Apportioning responsibility for heat-driven loss and damage

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The emerging impacts of climate change have motivated legal claims against major emitters to hold them responsible for these impacts. However, a dearth of evidence quantitively linking major emitters to the downstream economic impacts of their emissions makes the causal linkages between emitter and impact unclear, especially given the compounding uncertainties at each step in the causal chain from emission to impact. Here we simulate idealized contributions to regional changes in extreme heat and the resulting economic damages, accounting for diverse sources of uncertainty. We derive a generalizable relationship between an actor's contribution to global emissions and the loss and damage from extreme heat attributable to that contribution, allowing us to tie both major fossil fuel firms and major emitting countries to heat-driven loss and damage for the first time. The top five fossil fuel firms have collectively driven more than $7 trillion in heat-driven losses, primarily in lower-emitting tropical countries, and the top five emitting countries have driven more than $22 trillion. These results highlight the culpability of major emitters for the direct economic losses resulting from extreme heat and demonstrate the scientific underpinnings of claims for climate damage restitution.

Introduction

The world has warmed by more than one degree Celsius since the preindustrial era due to anthropogenic emissions of greenhouse gases (1). This warming has increased the intensity of heat waves (2), droughts (3), and tropical cyclones (4), with striking negative consequences for economic growth (5, 6), agricultural yields (7), and human mortality and morbidity (8). Importantly, the distribution of these impacts is deeply unequal, with stronger impacts in the warm, tropical regions that are least responsible for warming to date (5, 9, 10).

The recognition of these and other impacts has motivated legal claims against major emitters, seeking to hold them accountable for the impacts of their emissions (11). A critical requirement for the success of these legal claims is causation: the ability to establish a clear causal chain between the actions of emitters and damages suffered by plaintiffs (12). Given that greenhouse gas emissions are well-mixed and uncertainties compound across the causal chain from emissions to impact (13), establishing individualized causation for climate damages has been a key barrier for climate litigation to date (11).

Advances in attribution science that link climate change to specific extreme weather events has been proposed as a key evidentiary piece of these claims of causation (14–16). However, attribution of an impact to global warming writ large is not legally sufficient to demonstrate the causal role of any individual actor (15), and research linking the emissions of an individual actor to the impacts of the resulting warming is still in its infancy. There is a long history of work linking individual actors to global emissions (17–20), global warming (19, 21–23), regional warming (24, 25), and impacts such as sea level rise (26) and ocean acidification (27). However, partly given the complexities and uncertainties associated with linking local warming to economic damages (28, 29), research has generally not quantified the monetary culpability of individual emitting actors.

To close this gap, Callahan and Mankin (30) attributed economic damages from changes in country-level average temperature to national emissions, showing that countries like the U.S. and China could be quantitatively linked to trillions of dollars in losses in low-income and low-emitting tropical countries. These findings demonstrate a preliminary scientific basis for claims for restitution for climate damages, but several gaps remain. For example, victims of climate damages may desire restitution from fossil fuel firms or other non-state actors rather than countries, and impacts based on country-level average temperatures are potentially a poor proxy both for short-term periods of damaging extreme temperatures and for local impacts accruing to specific regions within countries.

Here we extend the three-part attribution framework developed by Callahan and Mankin (30), which uses a simple climate model to calculate emitter contributions to historical global mean surface temperature (GMST) change, pattern scaling to propagate GMST change to the local level, and empirically grounded damage functions to transform local warming into economic losses. We make three key advances over this previous work: (1) we simulate the effects of idealized emissions contributions rather than specific countries, which generalizes our findings; (2) we analyze historical economic losses due to extreme heat rather than average temperatures; and (3) we calculate economic damages at the subnational level, which captures regional heterogeneity obscured by a country-level focus. Collectively, these advances allow us to quantify the roles of a wide range of actors in shaping local heat-driven losses, and thus the potential financial obligations of those actors to affected regions.

The first step of our analysis uses simulations with the Finite amplitude Impulse Response (FaIR, v2.1) climate model (31, 32) to calculate the effect of idealized emissions contributions on GMST change (Methods). We subtract a set of percentage contributions (e.g., 10% of annual emissions over 1850-2020) from global emissions and calculate the resulting GMST change (Fig. 1A). We then combine these

GMST contributions with pattern scaling coefficients derived from the sixth phase of the Coupled Model Intercomparison Project (CMIP6) (Fig. 1B, Methods). This approach allows us to calculate the change in extreme heat, defined as the temperature of the hottest five days in each year ("Tx5d"), in subnational regions around the world due to each emissions contribution (Fig. 1B). For example, an actor responsible for 5% of global emissions on average over 1850-2020 can be linked to a 0.08 °C increase in Tx5d in the average subnational region over 1991-2010 (Fig. 1B). Finally, we combine these contributions with previous empirical estimates of the effect of Tx5d changes on subnational economic growth (Fig. 1C). The effect of Tx5d increases in economic growth varies as a function of annual mean temperature, with regions above ~14 °C experiencing noticeable losses in years with more-intense extreme heat (5). While the effect of any one heat wave is only transient rather than persistent (Fig. 1C, inset), multiple or repeated warming-driven heat waves can be linked to long-term economic slowdown (5). We calculate 1991-2020 economic damages from extreme heat attributable to total global warming as well as warming without a given actor, and difference these to calculate damages attributable to that actor (Methods).

At each step, our analysis incorporates uncertainty from the carbon cycle parameters in FaIR, from multiple climate models to derive the pattern coefficients, and from multiple bootstrap realizations of the empirical growth estimates. We also incorporate uncertainty in the construction of a global subnational GDP per capita (GDPpc) dataset, following Callahan and Mankin (5), necessary to fill in regions with missing data (Methods). Our final analysis samples uncertainty from all four of these sources to build distributions of attributable damages, distributions which we use to test the statistical significance of damages attributed to a given contribution in each region and year (30).

Results

On average, an actor contributing 3% of historical emissions from 1850-2020 is responsible for $1.4 trillion (2020-equivalent) in global economic losses due to extreme heat over 1991-2020 (95% confidence interval [CI]: $0.45T – $2.8T) (Fig. 2A). Above 3%, damages attributable to larger contributions rise approximately linearly: each additional percentage point in an actor's contribution increases its monetary responsibility to the rest of the globe by $500 billion (CI: $147B – $983B).

This analysis counts emissions from 1850-2020, but alternative start dates such as 1950 or 1990 are also legitimate accounting choices (22) and strongly affect our results (Fig. 2B). For example, only counting emissions over 1950-2020 makes an actor contributing 3% of these emissions responsible for $294 billion in global heat-driven losses (CI: $90B – $615B), while only counting emissions over 1990-2020 erases these damages entirely (Fig. 2B). The choice of start date is a political and legal one, and our results are consistent with other research showing that the subjective and political choices made in attribution discussions may have a substantial effect on the perceived culpability of major emitters (22).

Our analysis leverages uncertainty at each step of the causal chain from emissions to impact in order to determine the statistical significance of these damages. Above contributions of ~2%, the resulting damages are robust and statistically significant (Fig. 2A). Below 2%, the relationship between contribution and damages begins to break down because the “signal” of an actor’s contributions is too small to be statistically significant relative to the “noise”. Most strikingly, our methodology yields no attributable damages for contributions below 1.5% of global emissions (Fig. 2A). However, the level below which damages are no longer statistically significant is regionally variable (Fig. 2C). For regions in the global tropics most strongly affected by extreme heat, any actor contributing more than 1.5-2% of global emissions can be linked to local damages despite the uncertainties associated with those damages. In subtropical and polar regions, the signal of damages from extreme heat is weaker, so actors must contribute 4-5% or more of global emissions in order to be tied to damages in these regions (Fig. 2C).

These generalizable conclusions demonstrate the value of measuring the effects of percentage contributions, rather than specific actors. This approach allows us to abstract away from debates over, for example, territorial versus consumption emissions. It also allows us to assess the contributions of multiple categories of actors such as fossil fuel firms and countries (Fig. 3). We use data from Heede (33) to represent the contributions of fossil fuel firms (“carbon majors”) and from the Community Emissions Data System (34) to represent the contributions of countries (Methods), and linearly interpolate across the contribution-damages relationship (Fig. 1A) to assign responsibility to each actor (Methods).

The five top-emitting carbon majors can be collectively tied to more than $7.5 trillion in heat-driven economic losses (CI: $2.2T – $14.9T) (Fig. 3A), primarily in tropical and low-emitting regions (Fig. 3B). The top two, Chevron and ExxonMobil, are responsible for $1.8 and $1.6 trillion, respectively. Uncertainty is relatively large, with the *likely* (90%) range for Chevron’s contribution spanning $0.72T – $3.1T. However, the 99% range does not include zero for any of the top five carbon majors, indicating that it is *virtually certain* that these firms have made discernible contributions to global heat-driven loss and damage. On average, subnational regions around the world have experienced a ~0.84% reduction in annual GDP per capita due to the emissions of these top five carbon majors (Fig. 3B), with losses of 1% or more occurring in the tropical regions that have contributed least to warming (30).

Alongside their contributions to global warming, litigation against carbon majors like ExxonMobil claims that they sowed doubt about the science of climate change (35) while internally predicting global warming with striking accuracy (36). Our results highlight that at the same time carbon majors were actively attempting to prevent action on climate change, they were contributing to more-intense heat waves and resulting economic losses for the most vulnerable people globally.

Our methodology also allows us to link major emitting countries to similar losses. Based on their average contributions to historical CO_2 and CH_4 emissions, we find that the United States drove $10.2

trillion in heat-driven losses over 1991-2020, China drove $6.3 trillion, and Russia, India, and Germany each drove more than $2.5 trillion (Fig. 3C). Together, the top five emitting countries are responsible for $22 trillion in heat-driven loss and damage, primarily in the tropics (Fig. 3D). These results are consistent work on countries' contributions to loss and damage (30), but illustrate the role of extreme heat rather than average temperature and highlight the spatial heterogeneity of losses at the subnational level.

Discussion

Our results highlight the culpability of major emitters for warming-driven economic losses in the lowest-emitting and lowest-income parts of the world. Clearly connecting emitters to impacts in this way may help litigators demonstrate a causal nexus between defendants and the damages they may have caused. Additionally, our incorporation of uncertainty at each step in the causal chain illustrates that major emitters should not be able to claim plausible deniability for the effects of their emissions: the signal of their emissions is statistically identifiable against a robust characterization of the noise.

Importantly, however, we address only one piece of the climate damages puzzle. Extreme heat is only one of the physical impacts of climate change, which also include other extreme events such as tropical cyclones as well as slow-moving factors such as sea level rise (37). Further, economic damages are only one component of loss and may be secondary in subjective importance to declines in biodiversity or loss of cultural resources such as heritage sites. Finally, legal questions such as the time of emissions accounting and the inclusion of "fair share" emissions cannot be answered by scientific analysis. The outcome of climate litigation will be determined by courtroom discussions and legal principles such as sovereign immunity, and our results can only—at best—provide a scientific basis for these discussions.

Despite these caveats, our approach offers a flexible and generalizable framework to characterize loss and damage from individual emitters. Extreme heat is one of the starkest effects of climate change, and the simple emergent relationship between emissions contributions and heat-driven loss and damage implies that our results can be applied to other actors or groups of actors. As climate litigation against major emitters develops, this and other similar approaches may provide critical scientific support for claims for restitution from the most vulnerable people across the globe.

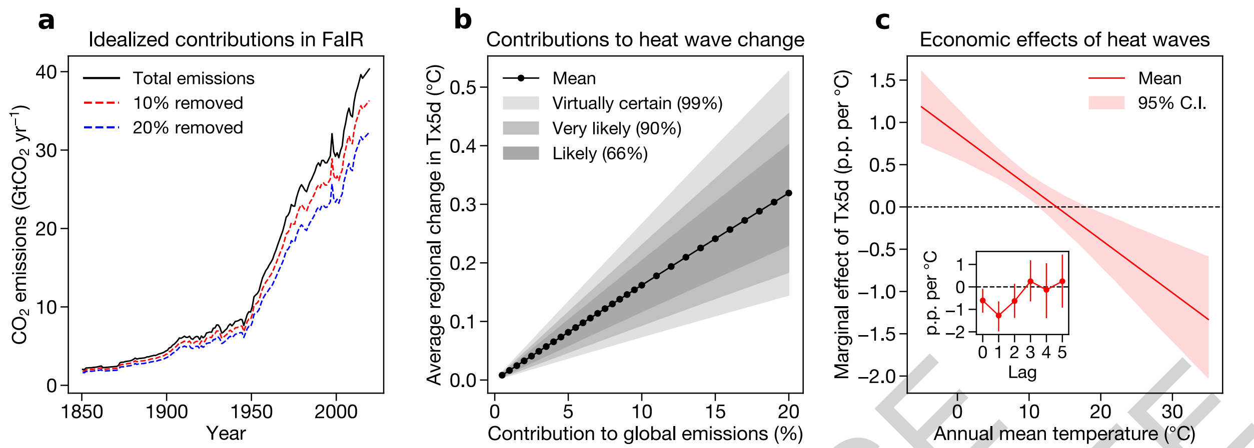

Fig. 1 | Simulating contributions to damages from extreme heat. A) Global CO_2 emissions from 1850 to 2020, with the global total (black line), a scenario in which 10% of emissions are removed (red dashed line), and a scenario in which 20% of emissions are removed (blue dashed line). B) Contributions of idealized actors to the global average regional change in Tx5d over 1991-2020. Black line shows the mean for each percentage contribution, where the mean is taken across all combinations of FaIR simulations and pattern scaling coefficients. Uncertainty is shown in gray, with the inner 66% ("likely"), 90% ("very likely"), and 99% ("virtually certain") percentiles shaded following Intergovernmental Panel on Climate Change (IPCC) convention. C) Effect of extreme heat on economic growth from Callahan and Mankin (5). Main plot shows the contemporaneous marginal effect of a 1-°C increase in Tx5d on economic growth across a range of annual mean temperatures, with the mean shown in the red line and the 95% confidence interval shaded. Inset plot shows the cumulative growth effect of Tx5d for an example warm region (average temperature of 25 °C), with the dots showing the mean and the vertical bars showing the 95% confidence intervals.

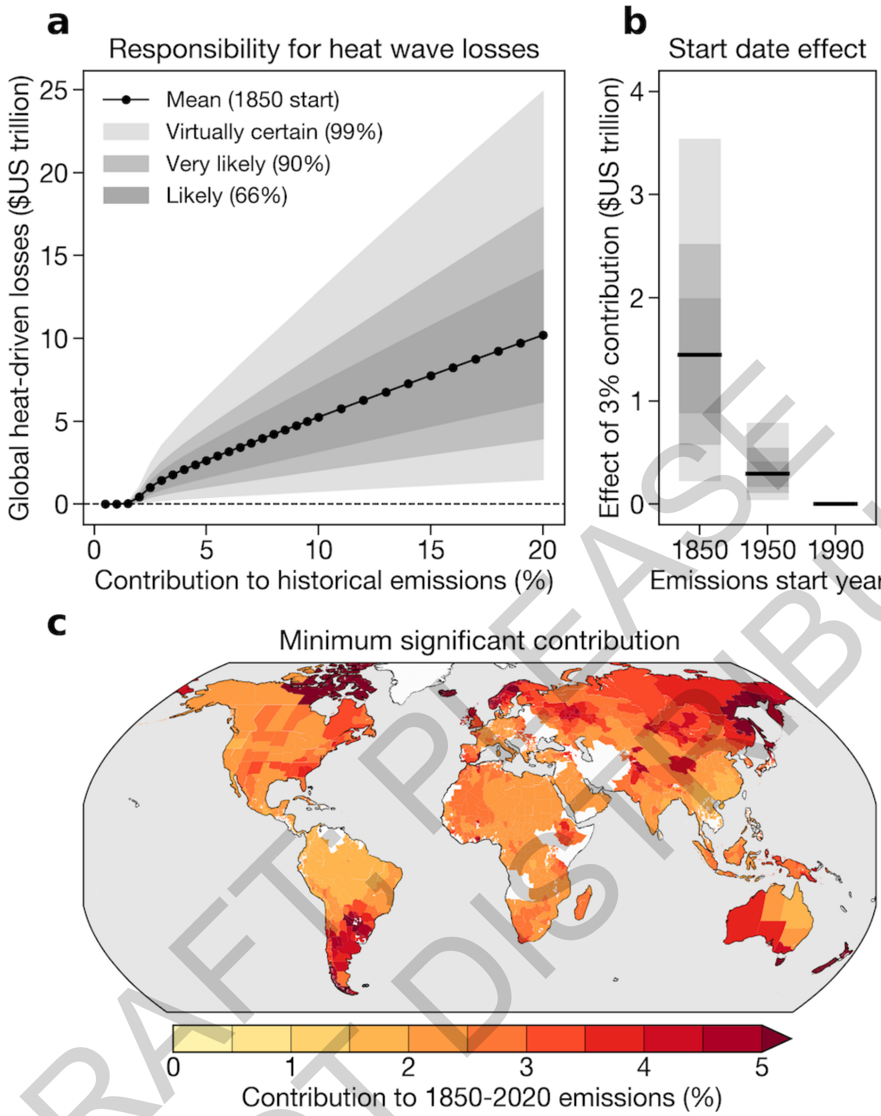

Fig. 2 | Generalized contributions to heat-driven damages. A) Cumulative global heat-driven economic losses, in trillions of 2020-equivalent $US, for a range of contributions to historical emissions. Emissions contributions are calculated over 1850-2020 while damages are calculated over 1991-2020. Black line denotes the mean across 10,000 Monte Carlo simulations (Methods), while gray shading shows uncertainty following IPCC convention. B) Heat-driven losses from a 5% contribution to global emissions with start dates of 1850, 1950, and 1990. In all cases, emissions contributions end in 2020 and damages are calculated over 1991-2020. C) Minimum statistically significant contribution to heat-driven losses in each subnational region. Any actor with a contribution above the level shown for a given region can be linked to damages in that region with statistical confidence. Missing data (white) in some regions results from a lack of continuous GDP per capita data over 1991-2020.

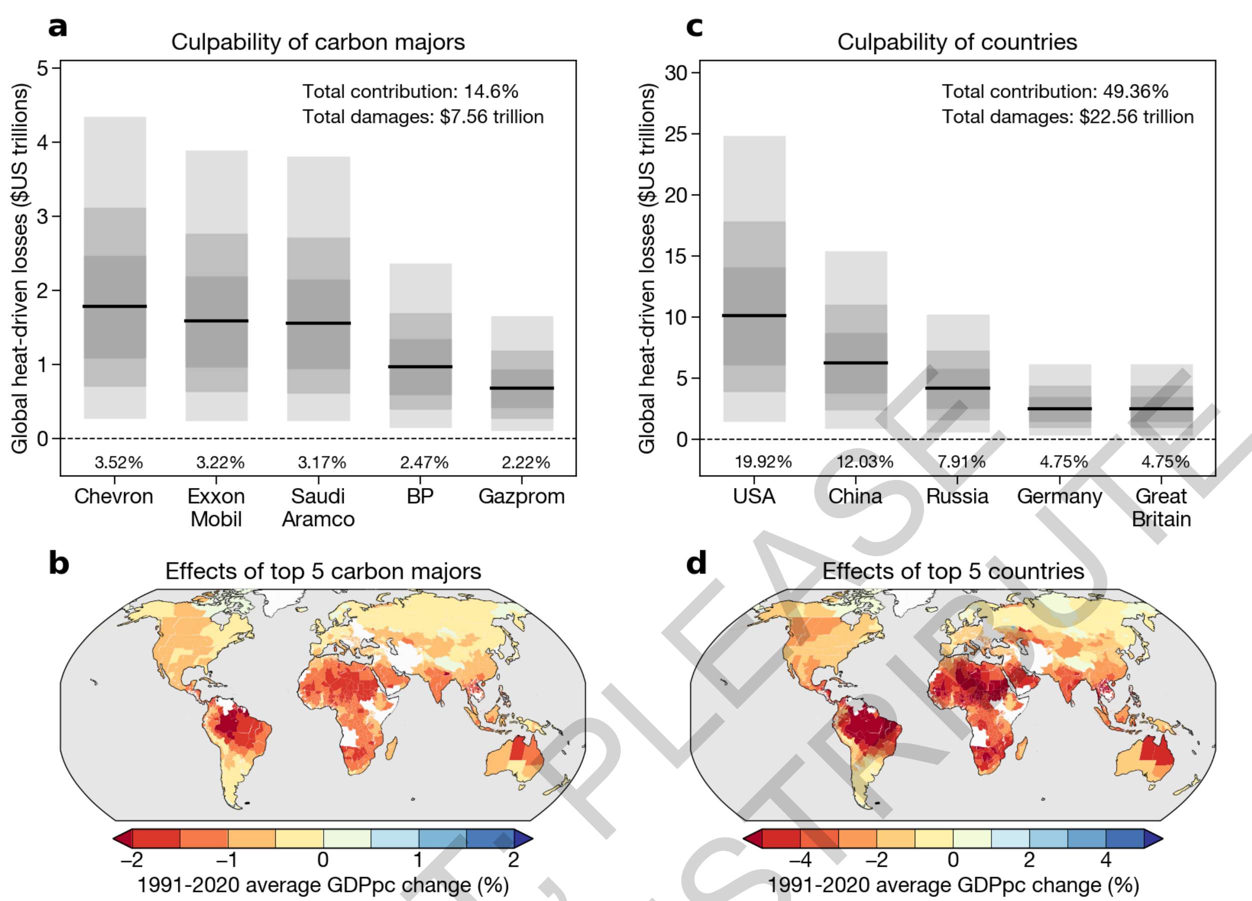

Fig. 3 | Specific contributions to heat-driven damages. A) The contribution of individual fossil fuel firms ("carbon majors") to global heat-driven losses, inferred from the generalized response shown in Fig. 2A. Black line and shading show mean and uncertainty as in Fig. 2A. Lower inset text denotes the emissions contribution of each firm. B) Average regional change in GDPpc due to the combined effects of the top five emitting carbon majors, shown in (A). C) The contribution of individual countries to global heat-driven losses. D) as in (B), for the combined effects of the top five emitting countries shown in (C).

Methods

Data

Observed climate data are drawn from the ERA5 reanalysis (38), from which we calculate regional Tx5d and average temperature. We calculate these variables at the subnational level by first calculating their values for each grid point and then averaging to regions using GADM shapefiles. We weight grid cells within each region by year-2000 population to capture the within-region distribution of economic activity. We similarly calculate regional Tx5d and average temperature from an ensemble of climate models from the sixth phase of the Coupled Model Intercomparison Project, or CMIP6 (39, 40). We use the "historical," "historical-nat," and "ssp245" experiments from 80 CMIP6 simulations. The natural simulations extend from 1850 to 2020, and we splice the historical simulations (which end in 2014) with the first six years of each model's ssp245 simulation to extend them to 2020 (40). Finally, we draw subnational economic data from the MCC-PIK Database of Subnational Economic output (41) and country-level economic data from the World Bank (42).

Historical contributions to global warming

We use the Finite amplitude Impulse Response (FaIR, v2.1) climate model (31, 32) to simulate idealized contributions to global warming in a "leave-one-out" approach, following Callahan and Mankin (30). We simulate a range of percentage contributions to emissions over the 1850-2020, 1950-2020, and 1990-2020 time scales. For each percentage contribution over each time scale, we subtract that percent of emissions from the global total, run FaIR with the reduced emissions, and extract the resulting GMST change time series. We also run simulations with global total emissions and with natural emissions only. The GMST change due to a single actor's contribution is the difference between the GMST change from the total-emissions simulation and that from the simulation in which that actor is excluded. In Figs. 1 and 2, we show contributions from 0.5 to 20%, though we simulate contributions up to 70% for application in Fig. 3.

We calculate contributions for CO_2, CH_4, N_2O, sulfur, black carbon, organic carbon, NH_3, NO_x, volatile organic carbons, and CO. CO_2, CH_4, N_2O are the primary greenhouse gases, while the rest of these species are aerosol precursors and ensure that our simulations capture both the warming effect of greenhouse gases as well as the cooling effect of aerosols.

We sample carbon cycle and climate uncertainty in FaIR following Leach et al. (32) , which is similar to the method previously used by Callahan and Mankin (30). Specifically, we focus on the r_0, r_u, and r_T parameters, which control the initial carbon uptake strength (r_0) as well as how carbon uptake varies with cumulative uptake (r_u) and temperature change (r_T). We generate distributions of 250 scaling factors for each of these parameters exactly following Table 5 in Leach et al. (32). We then run a separate simulation for each contribution level, contribution time scale, and set of carbon cycle scaling factors.

Pattern scaling

To calculate the local effect of an actor's emissions, we use pattern scaling to calculate the change in regional Tx5d and average temperatureas a function of changes in the global mean temperature. We do this by first calculating global mean temperatures, regional annual average temperatures, and regional annual Tx5d from an ensemble of 80 coupled climate model simulations from CMIP6. Global mean temperatures are spatially weighted by the square root of the cosine of latitude. We then take the difference between the historical and natural climate model simulations over 1991-2020 for each quantity to calculate the effect of anthropogenic climate change. Finally, for each climate model, we linearly regress each region's change in annual average temperature or Tx5d onto the change in global mean temperature. The coefficient from this linear regression denotes the anthropogenic change in regional average temperature or Tx5d produced by a 1-°C anthropogenic change in the global mean temperature.

We then multiply the FaIR-derived GMST time series by the pattern scaling coefficient for each region, yielding time series of predicted Tx5d and annual mean temperature for each region under the various FaIR contribution simulations. To quantify uncertainty in this procedure, we use 8 unique climate models, several with many realizations for a single model. This ensemble allows us to sample uncertainty resulting from differing model representations of the local response to global climate change. The different models sample different structural and parametric choices, whereas the different realizations from individual models sample the divergence that results from internal climate variability alone.

Inferring continuous regional income

Our analysis requires continuous regional GDPpc data to calculate damages, but many regions either have missing or incomplete GDPpc data over the 1991-2020 period of interest. This data gap risks skewing loss and damage analysis away from low-income places, which disproportionately lack data (43). To close this gap, we follow Callahan and Mankin (5) by inferring regional GDPpc from country-level GDPpc and regional nightlights data. For the regions in which we do have GDPpc data, we regress their GDPpc onto their country's GDPpc, their regional nighttime luminosity, and the interaction between country GDPpc and luminosity. The predictions from this model closely match observed regional GDPpc and outperform more complex models in out-of-sample cross-validation testing (5).

We use this statistical model to predict regional GDPpc globally based on country-level GDPpc and nightlights. We sample uncertainty in this procedure in two ways. First, we use bootstrap resampling on the statistical model to capture parametric uncertainty (sampling with replacement by country to preserve within-country spatiotemporal autocorrelation). Second, we add a draw from a random normal with mean zero and standard deviation equal to the standard deviation of the residuals to the final predictions to account for residual uncertainty. This procedure allows us to propagate uncertainty in this income extrapolation procedure into our final damages calculations.

Attributing damages from extreme heat

To calculate damages due to extreme heat, we first construct two counterfactual time series for regional Tx5d and annual mean temperature: One in which no anthropogenic emissions are produced ("natural") and one in which all emissions are produced except for an individual actor's contribution ("leave-one-out"). These counterfactual time series are constructed by differencing the observed Tx5d or annual mean temperature and the change in those quantities due to all emissions (to construct the natural counterfactual) or the emissions of a single contributor (to construct the leave-one-out counterfactual).

We then apply the regression coefficients from Callahan and Mankin (5) to the natural and observed time series for each region to calculate the damages due to total anthropogenic emissions. We include anthropogenic alterations to both Tx5d and annual average temperature in this calculation since changes in average temperature alter the marginal effect of Tx5d. We then perform the same calculation with the natural and leave-one-out time series, which yields damages due to all emissions other than a given actor. The difference between the total damages and these leave-one-out damages yields the damages attributable to the emissions of that actor. Supplementary Material Fig. 3 in Callahan and Mankin (30) provides a visual schematic of this calculation.

We incorporate uncertainty in this calculation by running 10,000 Monte Carlo simulations, where each simulation draws one sample from each of four distributions: one FaIR simulation, one set of Tx5d regression coefficients from Callahan and Mankin (5), one set of pattern scaling coefficients, and one regional income time series. When selecting the pattern scaling coefficients from the different climate model realizations, we down-weight models with more realizations, thus making each model equally likely to be sampled. The other samples are from uniform distributions. We use IPCC conventions for visualizing uncertainty, with the inner 66% range meaning "likely," the 90% range meaning "very likely," and the 99% range meaning "virtually certain" (44).

Significance testing

We test the statistical significance of the damages we attribute with a Kolmogorov-Smirnov test. Specifically, in each region and year, we test whether the damages without a given contribution level are statistically distinguishable from the damages including that contribution. If these two distributions—which incorporate uncertainty from the FaIR simulations, pattern scaling, income prediction, and Tx5d regression coefficients—are likely not drawn from the same distribution ($p < 0.05$), then we consider the damages attributed to that contribution level to be statistically significant.

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