way to measure the impacts of extreme heat, nor does such an assessment represent the totality of climate damages attributable to any one emitter. As such, our estimates of damages attributable to emitters should be considered lower bounds, as they do not include other hazards and damages that could be traced back to these emissions, nor does income loss represent the total damage associated with extreme heat.

Mechanically, 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, 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 reduced-complexity climate model (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[2] (DAMIP) run with the fully coupled Earth System Models participating in the sixth phase of the Coupled Model Intercomparison Project[3] (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.[3]). 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 that for the "historical," but this time we remove the emissions from a single firm from total historical emissions. This is called a "leave-one-out" experiment; it 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 Heede[4]; we use all available years of emissions data for each firm. 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 S1 shows the years over which emissions data are available for the five top-emitting firms in our data.

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[5]. Notably, 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 firm-level “leave-one-out” scenarios, 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[6] (in contrast to the country-level approach of previous studies[7,8], 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[9], we use the widely-used pattern scaling method to calculate changes in Tx5d in each region as a linear function of changes in 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 outlined above. 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 marginal 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”). For the CMIP6, only 8 distinct models are available, but we use as many ensemble members for each model as possible. This choice 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 and statistical significance*), we adjust the model sampling probabilities so that models with fewer realizations are equally likely to be sampled as models with more[6].

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.[6], 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. 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 reflect sampling uncertainty in our estimates.

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[6] and Diffenbaugh and Burke[10]. 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[1].

The effect of extreme heat on economic growth is not permanent. In previous work[6], 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. 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[6].

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[6] 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.[11]. 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[12]. (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[6]. 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 even country-level GDPpc data is not continuously available, such as Uzbekistan and Kenya, and in these regions we do not produce regional GDPpc data (see, for example, the white regions in Fig. 2).

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[6]. 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. In such cases, other heat metrics or approaches may be appropriate.

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. Previous work found that heat waves affect growth in both the year of the event as well as two years afterwards, before regions "catch up" to their previous growth rate in the third year following the event. Critically, this does not imply that these events have no effect on economies; it simply means that that effect is transient rather than permanently accumulating. Further discussion of this issue can be found in Callahan and Mankin[6]

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 and statistical significance

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.

Our damages analysis involves differencing two estimates: damages with and without a certain emitter. Each of these damage estimates has 10,000 values for each region and year. To test whether a firm's effect is statistically significant, we use a Kolmogorov-Smirnov test in each region and year to test whether the distributions with and without that firm are statistically distinct. If these two distributions are distinct with an alpha of 0.05 (i.e., significance requires $p < 0.05$), the firm has made statistically significant and quantifiable "but for" contributions to economic losses. If a given region and year is not significant, it is discarded and not added to a firm's total damages (e.g., the numbers shown in Fig. 2).

When we alter our threshold for the test of significance, we simply repeat our analysis with an alpha threshold of 0.5 rather than 0.05.

Supplementary Tables

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

Supplementary 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 Heede[4].

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