The Global Climate-Change-Attributed Costs of Extreme Weather

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The Global Climate-Change-Attributed Costs of Extreme Weather

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Abstract: Extreme weather events have significant adverse costs for individuals, firms, communities, regional, and national economies. Extreme Event Attribution (EEA), a methodology that examines the degree to which anthropogenic greenhouse gas emissions had changed the occurrence of specific extreme weather events, allows us to quantify the climate-change-induced component of these costs. We use EEA to aggregate the global economic damage from extreme weather events that is attributable to anthropogenic climate change. For that, we collect data from all available attribution studies which estimate the Fraction of Attributable Risk (FAR) for extreme events, and combine these FAR estimates with data on the socio-economic costs of these events. With extrapolation for missing data, we then arrive at our benchmark estimates. We find that US$ 143 billion per year, of the costs of extreme events during the last twenty years, is attributable to anthropogenic climatic change. This EEA-based method for calculating the costs of climate change from extreme weather differs fundamentally from other approaches to climate cost estimation. Those other approaches use macroeconomic modelling embedded within climate models in various types of Integrated Assessment Models (IAM). As we show, our research is not directly comparable, but it does provide a new form of evidence that suggests that most IAMs are substantially under-estimating the current economic costs of climate change. Given some of the data deficiencies we identify in terms of temporal and spatial coverage, the purpose here is not to produce a definitive quantification, but rather to sketch a path towards a more comprehensive and reliable estimation. As better EEA studies and more thorough and exhaustive economic costs estimates for extreme events become available over time, and the method is refined, the precision of this approach's estimates will increase in tandem.

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1. Introduction

Extreme weather events have significant adverse costs for individuals, firms, communities, and regional economies. Based on the available data from EM-DAT[1], the World Meteorological Organization (2021) reports that there has been a sevenfold increase in the reported disaster losses from extreme weather since the 1970s. The most recent Intergovernmental Panel on Climate Change Report ties this increase at least partly to climatic change (IPCC, 2022).[2] The detection of anthropogenic changes in the frequency, severity, spatial location, and extent of extreme weather events is consequently important.

Extreme Event Attribution (EEA) is a methodological approach that examines the degree to which anthropogenic greenhouse gas emissions had changed the occurrence of specific extreme weather events that have indeed occurred. Using climate modelling tools, EEA quantifies the causal link between anthropogenic climate change and the probability and/or the intensity of specific extreme weather events by focusing on their specific circumstances and characteristics. EEA was first conceptualized by Allen (2003), who, together with some co-authors, developed a method to analyze the contribution of climate change to the risk of an individual weather event that could be clearly defined and quantified.[3]

The EEA methodology compares the probability of an event that occurred with the probability or intensity of the same event occurring in a counterfactual world without anthropogenic emissions. From a probabilistic perspective, a Fraction of Attributable Risk (FAR) metric is calculated to describe what portion of the risk of an extreme weather event occurring is the result of climate change.[4] This is known as the "risk-based" approach to attribution (Otto, 2017). The alternative "intensity" approach calculates what share of a specific attribute of the risk (e.g., rainfall) was due to climate change. For instance, Frame et al. (2020b) and Smiley et

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[1] EM-DAT: The International Disaster Database. https://www.emdat.be/.

[2] Part of this increase is due to increased reporting of disaster damage (especially in lower-income countries or countries that were previously more isolated), and because of increased exposure brought about by population growth and internal migrations to more exposed urban and coastal areas. The IPCC notes it is "virtually certain" that there is still a climate change component in the increase in reported disaster damage (at least of some types, with weaker evidence for others). Still, some researchers are more sceptical that there is already an 'anthropogenic footprint' in the time-series of aggregate disaster damages (e.g., Pielke, 2021).

[3] Stott et al. (2004) first implemented this approach for the 2003 continental European heatwave – an event that led to high mortality, especially in France.

[4] Methodologically, these probabilistic methods have been approached from both a frequentist or a Bayesian perspectives (e.g., Risser et al., 2019), with possibly important consequences for the results thus obtained. We do not distinguish between these in our work here, given the relative paucity of Bayesian attribution work.

al. (2022) analyzed the "risk-based" and the "intensity-based" EEA economic costs for the 2017 Hurricane Harvey, respectively.

Here, we use the "frequency" approach to aggregate the global economic damage from extreme weather events attributable to anthropogenic climate change. For that, we collected data from all available attribution studies with a 'frequentist' analysis and extract their estimate of the Fraction of Attributable Risk (FAR). The FAR approach quantifies how much of the risk of a specific event occurring can be attributed to climate change. We then combine these FAR estimates with data on the socio-economic costs of these events.

The economic costs associated with extreme weather events can be measured in two ways: First, these include the direct economic damage, which occur during or immediately after the event. Using flooding as an example, where the hazard is heavy precipitation, direct economic damage may include destroyed housing and roads, or lost crops. However, an extreme weather event can also cause indirect economic losses. These are declines in economic value-added because of the direct economic damage. Examples of these indirect losses are wide-ranging. For the flood example, they could include microeconomic impacts such as revenue loss for businesses when access routes are inundated by floodwater, meso-economic impacts such as temporary unemployment in the affected area, or even wider ranging macro-scale supply-chain disruptions. These indirect economic losses can often spill out beyond the affected area, and indeed even beyond the affected country's borders. Indirect losses may also have long time lags, making them difficult to quantify. Because of these difficulties in quantifying indirect (flow) losses over a large variety of extreme weather phenomena in a large diversity of countries and affected regions, this paper only focuses on the more easily quantified stock of direct damages.

By combining the data on direct economic costs, with the attributable share of the risk of these events, we can quantify the climate change attributable cost of these events. This attribution-based method for calculating the costs of climate change (from extreme weather events) differs fundamentally from other approaches to climate cost estimation. Those other approaches use macroeconomic modelling embedded within climate models in various types of Integrated Assessment Models (IAM). Our research is not directly comparable to the IAMs, but it provides a new form of evidence that suggests that most IAMs are substantially under-estimating the current economic costs of climate change.

Given some of the data deficiencies in terms of temporal and spatial coverage, described below, the purpose of this paper is not to produce a definitive quantification. At the current rate of progress in attribution research in meteorological science, we are still years away from obtaining a thorough and reliable global coverage of most of socio-economically damaging extreme weather events. Our ability to measure the damage associated with these events, especially smaller ones, is also far from being sufficiently comprehensive. Therefore, our aim is to demonstrate the use-value of the methodology, rather than reach an unimpeachable set of estimates. As better EEA studies and more through and exhaustive economic costs estimates for extreme events become available over time, and the method is refined, the precision of this approach's estimates will increase in tandem.

2. The Methodological Building Blocs

Allen (2003) suggested EEA as a method of comparing probabilities to quantify the contribution of climate change to the probability of an individual weather event occurrence. From this type of estimation, a fraction of attributable risk (FAR) metric is calculated to describe what portion of the risk of an extreme weather event occurring is the result of climate change (Otto, 2017). For this methodological approach, the weather is simulated under the current climate, and similarly, simulated under a counterfactual climate that is free from human GHG emissions. This provides information on the degree to which climate change has altered the risk of event occurrence.

2.1. Economic Costs of Extreme Weather Disasters

An extreme weather phenomenon by itself is not a disaster, but when a weather-driven hazard intersects with an exposed and vulnerable population, the extreme weather event becomes a disaster (IPCC, 2022). These events, when they occur, can cause a range of economic impacts. The 'Intergovernmental Expert Working Group on Indicators and Terminology Relating to Disaster Risk Reduction' provides a set of relevant definitions. Firstly, a disaster can cause *damages* which occur during and immediately after the disaster. This is a stock amount that is measured in physical units and describes the total or partial destruction of physical assets, the disruption of basic services, and damages to sources of livelihood in the affected area. Relatedly, *direct economic loss* is the monetary value of these disaster damages, for example, the monetary value of totally or partially destroyed physical assets.

Secondly, disasters can cause *indirect economic losses,* defined as a decline in economic value-added because of direct economic loss (damages) and/or other disruptions caused by the disaster. These indirect losses can occur outside the disaster area and with a time lag and are measured as a flow variable (per unit of time). *Indirect losses* are more challenging to measure since they rely on developing a counterfactual (a without-a-disaster scenario). Finally, *impact* is the total effect of a disaster, including negative effects (e.g. *direct losses*) and positive ones (e.g. *indirect economic gains*). *Impact* includes economic, human, and environmental impacts, including death, injuries, disease, and other adverse effects on human physical, mental, and social well-being. Some of these are intangibles that are rarely measured systematically after disaster events. This research will attempt to understand disaster impacts in aggregate and present them in terms of monetary valuation, referred to as the *total economic cost.* This is predominantly comprised of direct losses and the statistical value of life lost, given the limitations of the data collected in EM-DAT.

2.2. Using Extreme Event Attribution to Estimate the Economic Costs of Climate Change

Allen's (2003) proposed that EEA enables differentiating economic losses from extreme weather between those that are caused by natural variability and those caused by past anthropogenic activity. Frame et al. (2020a) suggested how this approach can attribute climate change-induced economic costs when both a fraction of attributable risk and economic cost inputs are available for a set of individual events. The approach they used is straightforward – multiply the fraction of attributable risk (FAR) by the estimated economic costs. With some assumptions about aggregation and generalizability of the calculated FARs, this same process can be replicated across different types of economic impacts – including deaths, and even indirect losses – to provide individualized assessments of the climate change-attributed value of each of these impacts of extreme weather events.[5]

Here, we aggregate all the relevant and suitable EEA studies (see details below), and their corresponding economic impact assessments, and then extrapolate from these to obtain an overall estimate of the climate-change-attributed impact of all recent extreme weather events

[5] Frame et al. (2020a) estimated climate change-attributable insured costs of major flooding events in Aotearoa New Zealand at NZ$140 million for 2007-2017 – based on the aggregation of attributed costs from the 12 major flooding events that occurred there during this time.

globally, for which economic impact estimates are available. We then compare these estimates to some of the existing assessments of the current costs of climate change from the IAMs.

2.3. Other Methods for Estimating the Global Economic Impact of Climate Change

Most attempts to quantify the global impact of climate change use Integrated Assessment Models (IAMs). Well-known, well-regarded, and equally well-criticized examples include DICE (Nordhaus, 2017) and FUND (Anthoff and Tol, 2013). The IAMs, typically, link the economic system with the climate system by using damage functions that express the economic impact of climate change as a function of a global or regional mean of annual mean temperature (Diaz & Moore, 2017). This, of course, captures the change in the mean, but not in the tail ends of the distributions of extreme weather (Goodess, Hanson, Hulme, & Osborn, 2003). Therefore, these models tend to include the costs of extreme weather using ad-hoc additional modification to the damage function, or they are omitted entirely (Bouwer, 2011; Tol, 2005; van den Bergh, 2009; Nordhaus, 2017).

Given the limited availability of FAR studies, our approach cannot be applied across every extreme weather event. Consequently, the global application we pursue here relies on the extrapolation of known FAR values to other events for which there are no EEA studies, and a reliance on patchy economic data, to assess impacts.[6] Van Oldenborgh et al. (2021) argue that, with the current stock of EEA studies, we should consider the possible selection biases in the availability of EEA studies. Generally, events with higher human and economic impacts will be more likely to be analyzed, events in high-income regions and more densely populated areas are more likely to receive attention, and event types that become less likely because of climate change may be underrepresented in the analyses as well (Stott et al., 2013; van Oldenborgh et al., 2021).

However, given the fundamental importance of empirical evidence to drive an informed climate change policy response, we use aggregation and extrapolation based on available knowledge, while acknowledging the limitations and inherent biases that might detract from the accuracy of such an exercise. Implicitly, we assume that the significant disaster events for which attribution studies are available are representative of the other damaging disasters of the same type, occurring in the same geographical region. Given the lack of an alternative, we see

[6] We discuss these data limitations further in the following sections.

this is as a plausible approach. We argue that all current approaches to estimate the costs of climate change are flawed. Indeed, we argue below that the conventional IAM assessments stand on even more rickety legs. This makes the exploration of an alternative and complementary cost estimation method fundamentally important, even if this method has its own flaws.

3. Dataset collection and terminology

The fraction of attributable risk (FAR) is a metric that describes the portion of the risk of the extreme weather event for which anthropogenic climate change is responsible. When the risk of an event has increased due to anthropogenic GHG, it is calculated as shown in Equation 1. This can be referred to as the fraction of attribution *increasing* risk (FAIR).

$$FAIR = 1 - \frac{P_0}{P_1} \tag{1}$$

P_0 = Probability of a climatic event without anthropogenic GHG present

P_1 = Probability of the event occurring within the current climate system (with anthropogenic GHG)

A FAR value of 1 means that the event would not have been possible in the absence of anthropogenic climate change. While a FAR of 0 indicates that climate change had no influence on the probability of the event occurring (Jézéquel et al., 2018). As argued by Wolski et al. (2014), the FAIR is designed to assess the fraction of attributable *increasing* risk – which should lie between 0 and 1 - when climate change has a positive impact on event probabilities. Whereas, to assess events that become less likely because of human-induced climate change, the index definition should be changed to obtain the fraction of *decreasing* risk (FADR), which lies between 0 and 1, is calculated as:

$$FADR = 1 - \frac{P_1}{P_0} \tag{2}$$

Here, the FAIR and FADR abbreviations will be used in specific circumstances of increasing and decreasing likelihood of events, respectively. FAR will be used more generally to refer to the attribution metrics. More information on the data collection procedures we used is available in the appendix.

To assess the economic cost of mortality, we utilize Value of Statistical Life (VSL) calculations; this is the standard approach in many policy decisions (for example about road improvements for safety). The VSL describes a marginal rate of substitution between money and mortality risk in a defined period (Hammitt, 2000). The VSL we use here is an average of two VSL estimates used by governments of the United States and the United Kingdom. The first is the United States Department of Transportation estimate for 2020, which sets the VSL at US$ 11.6 million.[7] The second is from the UK Treasury, which assesses the VSL to be £2 million, estimated from average values from survey data looking at representative samples of the population (HM Treasury, 2018).[8] According to Viscusi (2018), the non-US median VSL is $7.36 million.[9] For this study, the benchmark results we use a VSL of US$ 7.08 million per life lost is used, which incidentally is not very far from the non-US median reported by Viscusi (2018). For simplicity, and more importantly on equity grounds, this same VSL is used for deaths in every country, and every year, implying that death has an equivalent economic value regardless of the time and place in which it occurred.

Data for individual extreme weather events were matched, where both a FAR and economic data had been collected. These events were collated to form the dataset that provides the basis for our empirical analysis. The available data were refined to ensure the master dataset contained the best available estimates for each included event. Firstly, when events with multiple attribution studies were considered, the Scimago Journal Rank (SJR), in the year of publication, was used as a proxy for the research quality.[10] A FAR measurement for a specific event is considered preferable if it comes from a higher SJR publication.[11] When there are multiple attribution studies for the same event, with the same SJR, the preferred FAR was that with the closet spatial and temporal match to available economic data (as FARs can differ based on temporal and spatial event definition). When the scale is matched closely to economic data,

[7] This figure itself is an average of VSL estimates from across the academic literature (Department of Transportation, 2021).
[8] Kniesner and Viscusi (2019) detail the reasons that estimates for the VSL differ very dramatically across countries.
[9] Adjusted to 2020 USD. Originally reported as US$10.25 million and $7.1 million in the paper published in 2018.
[10] The SJR is a calculated rank of a journal's scientific influence; a rank is calculated from a weighted measure of the citations a journal receives. The weighting is determined by the prestige of the publishing journal from which a citation originates (Scimago Research Group, 2007). We acknowledge, of course, that this procedure is not full proof, and papers that are sometimes consider 'better' are published in lower ranked journals. However, we wanted to use an algorithm that does not require subjective judgment.
[11] For rapid studies conducted by the World Weather Attribution network, there was no recorded SJR as they are not refereed but are done by a large group of specialized climate scientists. Therefore, the average of the SJR scores for all other studies in the database was used as a rank for WWA studies when comparing them to others. Moreover, in cases where the SJR did not differ between studies, the study closest to the spatial and temporal dimensions of the relevant economic cost data was utilized.

the attribution of the cost will be more accurate. The final dataset includes 185 events spanning 2000-2019. These events are gathered from 118 event attribution studies, as many attribution studies cover more than one event.

4. Method of Quantitative Analysis

"If [climate change] has trebled the risk over its 'pre-industrial' level, then there is a sense in which [climate change] is 'to blame' for two-thirds of the current risk...." (Allen, 2003, p. 891). This framing suggests that if anthropogenic climate change has made an extreme weather event three times more likely, then climate change is responsible for two-thirds of the economic cost caused by the set of similar events.[12] Consequently, for each event (i) in the master database, we use Equation 3 to estimate that individual event's climate change-attributed economic cost.

$$CCcost_i = FAR_i * cost_i \quad (3)$$

Applying this approach to all events in the master dataset provides an estimation of the climate change-induced costs associated only with these specific list of events. To generate an estimate of the global cost of climate change from extreme weather events, we used the FARs from attribution studies in the dataset we collected and all the economic cost of extreme weather events across 2000-2019 recorded in EM-DAT.[13] Two extrapolation methods were used – a global average extrapolation method and a regional average method.

The global average extrapolation method relied on obtaining, from the FAR results recorded in the dataset, an average FAR for each specific type of event occurring anywhere. This event-type average FAR was then multiplied by the economic costs and mortality of all the relevant events in EM-DAT over the 2000-2019 period. The average FARs are calculated from individual attribution studies in the dataset (118 observations) rather than the FARs from the 185 individual events.[14]

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[12] Put differently, 2 out of each three events of the same class, and with the same calculated FAR, were caused by climate change, while the third would have happened even in a pre-industrial climate.

[13] Limited to heatwaves, floods, droughts, wildfires, and storms, and implicitly employing the EM-DAT definition of an extreme event. For inclusion in EM-DAT, an extreme event is one for which at least one of the following three criteria must be fulfilled: (1) 10 or more deaths; (2) 100 or more people affected/injured/homeless; or (3) declaration by the country of a state of emergency and/or an appeal for international assistance.

[14] This is because some studies cover a large number of events. Calculating an average FAR with each event as an individual data point would lead to much greater weight being placed on a smaller number of multiple-event studies.

The regional average extrapolation method was conducted by calculating an average FAR per event type *and* per continent. This was, similarly, calculated from individual attribution studies rather than events. This regional average FAR was then multiplied by the relevant event type and region specific events in the EM-DAT database and subsequently aggregated. This (partial) accounting for differences in how climate systems influence extreme weather across different regions is clearly an advantage of the regional approach. However, there are no, or very few, FAR studies for some event-type and continental combinations. For example, only one study examined a heatwave in Africa, so a regional extrapolation result relies solely on this one study, creating potentially an over-reliance on one modelling approach.

Furthermore, where there are no available attribution studies, for example, on storms in Europe, the global average for that event type is used as a substitute to fill in this data gap. There are significant number of event type-region combinations for which this global compromise was necessary. The difference between the two methods, therefore, is not as large as it probably should be. In the future, with a more extensive set of attribution study results, it would clearly be preferable to use an approach that distinguishes between types of events, their location (even within continental-size regions), and potentially even their magnitude.

5. Data description

This section will provide some summary descriptions of the attribution and economic cost data that were collected in the dataset used here.

5.1. Extreme event attribution data

Of the 185 extreme weather events, the risk of 154 of these events increased because of anthropogenic climate change, while another 24 events were associated with decreased risk, and the risk of the remaining 7 events was unchanged (FAR=0). These events cover the period from 2000 to 2019, as shown in Figure 1. Notably, 77% of these events occurred after 2013, because EEA studies have been conducted increasingly frequently only in recent years. Given the rapid evolution of the EEA methodology, the dominance of more recent studies in our dataset means the FAR records used for the results reflect mostly the higher quality, recent EEA research practices. A significant number of events are recorded for 2015 because of the study by Zhang et al. (2016), which covers a large spatial and temporal scale.

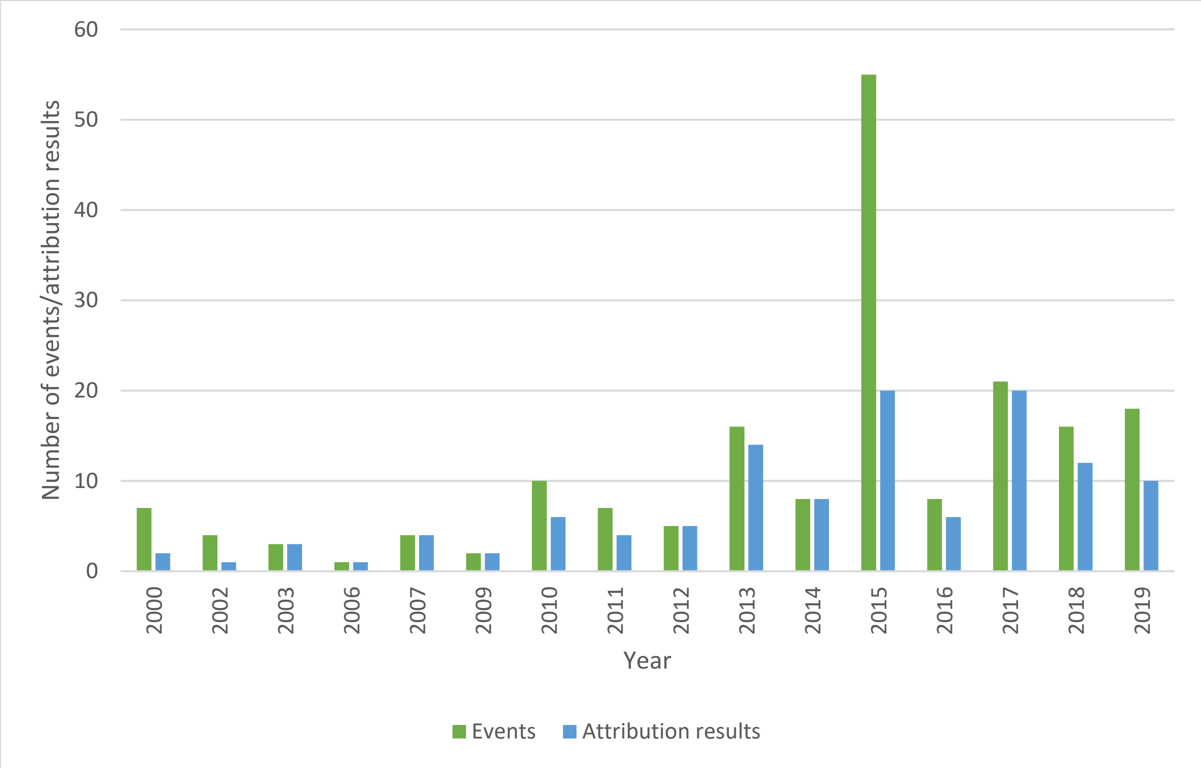

Figure 1: Count of matched events and attribution results in the master dataset

The geographical coverage of the matched attribution results included in the dataset is also important to note, as there are significant deficiencies in some regions. These studies cover Africa (10% of these studies), Asia (28%), the Americas (24%), Europe (20%), and Oceania (18%).[15] The matched events span 52 different countries. Events in China, the United States, New Zealand, Philippines, Japan, United Kingdom, and Australia combined makeup over half (54%) of the total dataset. Similarly, to the time-series coverage, this is impacted by attribution studies covering multiple events in a defined region, including Zhang et al. (2016) that covered 26 cyclones across the Western North Pacific.

By construction, the dataset contains six types of extreme weather events, as shown in Figure 3. Notably, 52% of the attribution results in the master database are associated with high-temperature phenomena – heatwaves, droughts, or wildfires (31%, 16%, and 4%, respectively). The remainder are either hydrological events–specifically floods (37%) and storms (5%)—or cold waves (6%).

[15] North America and South America are collected here as one grouping because there are very few FARs calculated for South America. Events in South America making up only 5.0% of the total matched events in the dataset (7 events in the aggregate across all event types).

In the initial search, we identified 112 weather events with at least one associated FAR, but which did not have matching economic data. A majority of these (51%) were heatwaves, since the science of attribution is well-established for heat events but measuring the economic impact of heatwaves is challenging and is rarely undertaken. After all, the main impact of heatwaves, aside from mortality, is their indirect losses in the flow of economic activity which are substantially harder to identify and measure than damages (stocks). These under-measured heatwave losses include economic disruptions due to disturbed hydro-electricity distribution, transport failures, ongoing harm to agricultural crop yields and health, and harm to the natural environment (Disher, Edwards, Lawler, & Radford, 2021). Moreover, a further 25% of events without economic data are droughts – with the majority occurring in Africa – which is reflective of the geographically uneven distribution of disaster cost records between lower and higher-income regions.

All the events included in the dataset have at least one FAR associated with them. Of the 185 events, 47 have multiple relevant attribution studies. For each, the 'best' FAR was selected based on two criteria: the highest-ranking journal and the spatial and temporal match between the FAR study and the available economic data. The distribution of FAR attribution results in is shown in Figure 2. The peak at 0.3-0.4 is predominantly due to flood events – which make up 80% of the attribution results in this range. While 90% of the events with a FAR of between 0.7-1 are high-temperature phenomena, namely heatwaves, droughts, and wildfires. Interestingly, 53% of the attribution results with a negative FAR are floods, while the remaining 47% are, less surprisingly, cold events.

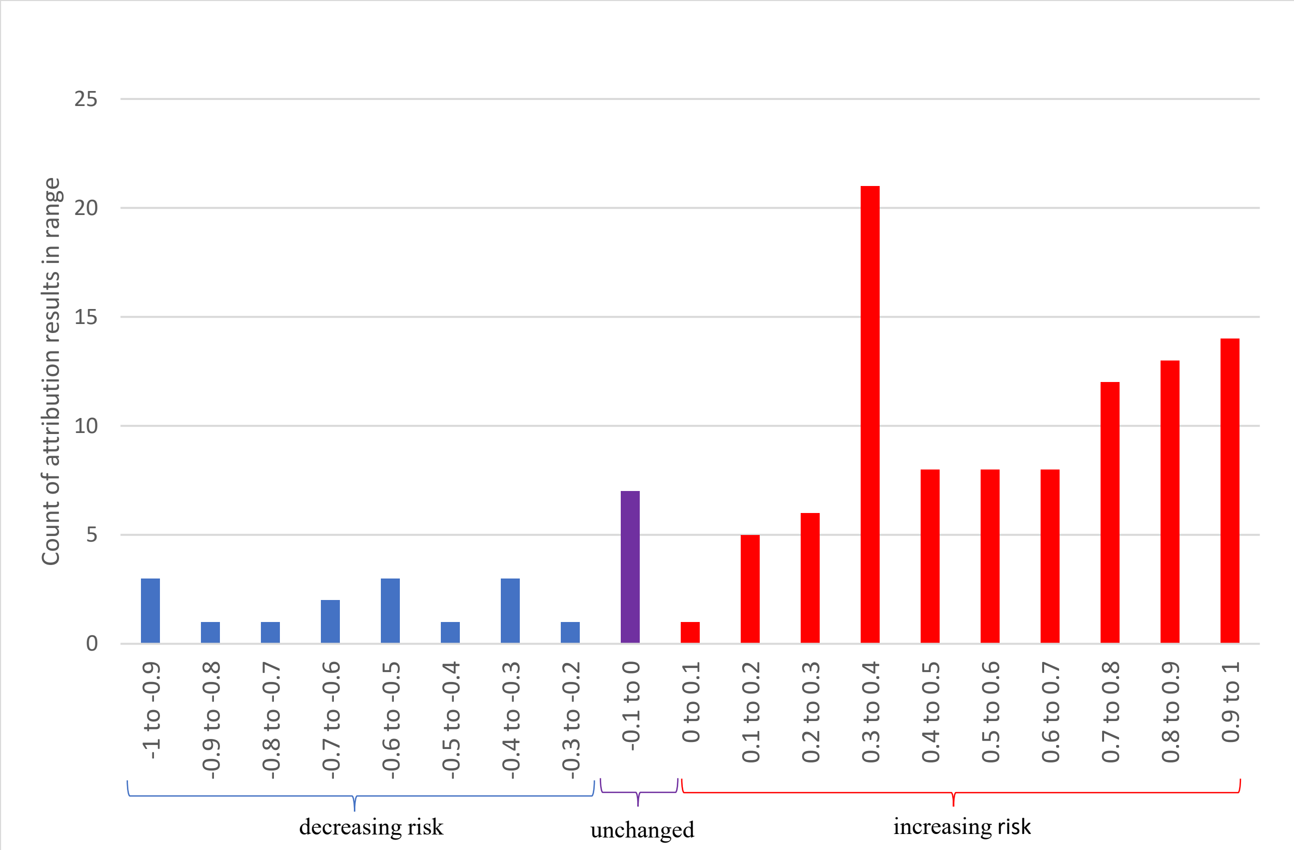

Figure 2: FAR distribution across matched events

To allow a global extrapolation of climate change-attributed costs to be made, a global average FAR for each event type has been calculated. On average, 77% of the risk of heatwaves occurring over the study period is due to anthropogenic climate change. Floods show the greatest distribution range and are the only event type where attribution results span both increasing and decreasing risk due to climate change. The global average FAR for floods, however, is 19%. Similarly, as for droughts (44%), wildfires and storms each have a FAR of 60%; however, these are calculated from a small number of data points. Lastly, on average, cold events are calculated as having a decreasing risk (-79%) because of climate change.

An average FAR per-continent per-event type has also been calculated to reflect the lack of uniformity in the global climate system (Figure 3). There were very few, or no, matched attribution results to form the basis of a regional average FARs in many continent-type combinations.

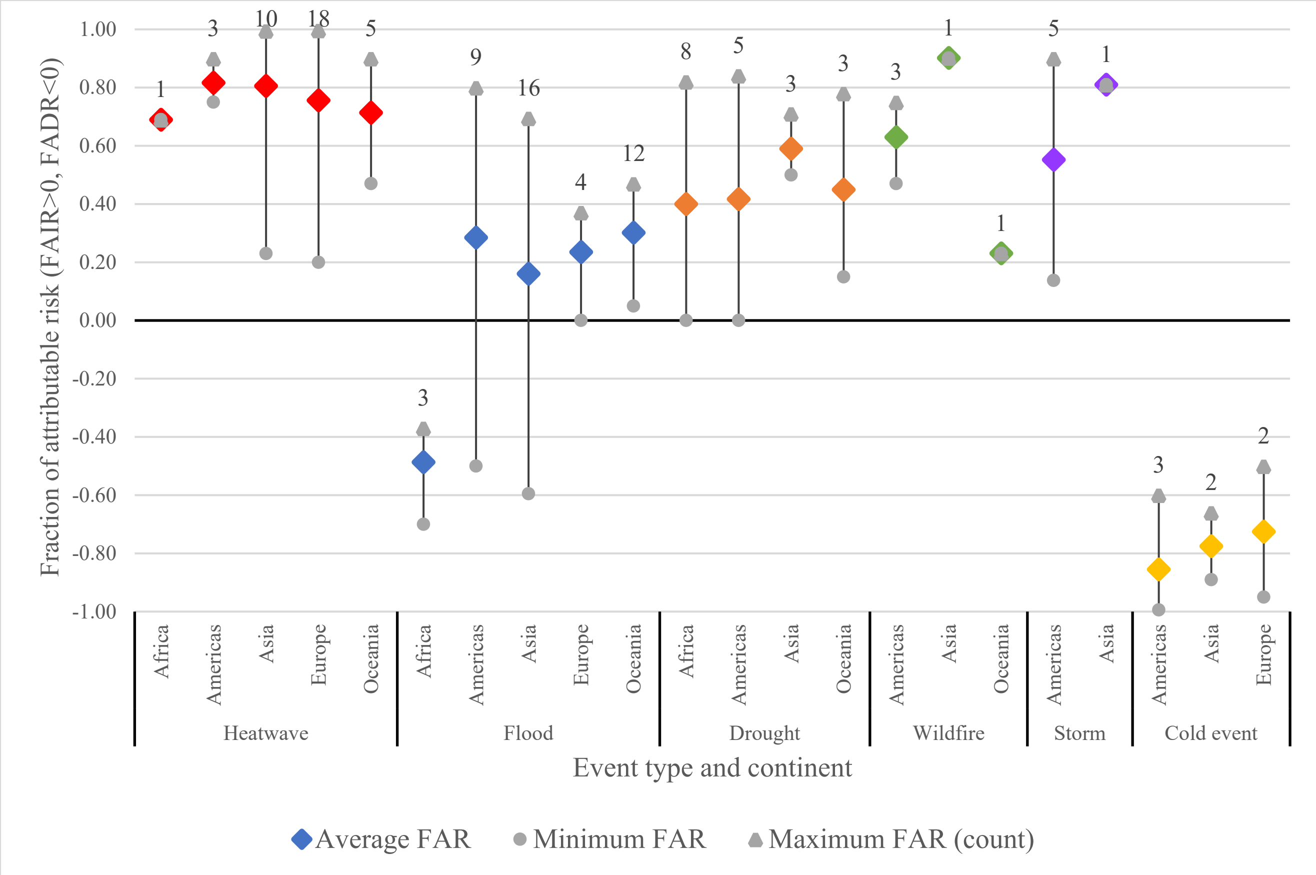

Figure 3: Regional average FAR by event type

Note: The number on the top of each bar represents the number of events)

5.2. Economic data

The following section describes the features of the economic cost data collected regarding the events in the master dataset. While for disasters more broadly, EM-DAT records deaths, dislocations, people affected, and monetary damages, here we use only the mortality metrics and monetary damage (if these are recorded). The other components include such a diversity of outcomes (from dislocation lasting just a few days to permanent and significant physical and mental injuries), are often inconsistently collected, and are missing for many disaster events, that we have decided to ignore them in our analysis. As such, our aggregation only includes death and damage (as defined earlier).

In the dataset, 114 of the 185 events have mortality estimates. Thirty-nine of these events are responsible for at least 100 deaths each, nine events with more than 1,000 lives lost, and four are responsible for the deaths of over 10,000 people – a heatwave in Russia (>55,000 deaths), a drought in Somalia (20,000 deaths), a heatwave in France (>19,000 deaths), and a cold event in the United Kingdom (27,500 deaths).[16] The total number of deaths recorded from the events in this dataset is 151,083, equivalent to a statistical value of life lost of US$ 1.07 trillion.[17]

Of the 185 included in the dataset, 115 events have estimates for the economic damages caused. Across these 115 events, the total disaster damages stand at US$ 492.2 billion. The event with the highest damage recorded in this list of events is Hurricane Harvey in the United States in 2017, at US$ 100.3 billion.[18] Eighty-four of the events have estimated damages greater than US$ 100 million, and 8 of those are over US$ 10 billion.[19]

6. Results

By examining the attribution information in conjunction with the cost information, we can calculate the climate change-attributed economic costs of extreme weather events. We first present these costs for the events in the master dataset, and then the results we obtain by extrapolating our findings to create a global estimate of these costs.

6.1. Attributed costs for events in the dataset

From the 185 events in the dataset – a net of 60,951 deaths are attributable to climate change - 75,139 deaths that occurred due to climate change in events that became more likely and 14,187

[16] For all of these events, indeed for all the events we analyse here, the causes of the damage are complex, and are not just due to the hazard itself. The 2010 heat wave in Russia is a good example. In Moscow, mortality mostly arose from air pollution from peat fires that occurred in the surrounding area. The fires occurred due to a combination of drought and heat, but also the legacy of a Soviet policy of draining bogs, widespread ignition by humans, and confusion and inaction following a new Russian policy shift that had just transferred wildfire control from the national to the regional governments. Our analysis, however, assumes a *ceteris paribus* world in which all other pre-conditions still exist, but the amount of GHG in the atmosphere is pre-industrial. Clearly, one should view this counterfactual as a thought experiment, rather a realistic scenario, since without the industrial revolution of the last 150 years, nothing in our world would have been the same.

[17] Calculated, as described earlier, using a VSL of $7.084 million.

[18] Harvey provides a useful example of some of the murkiness in definitions. EM-DAT classifies it as a tropical storm, and indeed the name refers to the Hurricane. However, by far most of the damage was caused by the flood the rainfall that came with the hurricane generated. The attribution papers that analysed the event focused on the changing likelihood or intensity of the rainfall event, and not on the storm (measured and classified by windspeed). We follow the EM-DAT classifications, since these are available for all events, but note that these distinctions are not always immediately apparent.

[19] A small number of events in the dataset have insured loss estimates associated with them (48 out of 179). These data are heavily skewed to small number of countries, notably the United States, New Zealand, Australia, and Japan, as well as China. The restricted quality and quantity of data collection in low-income countries is one underlying reason for this, but it is also symptomatic of higher rates of insurance penetration rates in high-income countries. Insurance costs from Hurricane Harvey in the United States and Hurricane Maria in Puerto Rico have the highest insurance payouts at US$ 31.7 billion each ($30 billion in 2017 US dollars).

deaths in events that have become less likely due to climate change. The net statistical value of life cost across the events in the master database is US$431.8 billion.

Anthropogenic climate change is responsible for a net $260.8 billion of extreme weather event damages in the master database. This is equivalent to 53% of the total damages recorded for these 185 events. More than 64% of the climate change-attributed damages are connected to storms, which is expected given the high damages from such events as Hurricane Harvey. Furthermore, 16% of the attributed damages resulted from heatwaves, while floods and droughts are each responsible for 10%, and wildfires account for 2% of the net attributed damages. Lastly, cold events, calculated as a fall in climate change-attributed damages, are responsible for only -2% of net attributed damages.

6.2. Extrapolated global climate change-related economic costs of extreme weather

Here, the results from extrapolating the attribution data across all global economic costs from extreme weather events are described for the two extrapolation methods. This also allows an examination of the impact of method choice on the results (Figure 4). Furthermore, we analyse the heterogeneity of globally attributed costs across time and event type.

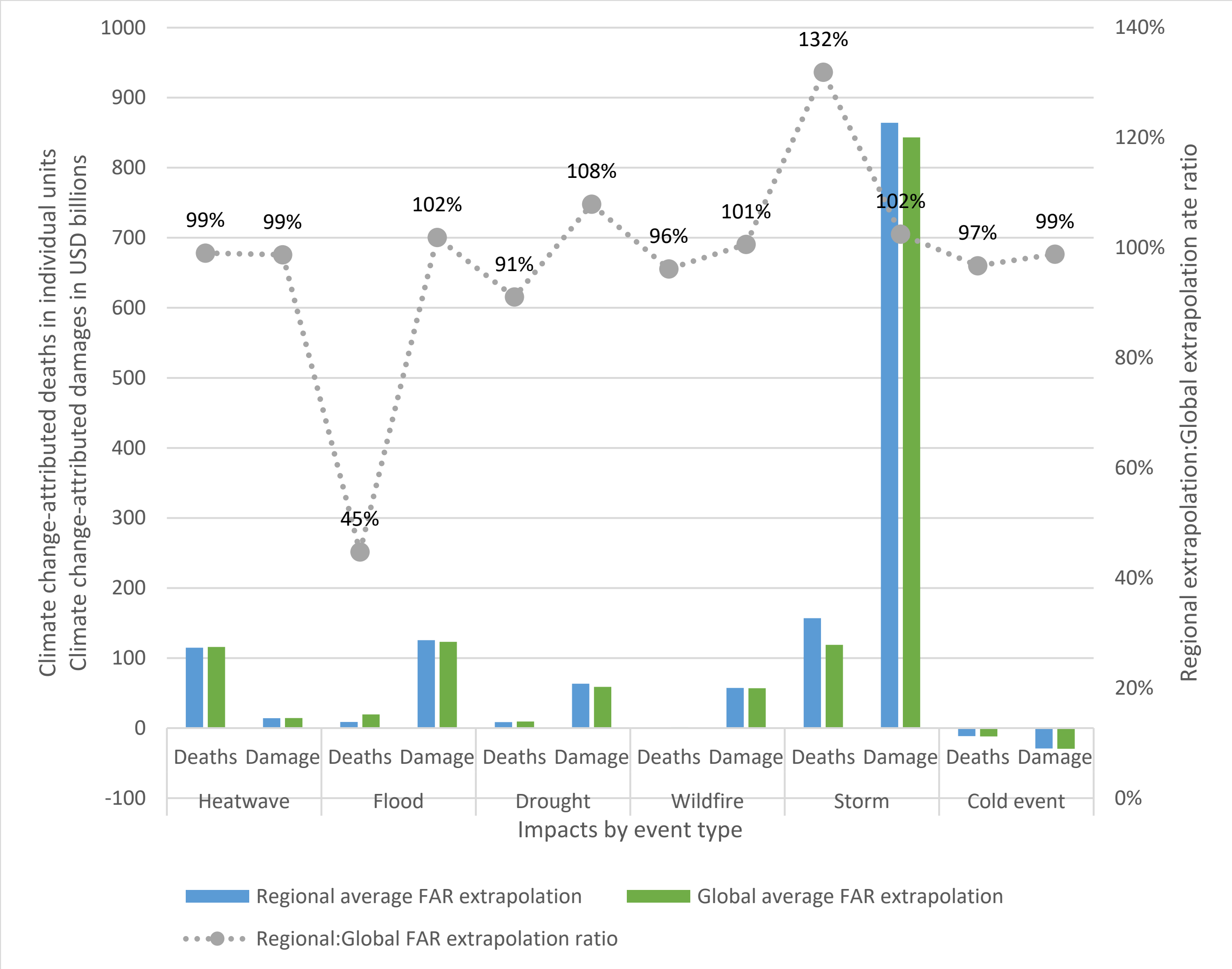

Figure 4: Global average and regional average extrapolation methods for the total attributable costs

The total climate change-attributed impacts, dictated by the respective extrapolation methods, have varying degrees of similarity. For heatwaves, the extrapolated estimates for deaths and damages are very closely aligned – less than one percentage point between the results from the two methods. For other event types, the disparities are wider. Notably, storm damages contribute substantially to total attributed economic costs, making up over 60% of the total damages recorded in the EM-DAT extreme weather event dataset. There are two data comparisons where the estimates differ widely (greater than ten percentage points) between a global and continental approach: flood deaths (45%) and storm deaths (132%). These discrepancies in flood cost calculations occur because the FAR data points vary widely across attribution studies. These flood results are significantly impacted by a regional average FAR for floods in Africa of a decrease of 0.49, meaning that an estimated 49% of the decrease of risk of flooding in Africa can be attributed to anthropogenic climate change. Comparatively, the regional average FAR for floods in all other regions is positive, indicating an increase in risk resulting from climate change. This has a relatively large impact on the regional extrapolation results as floods cause a relatively high number of deaths in Africa and a comparatively low level of damages.[20] Moreover, the discrepancy between climate change-attributed deaths from storms is primarily driven by a regional average FAR in Asia (0.81) at least 20 percentage points higher than the FAR in all other regions. This has a notable impact on the results given a high number of storm-related deaths in Asia. However, it is important to recognise that the two noted regional average FARs that impact these results are calculated from a few data points – 3 for floods in Africa and 1 for storms in Asia. Due to the lack of data relating to important event type and continental combinations, the global average extrapolation method is used from now on, to minimize over-reliance on a small number of attribution studies.

The economic value of life lost to climate change-attributed extreme weather is obviously very dependent on the assumed value of statistical life. When using the US-UK mean VSL (as described in the data section), the total climate change-attributed cost associated with mortality is a net US$ 1.79 trillion from the global extrapolation method. This is equivalent to an average statistical loss of life of approximately US$ 90.0 billion per year between 2000-2019.

The estimated global cost of climate change over the 2000-2019 period is summed up in Figure 5. These results are calculated using the global average FAR extrapolation method, which is less sensitive to singular studies than the regional average FAR approach. In aggregate, the climate change-attributed costs of extreme weather over 2000-2019 are estimated to be US$ 2.86 trillion, or an average of US$ 143 billion per year. The distribution of costs is highly variable across years. The year with the lowest costs attributed to climate change is in 2001 at $23.9 billion, while the year with the highest climate attributed costs is 2008 with $620 billion. The years in which costs reach high peaks - notably 2003, 2008, and 2010 – are predominantly because of high-mortality events. The events that drive these peaks are the 2003 heatwave across continental Europe; Tropical Cyclone Nargis in Myanmar in 2008; and the 2010 heatwave in Russia and drought in Somalia.

[20] This is a common pattern for disaster mortality and damage in low-income countries (Noy, 2016).

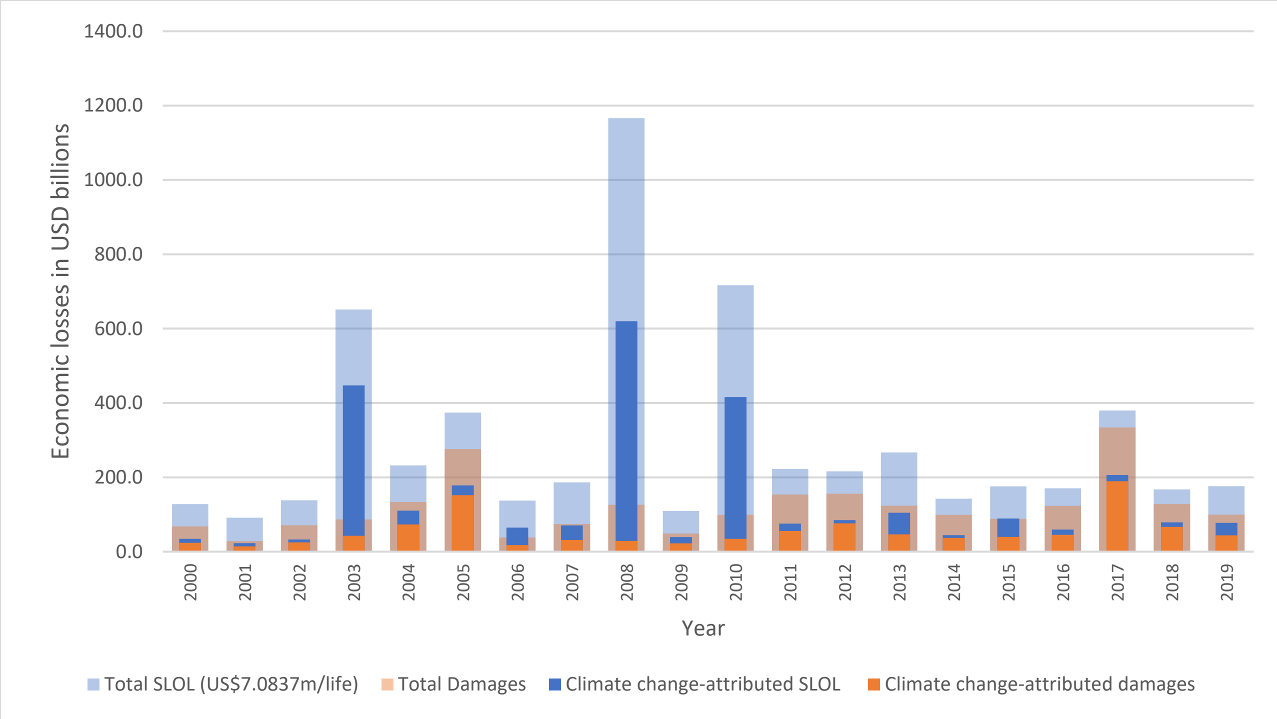

Figure 5: Total and climate change-attributed loss of life and damages from extreme weather events

The peaks in climate change-attributed costs differ when we look solely at damages and exclude the statistical loss of life, as shown in Figure 5. The greatest peaks in monetary damages occur in 2017 and 2005. Storm events in the United States drive these - in 2005, Hurricanes Katrina, Rita, and Wilma together caused $123 billion in attributed damages, and in 2017, Hurricanes Harvey, Irma, and Maria were responsible for $139 billion in climate change-attributed damages.

Figure 6 shows how total and climate change-attributed costs are distributed across high, upper-middle, lower-middle, and low-income countries. This provides context for how different countries, especially vulnerable ones, are being impacted by climate change-induced extreme weather. As per the available data, high-income countries have the highest climate change-induced economic costs at around 47% of the total. A few elements drive this, the primary being the United States has high asset exposure to storms.

However, the distribution of economic costs from extreme weather events across low to high-income countries is also likely a product of data availability and measurement. High-income countries have more resources and expertise to gather economic data when an extreme weather event occurs, while lower-income countries do not have this same level of resource availability.

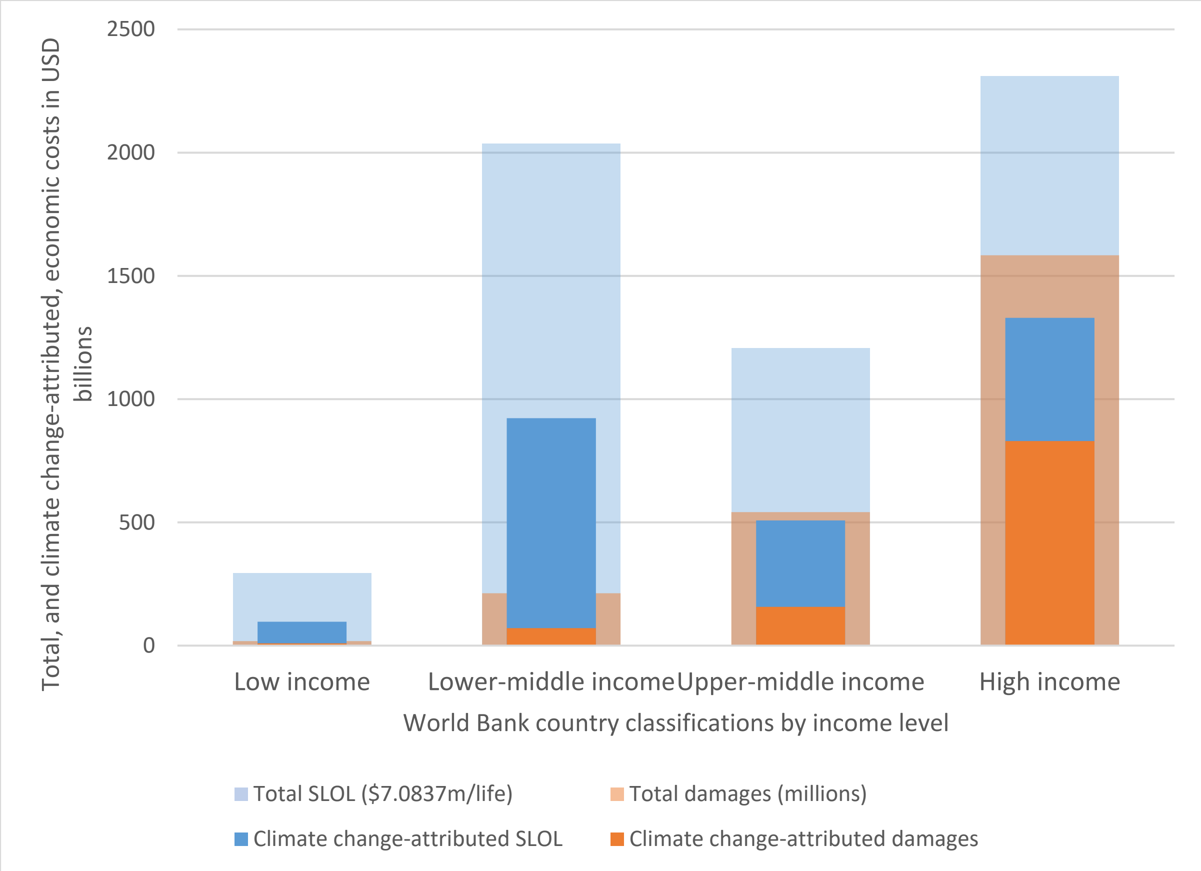

Figure 6: Economic costs from extreme weather events by income group (2000-2019)

These extrapolated estimates for the climate change-induced cost of extreme weather can be calculated as a proportion of GDP, as shown in Figure 7. Using the global average extrapolation method, the total economic cost, inclusive of damages and statistical loss of life, can be presented as a proportion of annual global GDP. This is not a direct comparison because GDP is a measure of economic flow, i.e. measured over a defined period, whilst damages and loss of life are a stock variable, i.e. measured at one point in time. It is, however, still a measure of the relative importance of these shocks on the affected economies. Climate change-attributed economic costs from extreme weather events vary between 0.05% to 0.82% of global GDP annually over the study period.

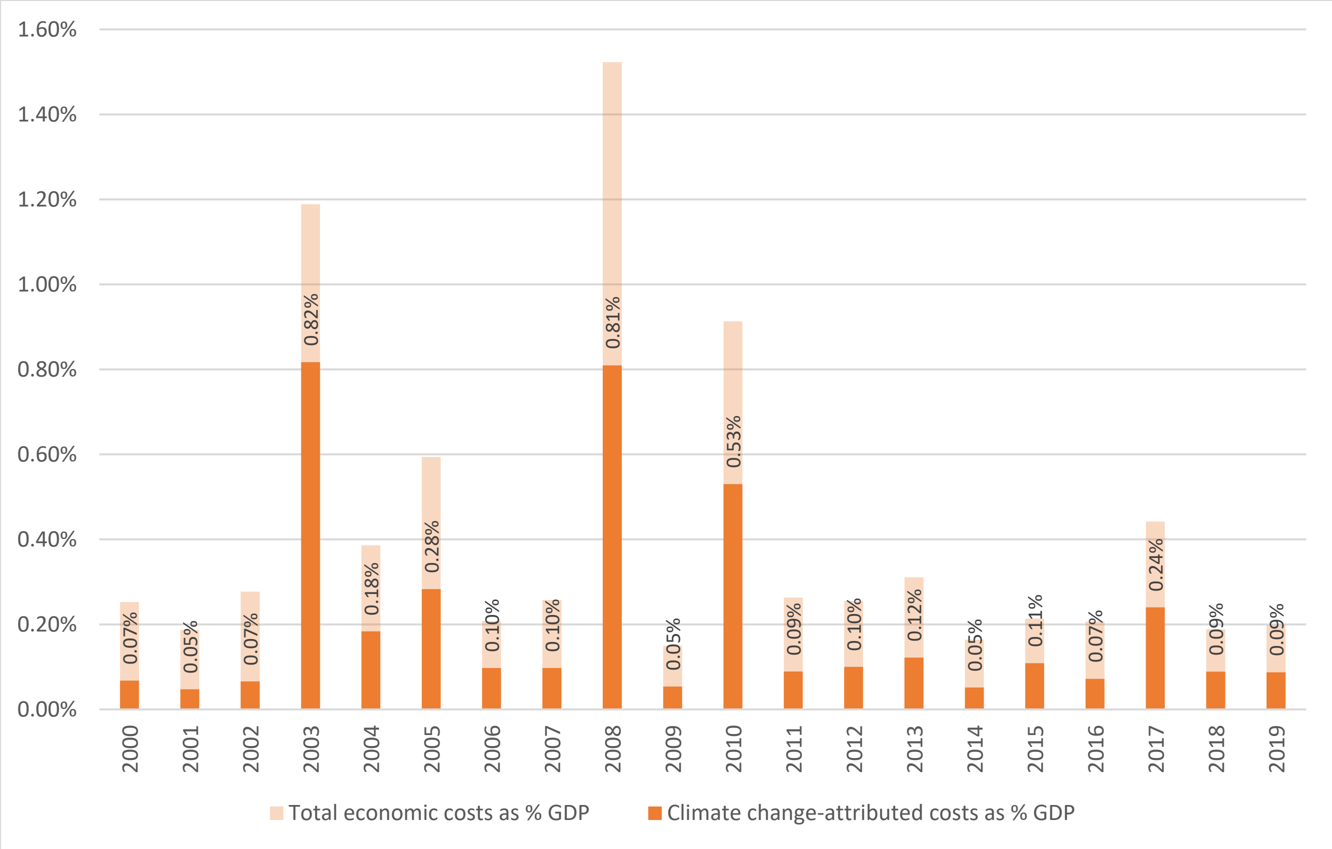

Figure 7: Economic costs from extreme weather events as a proportion of annual global GDP

7. Comparing the cost estimates with integrated assessment models

There are several different approaches used to estimate the economic impact of climate change, with the attribution-based method of this research a new inclusion. The attribution-based method is an event aggregation approach; it therefore differs significantly from the macroeconomic methodology used in Integrated Assessment Models (IAM). Commonly, IAMs characterize damages as a polynomial function of the deviation of average annual temperature from pre-industrial times, as done, for example in the Dynamic Integrated Climate-Economy (DICE) model (Nordhaus & Boyer, 1999; Nordhaus, 2017). DICE approximates the damages from climate change, as a proportion of the global economy, according to the damage function: $D(T) = \varphi_1 T + \varphi_2 T^2$.

Where T is the change in global mean surface temperature above the preindustrial threshold, currently estimated to be around 1.2℃ in 2020 (WMO, 2021A). To allow us to compare the results from attribution to those of DICE, we used the parameters from the DICE 2016R model: $\varphi_1 = 0$; $\varphi_2 = 0.00236$, and the same temperature deviation data. This approach from DICE is not unique for IAMs. The Policy Analysis of the Greenhouse Effect (PAGE) model, which was used in the Stern Report (2007), also calculates economic and non-economic damages from climate change using a polynomial function. However, PAGE uses regional temperature deviations rather than the global one (Hope, 2011).

From this basic calculation, as per the DICE model, the assessed global damages from climate change over 2000-2019 is estimated to be US$2.75 trillion. Based on an aggregated event attribution approach, the approximation in this research is $2.90 trillion, i.e. 5% larger than the DICE estimate. The comparative calculations of climate change costs from DICE and the attribution-based approach, by year, are shown in Figure 8. However, these two metrics are not attempting to measure the same quantity, with two key differences:

First, the IAMs produce a measure of decline in economic flow (proportional to global GDP) while attribution-based estimates measure loss in economic stock. This is the same distinction between damage and loss we described earlier.

Second, the attribution-based estimates solely measure the net economic cost of extreme weather events caused by anthropogenic activity, while IAM models attempt to estimate the overall annual loss caused by climate change. This should include extreme weather costs as well as many other types of costs and benefits from changing crop yields, ocean acidification effects, sea-level rise and its attendant impacts, environmental degradations and ecosystem disruptions, and many other types of impacts.

These factors limit the comparability of the IAMs measures and the attribution results. However, it is notable that extreme weather events are only one category of the damages that are, in theory, included in the DICE measure. The key limitation of IAMs, which is highlighted through comparison with the attribution-based approach, is that they account only for changes in average temperature rather than the change in temperature distribution, and specifically in the tail end of the distribution of weather attributed. By focusing on the deviation in the average temperature the IAMs fail to capture changes in extremes, plausibly the most important current impact of climate change.

Nordhaus acknowledges that that DICE, and other IAMs, generally omit the impacts extreme weather (as well as biodiversity, ocean acidification, catastrophic climate events, and more). The solution he used to account for this limitation is to add 25 percent of the monetized damages in the DICE model (Nordhaus & Sztorc, 2013). This is a very subjective adjustment, which would assume that extreme weather accounted for a maximum of $0.55 trillion[21] across 2000-2019. Relative to the climate attribution-based figure of $2.86 trillion. This suggests a large underestimate that exhibits how DICE fails to accurately assess the economic impacts of climate change from extreme weather.

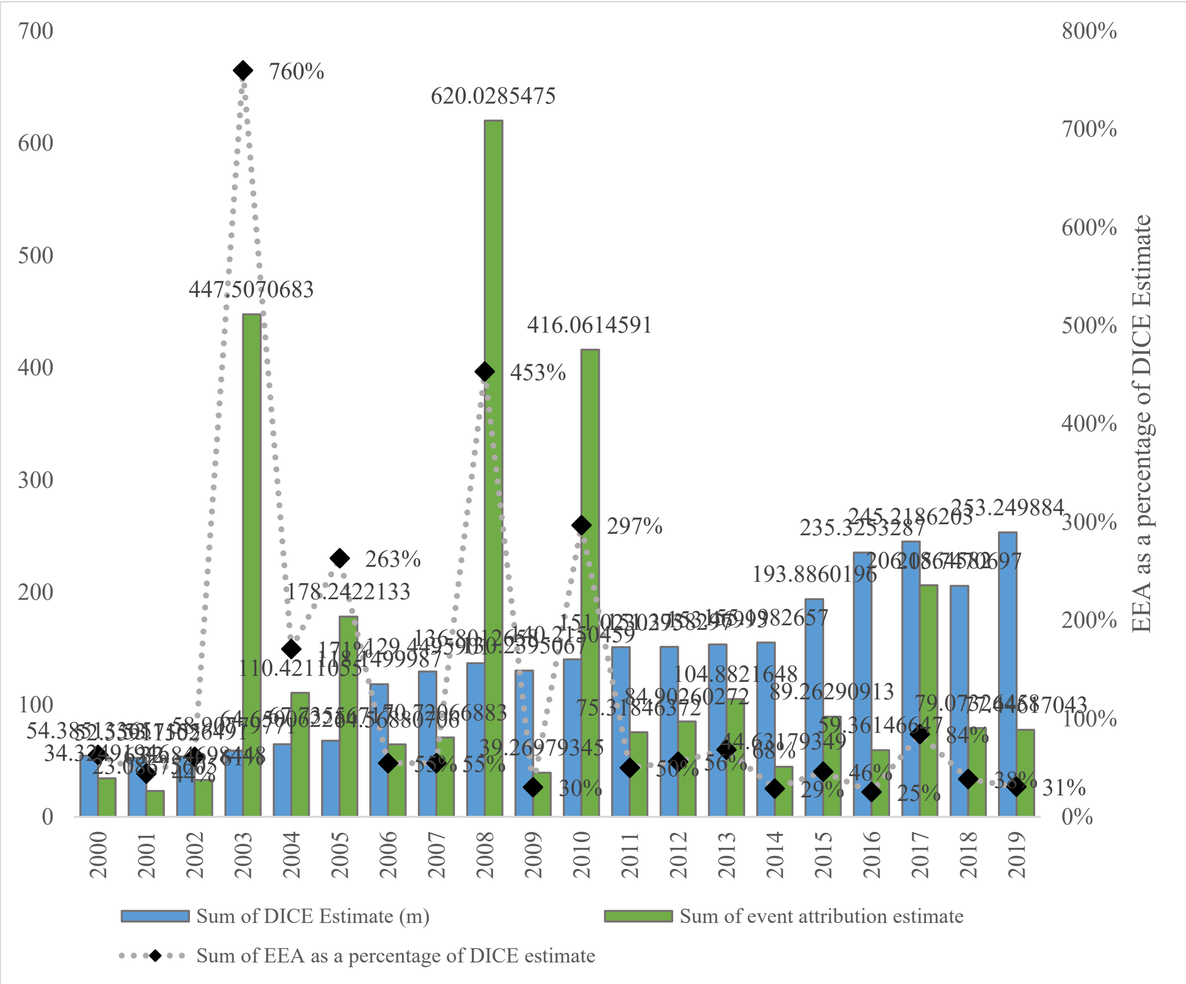

Figure 8: Economic costs from extreme event attribution and the DICE IAM estimates

Additionally, we can compare the attribution-based results to the Framework for Uncertainty, Negotiation, and Distribution (FUND) IAM, which is notably more complex than DICE. The FUND model differs from DICE as it calculates damages at a sectoral level, with nine sectoral damage functions operating across 16 regions of the world (Waldhoff, Anthoff, Rose, & Tol, 2014). The key sector of interest in FUND, for this research, is the storm sector which is the

[21] $0.55 trillion would mean that extreme events account for the full value of the 25% adjustment to the DICE estimate

only sector that is reflective of how climate change impacts the economic cost of extreme events. The FUND model calculates estimated damages (capital loss) and mortality for tropical and extra-tropical storms. This is a more sophisticated inclusion of extreme weather event costs compared to the DICE approach. As an example, the total damages and mortality from tropical storms in FUND are calculated for each region using the following two equations: $Total\ damage = \alpha * GDP * (\frac{y_{today}}{y_{1990}})^{\epsilon}[(1 + \delta * T)^{\gamma} - 1]$; and $Total\ mortality = \beta * population * (\frac{y_{today}}{y_{1990}})^{\eta}[(1 + \delta * T)^{\gamma} - 1]$. In the FUND model, the key inputs in the damage function are temperature change over preindustrial levels (T), per capita income (y), current damage as a fraction of GDP (α), current mortality as a fraction of the population (β), and income elasticities of storm damage (ϵ, η).

The MimiFUND web page, an accessible source for viewing the FUND model and results, estimates current damages from tropical cyclones as higher than the damages from extreme weather events calculated in the attributed results (MimiFUND, n.d.). FUND calculates the current damage from tropical cyclones as, on average globally, 0.08% of GDP. Comparatively, the climate change-attributed damages from storms calculated in this research are 0.06% of GDP on average per annum. Further, climate change-attributed damages from all extreme weather events in the research equate to an average of 0.07% of GDP per annum. The difference in the FUND tropical cyclone estimation and the climate change-attributed costs of storms is an interesting comparison. It may be a discrepancy that can, to some degree, be explained by under-estimated economic data recorded in EM-DAT the attribution estimates use. Furthermore, FUND estimates the current mortality from tropical cyclones to be on average 0.00015% of the population, while attribution-based results estimate that storms on average have a climate change-attributed mortality rate of 0.00009% per annum. These inconsistencies are illustrative of how, especially when data is lacking, it is beneficial to analyze multiple approaches to quantitative research – with the macroeconomic IAMs and event attribution techniques providing valuable contrasts.

8. Limitations of the attribution-based approach

This research explores the potential of an attribution-based method for estimating the human-induced climate change costs of extreme weather globally. Although event attribution has been used to measure the climate change-related economic impact of individual extreme weather events before, this methodology has not yet been extended to a global approximation (Clarke, Otto, & Jones, 2021; Frame et al., 2020a; Frame, Wehner, Noy, & Rosier, 2020b, Smiley et al., 2022). As such, this study does not provide a silver-bullet approximation of the cost of extreme weather events. There are important limitations of the attribution-based approach. These are primarily due to restrictions on the quantity and quality of data. These limitations are explored in detail below to highlight the progress required to make improve these estimations.

8.1. Extreme event attribution methodological limitations

Extreme event attribution is a young but rapidly expanding sub-field of climate science. The literature is limited, methodologies are continuously being refined, and the field's development faces some methodological and epistemological challenges. Notable limitations are the uneven geographical coverage of attribution studies and the lack of attribution studies conducted on several important classes of extreme weather events. These lacunae are significant, given the relatively small number of attribution studies conducted overall.

Extreme event attribution studies are more commonly conducted in high-income countries, with lower-income regions barely represented in the literature. In our database, only 8% of the attribution studies are conducted on extreme events in Africa, while over half of the events studied are in either North America (23%) or Europe (25%). In recent years, there has been a greater attempt to balance the geographical distribution. This includes research by the World Weather Attribution (WWA) network.[22]

Still, extrapolation based on the total average FAR per event type leans over-proportionately on event probabilities from high-income regions (and China). The data gaps in Africa and Oceania, in particular, result in over-reliance on few data points in the calculation of a regional average FAR, or the use of an imperfect substitute (e.g., the global average FAR). This is a notable limitation because different regions of the world are subject to different climatic systems and environmental conditions. Consequently, the FAR for specific extreme weather events will differ by region and even more locally within countries. Improved geographical

[22] The WWA use the following human-based threshold to determine which events to consider for study: the event resulted in greater than 100 deaths, 100,000 people affected, or more than half of the total population affected (van Oldenborgh et al., 2021). In contrast with an economic loss threshold, a human-based threshold leads to less bias against low-income countries where physical assets are of lesser value (Stott et al., 2015).

coverage of event attribution studies would improve the robustness of the methodology presented, especially if this allowed for greater granularity in the extrapolation method.

The second issue with event attribution data is the uneven spread of research across different event types. About a third of all attribution studies analyse the role of climate change in inducing heatwaves, the best-represented event category. Comparatively, storms, which are most important when considering the economic cost of extreme weather, make up only 8% of the studies in this dataset. One reason behind this discrepancy is the degree of difficulty associated with attributing different event types. Heatwaves, and similarly extreme cold events, generally result in the most reliable event attribution estimates as the direct thermodynamic effects for these events are comparatively straightforward (National Academies of Sciences, 2016). In contrast, events such as droughts are caused by several compounding factors - such as precipitation, temperature, and soil moisture - making the attribution process significantly more complex. Cyclones are also complicated to model, which means that large-ensemble attribution studies of these storms have only become feasible in recent years, though a high computational cost for each simulation still persists (National Academies of Sciences, 2016). As an example, Tropical Cyclone Idai that hit Malawi and Mozambique in 2019, and caused additional damage in Madagascar and Zimbabwe, was the costliest cyclone to have hit Africa with record setting intense winds and rainfall, but even it has not yet been analyzed in an attribution study.

Beyond the spatial and event-type coverage deficiencies, the framing of an event attribution study can induce large differences in how the role of anthropogenic emissions is quantified. Different framings would be appropriate for answering different questions (Stone et al., 2021). One such example, which gained significant attention, was the 2010 Russian Heatwave. Two seemingly contradictory event attribution studies were conducted – one finding a negligible role of human-induced climate change, and the other identifying a five-fold increase in likelihood (Dole et al., 2011; Rahmstorf & Coumou, 2011). However, the framing of this event was central to this difference, and it appears that both results were scientifically sound. The first paper analyzed the change in intensity, whilst the second analyzed the change in frequency. Moreover, subtle framing differences - such as whether attribution is conditioned on the background atmospheric conditions (e.g. ENSO), or sea surface temperature conditions, or whether the counterfactual removes a single factor (GHG emissions) or all anthropogenic factors - can have a notable impact on the attribution quantification (Hannart, Pearl, Otto, Naveau, & Ghil, 2016; Otto, 2017). More reassuringly, recent examination of the variability of results due to different methodologies used in the EEA studies themselves suggest these results do not vary that much (Stone et al., 2022).

An attribution study must also define the spatial and temporal boundaries of the event being analyzed. These decisions ultimately impact the final FAR that is calculated (Angélil et al., 2018, Uhe et al., 2016) As long as these definitions of the event in the attribution study align well with the extent of the economic estimates produced by EM-DAT, this issue may not be as important. However, given the paucity of attribution studies, and the lack of detail about the geographical span of the EM-DAT data we could use, this was not always the case.

Commonly, the event definition should reflect the main determinants of the event's impacts, as the authors seek to answer what role anthropogenic climate change played in creating the economic and societal impacts of an event (Otto, 2017). For example, calculating a FAR using a single day rainfall measurement (rather than, say a 7-day aggregate measure) may be preferable when a flood has caused devastation because of the short burst of intense rainfall that caused water to accumulate. For this study, attribution studies that define events based on the determinants of the most important human and economic impacts are beneficial.[23] This is because it allows a closer geographical and temporal match between the FAR and economic impact data recorded in the dataset, making the calculation of attributed costs more reliable. However, events are not always defined in this way, as there may be barriers that prevent author(s) from using such impact-based definitions. For example, it is often found that meteorological observational datasets are not extensive enough – across time or in granularity – to allow an attribution study based at a specific locality or on a specific factor. Therefore, the event definition sometimes must deviate from the boundaries of the actual impacts to ensure the adequacy of data records (Otto, 2017).

Finally, it could be argued that attribution studies using the intensity approach, together with well-calibrated damage functions (that define the functional relationship between damage and the intensity of an event) might be a more appropriate input into our analysis. Two reasons led us to prefer relying on FAR quantifications. First, these are much more common in the

[23] There of course can be multiple impacts, and these can be related to different event definitions. It is therefore not always clear which impact should be used when defining the event parameters. This is particularly salient for extreme events that are not meteorological in nature, such as flooding (hydrological) and wildfire (ecological), as these are also related to multiple climate parameters.

attribution literature, allowing us to expand our sample of events. Second, we do not have well-calibrated damage functions, as these can be spatially and temporally specific, and are unique to each type of event (even different types of storms, for example, will necessitate different damage functions). (Perkins-Kirkpatrick et al., 2022).

8.2. Events made less likely by climate change

This research looked at events that became more or less probable due to anthropogenic climate change. However, there may still be an embedded underrepresentation of events that have become less likely because of human-induced climate change; maybe because of publication bias, or because other factors that are associated with event selection. This is because attribution studies are typically conducted on 'important' events, one that attracted the researchers' attention, and are not conducted at all on events that became milder because of climate change or have not occurred at all. For example, Van Oldenborgh et al. (2017) indicate that a flood that results from snowmelt has not occurred in England in recent decades but did occur occasionally in the nineteenth and early twentieth century. This type of event may have become less likely because of climate change, but since there have been no recent occurrences, it is impossible to quantify reliably their economic costs. There is no way to overcome this bias, but the available evidence seems to suggest that even before the main impacts of climate change has started to be felt, the importance of these type of 'decreasing frequency or intensity' events have been relatively less prominent than that of increasingly likely ones.

8.3. Economic impact data limitations

The economic data used to quantify the global cost of climate change-attributed extreme weather events in this study are subject to an additional set of limitations. They reflect the current best-available estimates, but there are possible limitations regarding the data's quality, coverage, and granularity.

The economic cost data used in this research underestimates the true costs of climate change over the study period. Most importantly, our estimates include only direct loss (damage) and not indirect loss ones. These later losses are difficult to measure, for example, productivity losses in a heatwave (e.g., Orlov et al., 2021). For example, the Australian Climate Council attempted a thorough approximation of the total economic impact of Australia's southwestern heatwave in 2009 (Steffen, Hughes, & Perkins, 2014). They estimated that the heatwave was responsible for up to AU$800 million in indirect financial losses – predominantly caused by power outages and transport system disruptions. This same event, as recorded in EM-DAT, detailed no asset damages at all. An inventory of events with the economic impacts differentiated into direct and indirect economic losses, at a bare minimum, would give decision-makers a better understanding of the wider economic impact of anthropogenic climate change (Clarke, Otto, & Jones, 2021).

The number of people affected by disaster events is recorded in EM-DAT. With the global average extrapolation approach, we found that climate change 'affected' 1.4 billion people through extreme weather events between 2000-2019. *Affected,* in line with the EM-DAT definition, means requiring immediate assistance following the event. This could range from an acute need for life-saving medical attention and potentially sustaining life-long injuries, to the long-term provision of basic survival resources, or just supply of very short-term (hours or days) of emergency provisions. Clearly, there are significant economic costs associated with these 'affected' people, including healthcare costs, costs of provision of other basic services such as emergency shelters, and potentially other longer term welfare costs. However, given the extensive but imprecise range of costs that could be associated with someone being classed as 'affected', using a single monetary value for this group may be misleading. Therefore, these costs are not included in our calculations, but form an additional source of underestimation that is embedded in our results.

Additionally, people can be adversely affected by an extreme weather event in ways that do not include requiring immediate medical assistance or basic survival needs. For example, people may suffer from mental health impacts (e.g., post-trauma), the loss of access to education, or the loss of their job if their place of employment is harmed. These will not be counted as having been affected, under the EM-DAT definition, yet suffer high economic loss. These costs are not captured in any available dataset.

While the limitations of this approach are significant, this research demonstrates how a more global approximation of the human-induced extreme weather event economic costs could be constructed. Each of the limiting factors described above has the potential to be reduced with more research.

9. Policy implications for climate change adaptation

This research results rely on two elements – the level of anthropogenic emissions and their consequential effect on climatic extremes (captured by the FAR), and the economic costs from extreme weather events. To minimize the climate change-attributed costs from extreme weather in the coming decades, there would need to be increased mitigation that will reduce the FARs, or an increased adaptation that will reduce the economic costs associated with extreme events, or preferably both.

Adaptation can make a considerable difference to the climate change-attributed economic impact of extreme weather events right now. Adaptation policies could include infrastructure development such as building flood protection or improving early warning signal systems for extreme weather events. A pertinent example of this, in our context, has been implemented in continental Europe, where the 2003 heatwave claimed upwards of 70,000 deaths, 55,400 of which were attributed to climate change. The extremely high mortality of this event shocked European countries into creating effective heatwave adaptation strategies to prevent a repeated high volume of deaths in the future. France, as an example, introduced a heat warning system that is triggered after three days of persistently high temperatures (Pascal et al., 2021). This system can enact the closing down of schools and public areas, the operation of a public heatwave helpline, and the opening of 'cool rooms' in public buildings. This made a marked impact on the fatality of subsequent heatwaves. The heatwave in 2019 was hotter than that of 2003 in many locations, yet, in France, there were less than 1500 deaths, compared to over 19,000 in 2003. This clearly demonstrates how a well-designed and implemented adaptation policy can help reduce the climate change-attributed costs of extreme weather significantly. The results of this research, we hope, can provide an impetus to increase spending on climate change adaptation policies as it clarifies some of their benefits, in terms of avoided harm. It can also allow for better targeting of adaptation spending. This should ultimately help reduce climate change-attributed economic costs from extreme weather in the future.

For now, at the very least, more event attribution studies are needed, and the geographical and event type representation of studies improved to align better with human impacts. This, in addition to better economic data, will allow the approximation of the global climate change-attributed economic cost of extreme weather to be improved. As such, this attribution-based method can increasingly provide an alternative tool for decision-makers as they consider key adaptations to minimize the adverse impact of climate-related extreme weather events.

Supplementary Material

The full economic attribution database we collected can be accessed here:

https://www.dropbox.com/s/5luphxtge5wqu10/Global%20attribution%20data.xlsx?dl=0

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Appendix: Data collection

The data collection process formed a substantial portion of this research. Given that there was no existing database of global FAR measurements, and additionally no database with the matching economic cost data, this data had to be collected before any analysis could occur.

FAR data

The FAR measurements for individual extreme weather events were gathered from a review of the extreme event attribution literature. The starting source for accessing a wide range of this literature was the CarbonBrief (2021) Google Sheet. This spreadsheet compiles papers that attribute weather events to climate change, including a mixture of published scientific papers and rapid studies. A copy of this CarbonBrief spreadsheet is available in the supplementary material. The results from these attribution studies, and the details of the events they study, are not recorded in the spreadsheet. Studies from the CarbonBrief sheet were not examined for this research if:

1. The study recorded inconclusive results of anthropogenic climate change; as these do not provide any useful insight into the human-induced cost of extreme weather events.
2. Studies analysing events with no direct link to economic damages or losses. These include studies about sunshine hours, ocean/marine events, coral bleaching, river flow measures, and ecosystem functioning.
3. Studies attributing global events or weather trends; because economic costs are not clearly linked to events with either large spatial or temporal scope.
4. Studies that did not use a FAR metric or a transformable measure such as a risk ratio to ensure a consistent methodology could be applied.

Once the collection of studies was refined, as per these criteria, the remaining papers were read and key data compiled. This was an extensive process which involved reading over 200 climate attribution papers to, firstly, determine if the paper contains a FAR or transferable metric that could be used in this research; and, secondly, extract key information about the event study and how it was defined. The data collected from each study included countries for which the event was relevant, the spatial and temporal definition used to study the event, the nature of the event, and the FAR measurement. If the study did not include a FAR directly, it was calculated from the risk ratio ($FAIR = 1 - RR^{-1}$ or $FADR = 1 + RR$), or from the provided event probabilities for a factual and counterfactual climate. This data is available in the 'Combined' sheet in the economic attribution spreadsheet provided in the supplementary material.

Economic data

Economic cost data was collected for the extreme weather events for which a FAR was found in the attribution literature. A hierarchy of sources was used to gather economic data, as follows: EM-DAT, DesInventar, estimates from academic literature, estimates from national or international governmental organizations, and, finally, estimations from non-governmental organizations or media reports.

Given that EM-DAT was the primary source of economic data for extreme weather events, their categorizations were adopted for wider data collection. EM-DAT data covers four key variables, but only two were used in our analysis, the number of deaths caused by the event, and the amount of economic damage. EM-DAT defines this as the damage caused to livestock, property, and crops. It includes both uninsured and insured economic damages. The EM-DAT definition is thus similar to the aforementioned definition of direct economic loss from the UNDRR Intergovernmental Expert Working Group on Indicators and Terminology relating to disaster risk reduction.

The economic data collected from other sources did not always fit directly into these cost categories. However, since by far most estimates are of direct losses, any monetary estimates from sources outside of EM-DAT were recorded. The economic data in EM-DAT is recorded in US dollars at the time of the event occurring. To allow accurate aggregation, all economic cost data has been adjusted for inflation to reflect the average price of the US Dollar in 2020. Cost estimates provided in alternative currencies were also exchanged to reflect the 2020 USD. Unless otherwise specified, all results will be stated in USD (2020 value).

Additionally, all the data provided by EM-DAT on the economic costs of extreme weather events over 2000-2019 was collected to input into the extrapolation of a global climate change cost estimate. All data covering heatwaves, droughts, precipitation/floods, storms, wildfires, and cold events covering the study period were collected and formatted in a separate database. This data was collected separately irrespective of whether the event had a matched FAR study.