The Climate Change-Attributed Economic Cost of Extreme Weather.

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Abstract

Climate change is changing the nature of extreme weather events across the globe. Extreme event attribution is used to quantify the extent to which anthropogenic climate change is responsible for the change in frequency or severity of a specific extreme weather event. Using this quantification, we can estimate the proportion of economic costs from a specific extreme weather event that are attributable to climate change. However, research is yet to use this approach to estimate the value of climate change-attributed economic costs from extreme weather that have already been experienced globally. In this paper, extreme event attribution data has been collected, allowing us to estimate an average fraction of attributable risk (i.e. the portion of risk for which climate change is responsible) for different classes of extreme weather events – including heatwaves, droughts, floods, storms, wildfires, and cold waves. We then combine this with existing economic cost data from EM-DAT, including the number of deaths (converted using a value of statistical life) and economic damages, to approximate the climate change-attributed global cost of extreme weather using extrapolated reasoning. From this, we estimate that US$2.90 trillion in economic costs from extreme weather are attributable to climate change over the period from 2000 to 2019, equivalent to an annual average cost of US$145 billion. This shows that present estimations of the global cost of climate change are largely underestimated. This attribution-based estimate is higher than estimates from some Integrated Assessment Models, including William Nordhaus's DICE model, which are designed to measure the total economic impact of climate change inclusive of, but not limited to, extreme weather-related costs. This demonstrates that the crude nature of climate inputs in existing climate-economy modelling has a limited ability to capture costs from tail-end extreme weather events. The experimental attribution-based approach to global estimation is a best first-attempt which provides a new, alternative tool for measuring the costs of climate change.

Introduction

The future economic impact of climate change is a matter of much concern and debate. Surprisingly, less attention is given to the costs the world has already endured because of climate change. Estimating the economic cost of climate change involves analysing many complex interacting systems, all of which have embedded uncertainties. Therefore, it is inherently difficult to put a definitive number to the nuanced question of how much climate change is costing our global economy. However, an attempt at quantification is essential so as to enable policymakers to make well-informed decisions about mitigation and adaptation policies. A critical piece of this puzzle is understanding how the costs associated with extreme weather events globally are caused by anthropogenic climate change. What we do know is that human activity and associated greenhouse gas emissions are changing the location, spatial extent, intensity, and frequency of extreme weather across the globe (IPCC, 2021). By extension, climate change is responsible for some of the costs of extreme weather events. A better understanding of the magnitude of the role of climate change in the economic impact of extreme weather would prove helpful to global decision-makers as they plan for a future characterized by even hotter temperatures and more extreme weather events. Considering this, Allen (2003) proposed using extreme event attribution studies to quantify the economic costs associated with climate change. This research here uses an attribution-based approach to quantify the global cost of extreme weather events induced by anthropogenic activity over the last 20 years.

The economic costs associated with extreme weather events vary. They include direct economic losses, which occur during or immediately after the event. Using flooding as an example, where the hazard is heavy precipitation, direct economic loss may include destroyed housing or lost crops. Moreover, an extreme weather event can also cause indirect economic losses. These are declines in economic value-added because of the direct economic losses. The examples of these indirect losses are wide-ranging. However, for the flood example, they could include microeconomic impacts such as revenues lost by businesses when access routes are inundated by floodwater and meso-economic impacts such as temporary unemployment in the affected area or even more wide ranging supply-chain disruptions. These indirect economic losses can often spill out beyond the affected area and have long time lags, making them difficult to quantify.

Extreme event attribution is a relatively young field of climate science – it aims to determine the contribution of anthropogenic climate change to an extreme weather event. Often this is done by quantifying the fraction of attributable risk (FAR), i.e. how much of the risk of a specific event occurring can be attributed to climate change. By extension, this can be combined with economic impact estimates to approximate the fraction of the cost of an extreme event for which climate change is responsible. Aggregation of these economic cost estimates can be used to approximate the cost of climate change-induced extreme weather. This attribution-based method fundamentally differs from other approaches to climate cost estimation where macroeconomic modelling methods are employed, specifically in various types of integrated assessment models (IAM). The approximation in this research is not a direct comparison, nor a substitute, for other economic estimations such as the IAMs. Instead, it is a new form of evidence that enhances the current knowledge regarding the economic cost of climate change, specifically extreme weather events.

As is the nature of first-attempt research, the purpose of this paper is to be exploratory and prove the use-value of the employed methodology. This approach has many limitations, mostly regarding data availability and coverage, which are examined in this paper. However, as better data becomes available over time and the method is refined, the robustness of this approach's estimation will increase in tandem. Ultimately, the aim of this research is to provide ever-improving information on the cost of climate change that feeds into better public and private decision-making globally.

1. Literature review

1.1. The economic impact of extreme weather events

Extreme weather events have devastating impacts on individuals, communities, economies, and environments. Extreme weather events, by definition, are rare weather events at a particular place and time of the year (IPCC, n.d.). 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, 2012). 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 definitions that allow for effective communication and categorization of disaster-related economic impacts. Firstly, an event can cause *disaster damages* which occur during and immediately after the disaster. This is usually 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 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 human or environmental damages (Frame et al., 2020A). These indirect losses often occur outside the hazard area and with a time lag, sometimes meaning they are intangible and/or challenging to measure, a gap which can sometimes be filled by modelling (Jahn, 2015). Finally, *disaster impact* is the total effect of a disaster, including negative effects (e.g. economic losses) and positive impacts (e.g. economic gains). This term includes economic, human, and environmental impacts, including death, injuries, disease, and other adverse effects on human physical, mental, and social well-being. 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 loss, given limitations on the data collected in EM-DAT.

The availability of well-categorized economic impact data for extreme weather events is limited. Chatterton et al. (2010) provides an excellent example of an in-depth and well-categorized recording of the economic impacts of an extreme weather event, notably the 2007 floods in the United Kingdom. This paper shows that economic impacts can be highly variable across the short and long term. The total economic cost of the UK floods is assessed at USD$6.4 billion (£3.2 billion[1]) – which includes direct economic losses and indirect economic losses. An example of a direct economic cost, which is relatively easy to measure, is the US$660 million (£330 million) in power and water utility damages. Moreover, indirect economic losses from this flooding event included mental health costs which accounted for US$520 million (£260 million). Indirect costs, such as these, are much more difficult for researchers, organisations, and governments to measure. Therefore, it is rare to have estimates for the total economic cost that are as comprehensive and detailed as that in Chatterton et al. (2010). There is a paucity of economic impact data globally and an even

[1] 2007 average GBP USD XR = 2.00, in 2007 prices.

more significant limitation on well-categorized economic data. Consequently, when researching this space, there is often a reliance on incomplete data.

Understanding the total economic costs for an individual event is important. However, we also need to understand the global impact of extreme weather from a macro-lens. From the available data, the World Meteorological Society (2021B) reports that there has been a seven-fold increase in the reported disaster losses from extreme weather since the 1970s. The reported losses from 1970-1979 were on average US$49 million per day, while this increased up to US$383 million in 2000-2019. This is of notable concern and prompts the question of what is causing these changes. Many underlying reasons could be driving this rise. For example, a higher level of development may mean assets of greater value are vulnerable to damage (although better building quality should reduce vulnerability), improvements in the reporting of economic losses, global shifts to exposed coastal areas, urbanization, and many other factors. However, the a fundamental question for policymakers is how this increase is related to anthropogenic changes in the climate system. To properly make decisions to mitigate climate change, we first need to understand how climate change alters the patterns of occurrence, severity, and economic impact from extreme weather events globally.

1.2. Detecting a relationship between climate change and extreme weather events

Changes in the frequency and nature of extreme weather events have been observed (IPCC, 2013). Extreme weather events can occur because of natural variability in the climatic system, external forcings such as greenhouse gas emissions, or – in most modern cases – from a combination of the two. The act of observing changes in extreme weather patterns is formalized through the 'detection' process. Detection involves identifying a statistically significant change in the extreme values of a climate variable over time; for example, this may involve detecting a significant change in the severity or frequency of a type of extreme weather event (Easterling, Kunkel, Wehner & Sun, 2016). The climate system is well-monitored, and despite some challenges regarding data availability, changes in extreme weather events over the latter half of the twentieth century have been detected. The most recent research from the IPCC AR6 report (2021) finds that it is *virtually certain* that the frequency and severity of hot extremes have increased (Seneviratne et al., 2021). While the frequency of cold extremes has decreased since 1950, human-induced greenhouse gas forcing is the primary driver of this global change (Seneviratne et al., 2021). For other climatic variables, the changes are less distinct. It is *likely* that the frequency and intensity of heavy precipitation events have increased over the majority of land areas globally, with human influence the *likely* main driver. Moreover, with *high confidence,* the IPCC finds that the land area affected by increasing drought frequency and severity is increasing with increased global warming. While it is *likely* that the global proportion of major tropical cyclones intensities has increased over the past four decades, this cannot be explained by natural variability alone (*medium confidence)* (Seneviratne et al., 2021). The detection of these changes in the frequency, severity, and geographical coverage of extreme weather events and the evident links to anthropogenic climate change help inform us of patterns observed in the past and what may occur in the future. However, these detected changes exhibit generalised changes in the climatic system and cannot be directly applied to an individual extreme weather event. Therefore, there is additional demand for evidence to show how anthropogenic activity changes the nature of specific events. Resultantly, there is a need to go through the climate change attribution process.

1.3. Attributing climate change as a causal factor in extreme weather events

Climate change attribution is a process that examines the degree to which anthropogenic emissions caused a specific extreme weather event to occur. It is especially common in the aftermath of high-impact extreme weather events for there to be heightened interest in the causal factors that contributed to the event – from government, individuals, businesses, and others. In these circumstances, it is commonplace to see some sectors of society arguing that it is impossible to link an event to climate change, whilst others confidently attribute the event to human causes in the absence of scientific backing (Stott et al., 2013). However, a process of attribution needs to formally identify the causal link between anthropogenic climate change and the changing nature and frequency of extreme weather events. At the beginning of the century, there was no formal practice for attributing an individual weather event to anthropogenic climate change. This allowed climate change scepticism and denialism to promote a narrative based on "no proof". Until in 2003, Allen (2003) observed a rising flood in his backyard and wondered – with a method of averaging over probabilities – whether the contribution of climate change to the risk of an individual weather event could be quantified. This seminal paper spurred the rise of extreme event attribution as a sub-discipline of climate science.

The proposed methodology compared the probability of the event occurring in a factual world, where anthropogenic climate change is existent, to the probability in a counterfactual world – the world without any presence of anthropogenic emissions. From this, 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. This is known as the risk-based approach to attribution (Otto, 2017). To undertake this methodological approach, the weather must be simulated under current climatic conditions and, similarly, simulated under counterfactual climatic conditions, free from human influence, to determine the likelihood of that weather event occurring in each state. This provides information on the degree to which climate change has altered the risk of event occurrence. This method was first used to quantify the role of climate change in the 2003 European heatwave and has been evolving in methodology and sophistication ever since (Stott, Stone, & Allen, 2004). Other attribution methods have also been developed to approach these critical research questions. This includes the Boulder approach, sometimes also called the storyline approach, this involves disentangling the causal factors which contribute to the likelihood of event occurrence with a lesser focus on statistical quantification (Otto, 2017). This approach tends to focus more heavily on the role of sea surface temperatures and other large circulation patterns. In the subsequent literature examination and research, the focus will primarily be on the risk-based approach as the quantifiable nature is beneficial to the economic lens.

1.4. Methods for estimating the global economic impact of climate change

As previously discussed, extreme weather events have large and varying economic impacts and established scientific causal links to anthropogenic climate change. Therefore, these separate pieces of information can be used in conjunction to retrospectively quantify the economic costs of climate change as related to extreme weather events.

There have been many attempts to quantify the global impact of climate change. Well-known, well-regarded, and equally well-criticized examples include Nordhaus (2017) and Stern (2007). The primary tool used to quantify the economic impact of climate change, used in both these reports, are integrated assessment models (IAMs). Integrated assessment models are defined by Nordhaus (2011) as "approaches that integrate knowledge from two or more domains into a single framework", in this context this refers to an integrated analysis of the climatic and economic systems. These IAMs, typically, use damage functions that express the economic impact of climate change as a function of a global or regional mean temperature (Diaz & Moore, 2017; Keen, 2020). This method fails to capture the change in extreme temperatures or the variability in daily weather, which is fundamental to patterns of extreme weather events across the globe (Goodess, Hanson, Hulme, & Osborn, 2003). Resultantly, these models only tend to include the costs of extreme weather crudely, or they are omitted entirely (Bouwer, 2011; Tol, 2005; van den Bergh, 2009). For people outside of the field, including policymakers, it may not be immediately apparent upon viewing the results of an IAM that costs from extreme weather are included in such a simplistic manner. This, alongside wider concerns such as a misrepresentation of climatic tipping points, has driven a call for improved transparency around modelling techniques and limitations embedded in IAM findings (Keen, 2020; Vaidyanathan, 2021).

1.5. Using extreme event attribution to estimate the economic costs of climate change

An idea emerging within the literature is to use extreme event attribution to fill gaps in the current knowledge regarding the climate change-attributed cost of extreme weather events. Allen's (2003) paper initially prompted using event attribution to assign liability. It was proposed that liability relating to economic losses from extreme weather could be proportionately split between natural variability and anthropogenic activity, using risk-based attribution. Frame et al. (2020A) illustrates how this approach can attribute climate change-induced economic costs when both a fraction of attributable risk and economic cost inputs are available for an individual event. The methodology used to reach this estimate is simple – multiply the fraction of attributable risk (FAR) by the estimated economic costs (Frame, Wehner, Noy, & Rosier, 2020B). These assessments essentially allow researchers to describe the monetary cost from a particular extreme weather event for which climate change can be considered responsible. This process can be replicated across different types of economic impacts – including deaths, damages, and losses – to provide individualized assessments of the climate change-attributed value of each. Furthermore, Frame et al. (2020A) is an example of how the aggregation of attributed costs creates a retrospective estimate of the impact of climate change over a specified period and locality. For example, this paper estimated climate change-attributable insured costs of major flooding events in New Zealand at NZ$140 million for the decade 2007-2017 – based on the aggregation of attributed costs from 12 major flooding events. This was calculated based on individually calculated FARs for each event and individual economic cost measurements. At the current point, research has not been conducted that extrapolates further by using known FARs to estimate the climate change-attributed cost of an extreme weather event that has not been formally attributed.

There is no study in the current academic literature that attempts to use this climate change attribution method to assess extreme weather's cost globally and retrospectively. Given the limited availability of FARs in the literature, the FAR*Cost methodology cannot be applied across every extreme weather event using an individualistic and linear multiplication approach. Consequently, a global application relies on the extrapolation of known FAR values and patchy economic data at best. Moreover, Van Oldenborgh et al. (2021) argue that, with the current existence of event attribution studies, there are issues in attempting to aggregate economic impacts. Firstly, there are biases in the selection of attribution studies conducted. Generally, events with higher human and economic impacts will be favoured, there is a skew of studies toward events in high-income regions and more densely populated areas, and events that become less likely are underrepresented in the analyses (Stott et al., 2013; van Oldenborgh et al., 2021). Additionally, the economic impacts of past events are recorded in an ad-hoc manner across a wide variety of sources – from disaster databases, government agencies, academic literature, and media publications (Clarke, Otto, & Jones, 2021). These issues, when combined, impact the accuracy of aggregate results. However, given the fundamental importance of empirical evidence to drive an informed climate change policy response, aggregation and extrapolation based on available knowledge would be of use, given that limitations and inherent biases are transparently acknowledged. This research gap will form the foundation of this study, with the purpose being to show the application of a new methodology on a global scale.

2. Research Problem

“Using the extreme event attribution methodology, estimate the climate change-attributed global economic cost of extreme weather events over the period from 2000-2019.”

This research will show how extreme event attribution can be used to estimate the climate change-related cost of extreme weather events globally for a period dictated by the availability of FAR studies. Rather than being interpreted as an accurate estimate, the purpose of this paper is to prove the valuable nature of an attribution-based estimation of the cost of climate change-induced extreme weather. This will provide a starting point for developing this methodology, which will evolve as data availability and quality improve.

The economic cost of climate change must be estimated, to the highest degree of accuracy possible, to drive important policy decisions with precision. Current approaches used to estimate the global cost of climate change, such as IAMs, are flawed. This makes the exploration of new, alternative, and complementary cost estimation methods, such as this, fundamentally important.

3. Data collection and terminology

3.1. Terminology: Fraction of attributable risk

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. Risk, in this sense, refers to the probability of occurrence. The FAR is equivalent to necessary causality pertaining to human activity (Otto, 2017). The FAR is a ratio of the difference between the probability of occurrence in a factual climate and a counterfactual climate where the counterfactual is devoid of anthropogenic influence (Jézéquel et al., 2018).

When the risk of an event has increased due to anthropogenic behaviour, it is calculated as shown in Equation 1, in line with the IPCC (n.d.) definition. This is referred to as the fraction of attribution *increasing* risk.

Equation 1: Fraction of attributable increasing risk

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

P_0 = Probability of a climatic event occurring if anthropogenic forcings had not been present

P_1 = Probability of the event occurring in the presence of anthropogenic forcings in the climate system

A FAR value of 1 means that the event would not be possible in the absence of anthropogenic climate change. While a FAR of 0 indicates that climate change did not influence the probability of the event occurring (Jézéquel et al., 2018). A FAR less than 0 means that the event became less likely because of anthropogenic climate change.

As argued by Wolski, Stone, Tadross, Wehner and Hewitson (2014), the FAR 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, calculated as $FADR = 1 - {}^{P_1}/_{P_0}$. In this study, the FAIR and FADR abbreviations will be used in specific circumstances of increasing and decreasing events, respectively. FAR will be used more generally to refer to the attribution metrics.

3.2. 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.

3.2.1. FAR data collection

The FAR measurements for individual extreme weather events, which form the basis of the dataset, are gathered from a review of the extreme event attribution literature. The starting source for accessing a wide range of extreme event attribution 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. To collate FAR measurements from extreme weather events globally, literature in the CarbonBrief spreadsheet was refined to papers that are relevant to this research question. Studies from the CarbonBrief sheet were not examined for this research if:

1. The study recorded inconclusive results or a null effect of anthropogenic climate change. These studies 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 – includes sunshine hours, ocean/marine events, coral bleaching, river flow, and ecosystem functioning. This refinement meant that all this research focused on heatwaves, precipitation/flooding, drought, storms, and wildfires;
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 (RR) 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 ($FAR = 1 - 1/RR$), 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.

3.2.2. Economic data collection

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, academic literature, national or international governance organisation estimates, and, finally, estimations from non-governmental organisations, 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:

- Number of deaths caused by the event: *This measures the number of lives lost because of the event occurring. For this study, the economic cost of mortality is assessed using statistical value of life estimates. The primary statistical value of life estimate used is $7.08 million (USD 2020), which is the mean of the value used by the United States of America's Department of Transportation estimate and the United Kingdom's Treasury estimate*[2].

- Number of people affected: *This captures the people who required immediate assistance following the disaster during a period of emergency, i.e. requiring basic survival needs such as food, water, shelter, or requiring immediate medical attention.*

- Economic damage: *EM-DAT defines this as the damage caused to livestock, property, and crops. This includes uninsured and insured economic damages. This is similar to the aforementioned definition of direct economic loss from the Intergovernmental Expert Working Group on Indicators and Terminology relating to disaster risk reduction.*

- Insured losses: *Defined as a measurement of insurance payouts that occurred to cover losses resulting from the events. The data availability for insured losses is limited in this dataset and is highly skewed towards high-income countries.*

This data collection format from EM-DAT constituted the basis of the economic data collection categories for this research. The economic data collected from other sources did not always fit directly into these cost categories. For example, estimates of indirect economic losses are not technically economic damages nor insured losses. For consistent categorization, any monetary estimates from sources outside of EM-DAT – which were not insured - were recorded as economic damages.

The economic data in EM-DAT is recorded in US dollars from the time of the event occurring. To allow accurate aggregation, all economic cost data has been adjusted for

[2] These estimates and their impact on results are discussed further in the results section of this report.

inflation to reflect the average price of the US Dollar in 2020. Furthermore, cost estimates from sources outside EM-DAT 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, the data provided by EM-DAT on the economic costs of extreme weather events over 2000-2019 was collected to input into the calculation of a global climate change cost estimate. All EM-DAT data covering heatwaves, droughts, precipitation/floods, storms, wildfires, and cold events covering the study period were collected and formatted in a separate database. The same categorization of deaths, affected, damages, and insured losses are the data points used for global estimation data. This data was collected irrespective of whether the event had a matched FAR study, as it was used for the extrapolation calculations.

3.2.3. Finalising data for matched events

Data for individual extreme weather events were matched, where both a FAR and economic data had been acquired. These events were collated to form the 'master database', where each matched event was listed with the best estimate FAR and economic data available.

The available data were refined to ensure the master database contained the best estimates for each event. Firstly, 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. 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). A FAR measurement for a specific event is considered superior if it has a higher SJR, inferring greater scientific influence. Therefore, when multiple studies were relevant to one event, the FAR from the study with the best SJR rank was included in the master database. For rapid studies conducted by the World Weather Attribution network, there was no recorded SJR as they are not published studies (WWA, n.d.). Resultantly, the average of the SJR scores for all other studies in the database was used as a rank for WWA studies. 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. This was done because a FAR can differ based on event definition. Therefore, when the scale is matched closely to economic data, the attribution of the cost will be more accurate.

On the final master database, there are 179 events spanning 2000-2019, 87% of which increase in probability due to anthropogenic forcing, and the remaining have decreased in risk probability. These 179 events are gathered from 112 event attribution studies, as many attribution studies cover more than one event.

4. Methods

4.1. Attributing the economic cost of events in the master database

For this research, the climate change costs of extreme weather events have been estimated using a simple FAR*Cost method. As proposed in Allen (2003, p. 891):
"If A has trebled the risk over its 'pre-industrial' level, then there is a sense in which A is 'to blame' for two-thirds of the current risk..."

By extension, this 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 that event. Resultantly, for each event in the master database, we use Equation 2 to estimate that individual event's climate change-attributed economic cost.

Equation 2: Climate change attributed economic costs

$$Climate\ change\ cost\ of\ event\ A = FAR\ of\ A * Economic\ cost\ of\ A$$

Applying this approach to all events in the master database provides an estimation of the climate change-induced costs associated with these individual events.

4.2. Extrapolation methods

To create an estimate of the global cost of climate change, the FARs from attribution studies in the master database and the economic cost of extreme weather events[3] across 2000-2019 recorded in EM-DAT were utilised. Two extrapolation methods were adopted – these two

[3] Limited to heatwaves, floods, droughts, wildfires, and storms.

approaches are referred to as the global average extrapolation method and the regional average extrapolation method. These will be described further and assessed for their validity.

4.2.1. Global average extrapolation

The global average extrapolation method was conducted as follows. Using the FAR results from individual attribution studies in the master database, an average FAR for each specific event type was calculated. This average is based on all the FARs for a given event globally. This event type-specific average FAR was then multiplied by the economic costs and mortality of all relevant events in EM-DAT over the 2000-2019 period. The average FARs are calculated from individual attribution studies in the master database (from which there are 112 observations) rather than the FARs from the individual 179 events. This is because some studies cover a large number of events, such as Zhang et al. (2016) covering 26 events; therefore, calculating an average FAR with each event as an individual data point would lead to a greater weight being placed on a smaller number of multiple-event studies.

For example, the global average FAR for a heatwave in the dataset was 0.77, indicating that, on average, climate change was responsible for 77% of the risk of a heatwave occurring. This FAR was then multiplied by all global heatwave costs recorded in the EM-DAT database between 2000 and 2019. This method was repeated for each event type, creating an estimate for the global cost of climate change-attributed economic costs for heatwaves, droughts, floods, storms, wildfires, and cold waves across the study period. The calculated climate change-attributed costs from each event type were then aggregated to estimate the total climate change-attributed economic impact from all extreme weather between 2000-2019.

4.2.2. Regional average extrapolation

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 results (FARs) 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 attempts to account for differences in how climate systems influence extreme weather across different regions. There are no, or very few, FAR studies for some event-type and continental combinations. For example, only one study in the master database examines a heatwave in Africa, so the extrapolation result relies solely on this one study, creating potentially an over-reliance on one modelling approach. Where there are no FAR studies conducted, for example, on storms in Europe, the global average for that event type is used as a substitute to fill the data gap. For example, the average FAR of a heatwave in Asia was 0.81; this was then be multiplied by the cost of all heatwaves in Asia recorded in EM-DAT throughout the study period. At the same time, the costs from heatwaves in Europe were multiplied by the European-heatwave average FAR of 0.76. The regional, event type-specific extrapolated costs were summed together to create a global estimate of the human-induced cost of climate change. This is an imperfect substitution method. Therefore, given the high number of event-continent combinations with no, or few, FARs recorded, this method is not heavily relied upon in the final results. However, it would most likely be preferable to use this approach when more granular attribution data is available; potentially delving into more fine-grained spatial differentiation beyond the continental aggregate.

4.3. Assigning a statistical value of life to extreme weather event mortality

To assess the economic cost of mortality from climate change-attributed extreme weather, a value of statistical life (VSL) was employed. The value of statistical life describes a marginal rate of substitution between money and mortality risk in a defined period (Hammitt, 2000). A VSL is deployed in this research to estimate the economic cost of mortality from climate change. The VSL used here is an average of two VSL estimates used in well-respected organisations across the United States and the United Kingdom. The first is the United States Department of Transportation estimate for 2020, which sets the VSL at $11.6 million, which itself is an average of VSL estimates from across the academic literature (Department of Transportation, 2021). The second is from the UK Treasury, which assesses the VSL[4] to be £2 million ($2.57 million), estimated from average values from survey data looking at representative samples of the population (Dolan & Jenkins, 2020; HM Treasury, 2018). Kniesner and Visusi (2019) explain that estimates for the VSL differ across countries, which can be affected by the demographic profile differences across regions, but additionally an increase in VSL in areas with higher incomes given reducing mortality risk acts as a normal good. This is one reason why estimates from the United States tend to sit higher than that from non-United States countries. According to Viscusi (2018), across a full sample set of VSL estimates, the US median sits at $10.57 million while the non-US median sits at $7.36

[4] They refer to the VSL as the 'Value of a Prevented Fatality', but is reflective of the same concept.

million[5]. For this study, the cost of death is presented using both the estimates from the US Department of Transport and the UK Treasury to demonstrate the significant impact the choice of VSL can have on policy decisions. However, for the dominant presentation of results in this paper, a VSL of $7.08 million per life lost is used, an average of the two estimates discussed above which sits near the non-US median seen in Viscusi (2018). For simplicity, this 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 it occurs.

5. Data description

This section will describe the characteristics of attribution data and economic cost data collected in the database for this research.

5.1. Extreme event attribution data

Following the data collection method above, 179 extreme weather events were found to have both a FAR result and economic data available. The risk of 155 of these events increased because of anthropogenic climate change (FAIR), while the remaining 24 studies decreased in risk (FADR). Of these studies, there are 21 singular attribution studies (i.e. with one FAR) that cover multiple events in the database. For example, Zhang et al. (2016) studied the attribution of tropical cyclone energy across the Western North Pacific in 2015. This study alone covers 26 events in the database across China, the Philippines, Japan, and Taiwan. After accounting for multiple event coverage, such as this, there are 112 individual attribution results recorded. These 112 attribution results are a combination of papers with singular FARs or circumstances where one paper has attributed multiple events separately (each with an individual FAR). These attribution results formed the basis of the master database used for the analysis in this research. The relatively low number is primarily a product of the restrictive availability of FAR studies.

5.1.1. Time series coverage

The 179 matched events for which the risk of occurrence has been impacted by anthropogenic climate change cover the period from 2000 to 2019, as shown in Figure 1.

[5] Adjusted to 2020 USD. Originally reported as US$10.25 million and $7.1 million in 2018 paper.

Notably, 78% of these events, and similarly attribution results, occurred post-2013 because extreme event attribution studies have been conducted increasingly frequently only in recent years. Given the nature of this ever-improving science, the methods for climate attribution have been refined over time. Therefore, the dominance of more recent attribution studies in our dataset means the FAR records used for the results reflect the highest quality, up-to-date event attribution research. A significant number of events appear in 2015 because of the previously mentioned study by Zhang et al. (2016), which covers a large spatial and temporal scale. Calculating average FARs from matched events would create an overreliance and skew from singular FAR data points that cover multiple events. To refrain from this over-reliance on individual studies, the average FARs used to extrapolate have been calculated from individual matched attribution results, meaning each FAR datapoint is only included once in the averaging calculation.

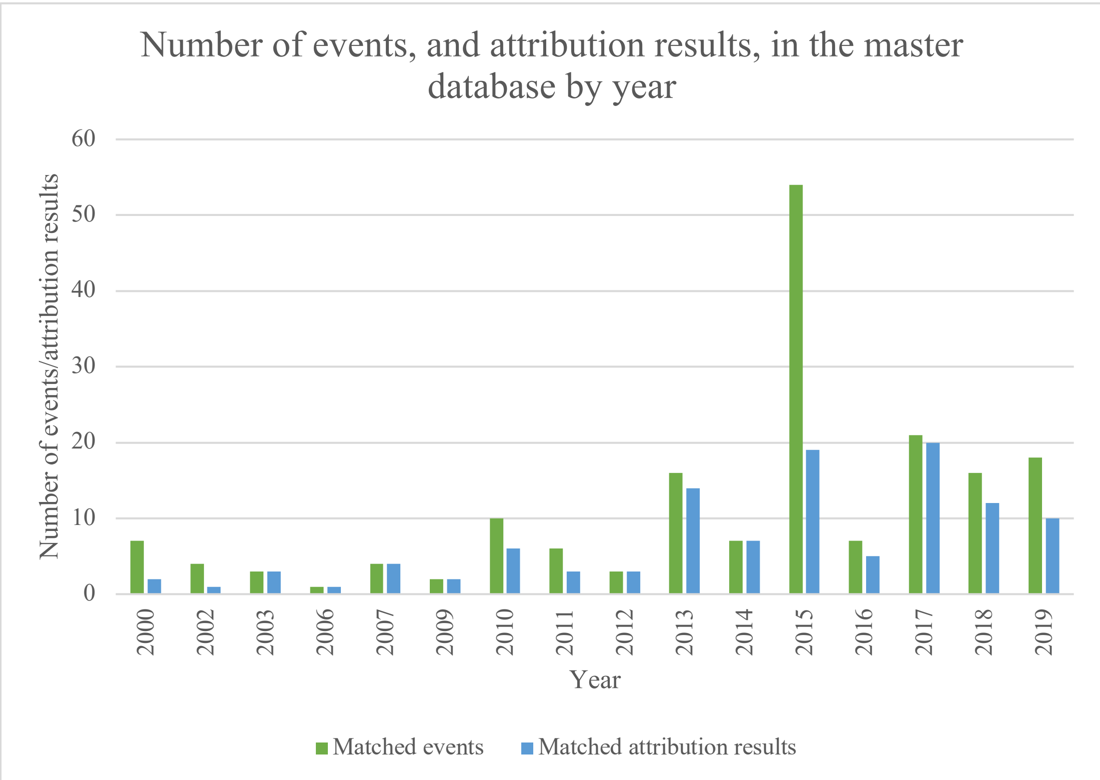

Figure 1: Count of matched events and attribution results in the master database by year

5.1.2. Geographical coverage

Figure 2 shows the geographical coverage of the matched attribution results included in the dataset. These results cover continental regions including Africa, Asia, the Americas, Europe, and Oceania. North America and South America are collected as one continent because there are very few FARs in South America. Events in South America making up only 5.0% of the total matched event in the master database, consequently, to use South America as its own continental region would lead to a reliance on only seven attribution results across all disaster types. Therefore, North and South America are combined for regional estimations. The matched events in the database 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 the Zhang et al. (2016) study that covered 26 cyclones across the Western North Pacific Ocean and the Frame et al. (2020A) that studied 14 droughts and floods in New Zealand.

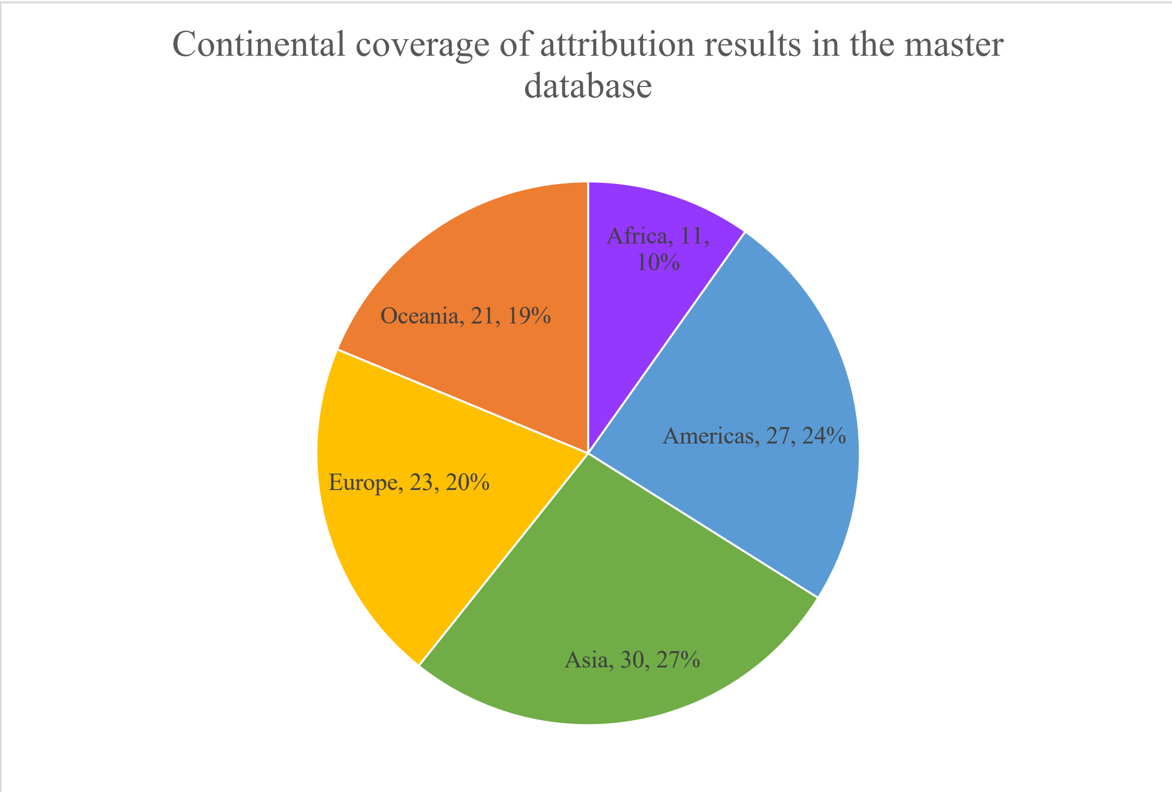

Figure 2: Coverage of matched attribution results by continental region in master database – continent, count, percentage of total

5.1.3. Disaster types

By construction, the dataset contains six types of extreme weather events, as shown in Figure 3. Notably, 53% of the attribution results in the master database are associated with high-temperature phenomena – heatwaves, droughts, or wildfires. The remainder are either hydrological events, floods or storms, or cold weather events. In the original search for data, there are also 105 events with a FAR which do not have matching economic data – 53% of these are heatwaves, which is expected as the science of attribution is well-established for heat events, but the process for measuring the economic impact of heatwaves is challenging. This is because the main impact of heatwaves, aside from mortality, are indirect economic losses (flows) which are substantially harder to identify and measure than damages (stocks) and may be intangible. This is because indirect economic losses often occur outside the distinct hazard area and with a time lag (Frame et al., 2020A). These under-measured heatwave losses include economic disruptions due to disturbed electricity distribution, transport failures, ongoing harm to agricultural crop yields and health, and harm to the natural environment, as a few examples (Disher, Edwards, Lawler, & Radford, 2021). Moreover, a further 27% of events without economic data are droughts – with a majority occurring in Africa – which is reflective of the uneven distribution of disaster cost records between lower and higher-income regions. This makes it difficult to accurately assess how different countries, or even continents, across the world are affected by economic disruptions resulting from climate-attributed extreme weather.

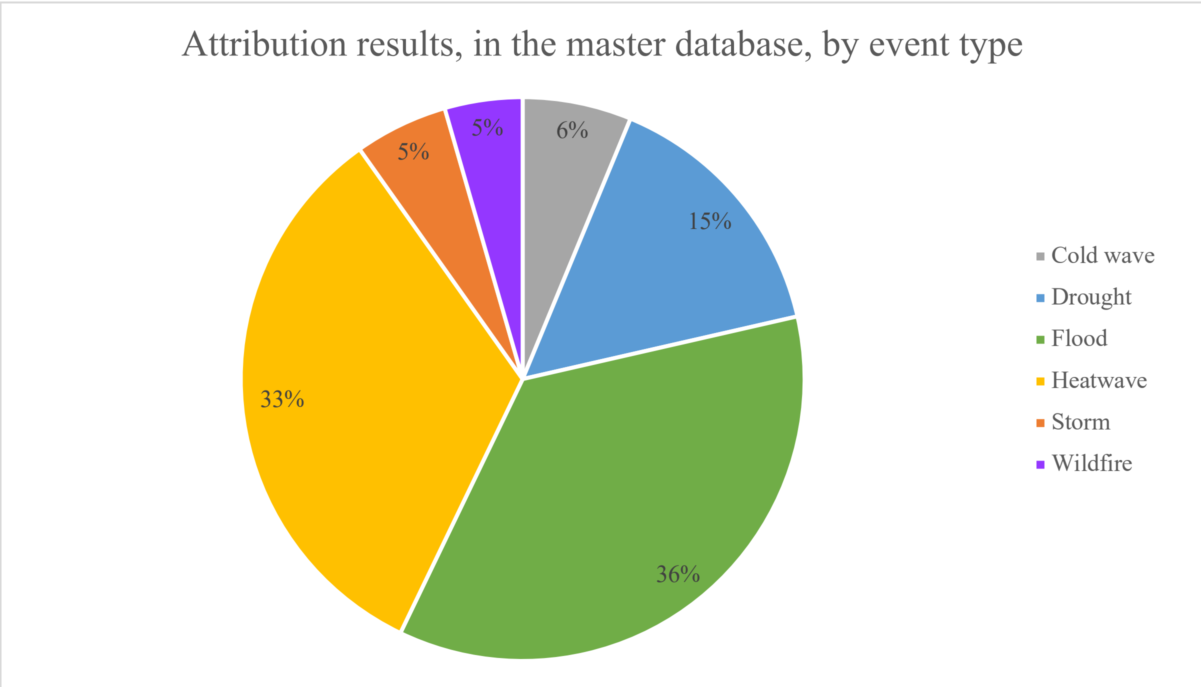

Figure 3: Coverage of matched attribution results by event type in the master database

5.1.4. FAR estimates

All the events included in the dataset have at least one FAR associated with them. Of the 179 events, 37 have multiple relevant attribution studies – 32 have two studies, 3 have three, and

2 have four. The 'best' FAR was selected based on two criteria – highest Scimago Journal Rank (SJR) of the publishing journal and spatial/temporal match to available economic data[6]. The distribution of FAR attribution results in the master database is shown in Figure 4. 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 (or FADR) are floods, while the remaining 47% are cold events.

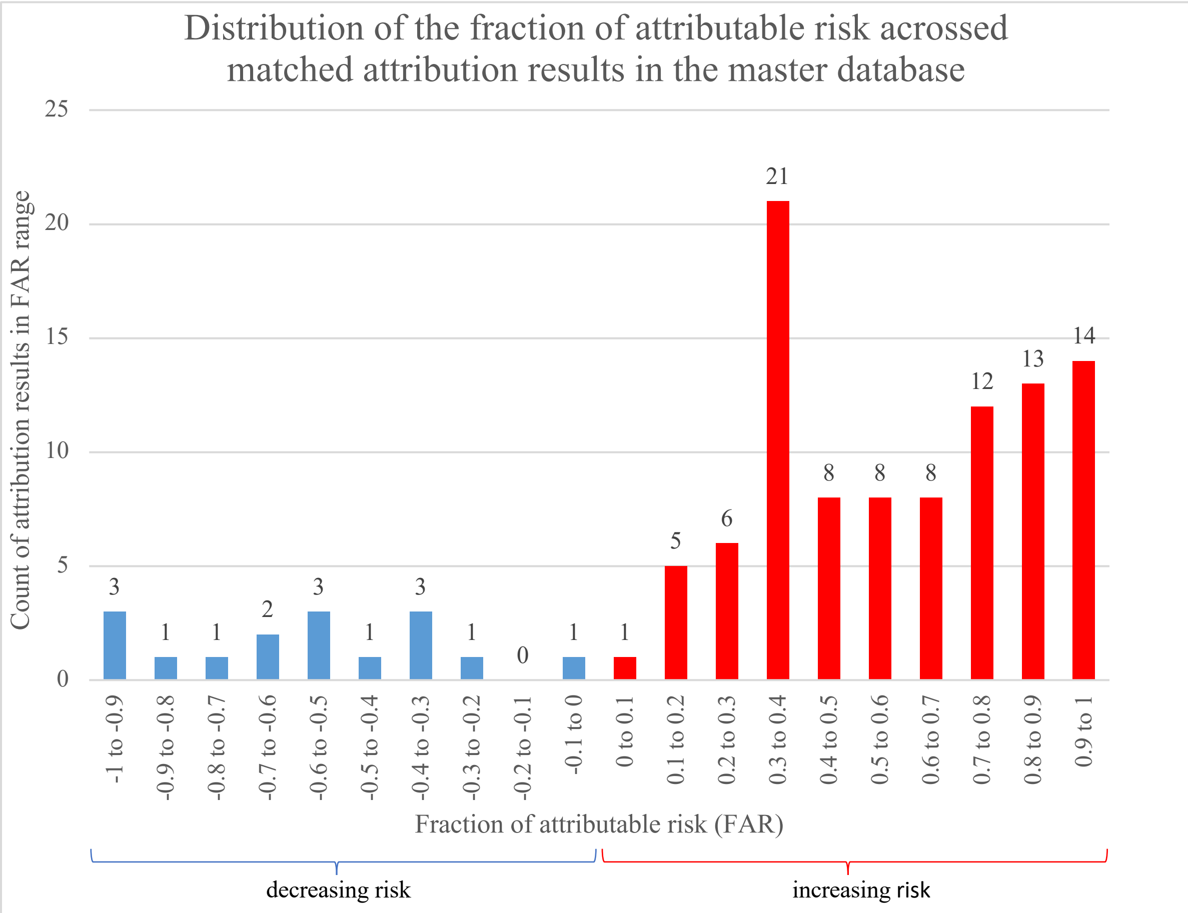

Figure 4: FAR distribution across matched attribution results in the master database

To allow a global estimation of climate change-attributed costs to be made, a global average FAR for each event type has been computed, as shown in Figure 5. Based on this analysis, it appears that, on average, 77% of the risk of heatwaves occurring over the study period is due to anthropogenic climate change. Floods have the greatest number of attribution results and show the greatest distribution range. Floods, moreover, are the only event type where

[6] Refer to data collection for explanation of SJR.

attribution results span both increasing and decreasing risk due to climate change. The global average FAR for floods, however, is 0.21. While, for droughts, globally, anthropogenic climate change is responsible for 49% of the risk. Wildfires and storms each have a FAR of 0.60; however, this is calculated on a low number of data points, five and six attribution results, respectively. Lastly, on average, cold events are calculated as having a FADR of 0.79, meaning that 79% of the decrease in risk of cold events can be attributed to climate change.

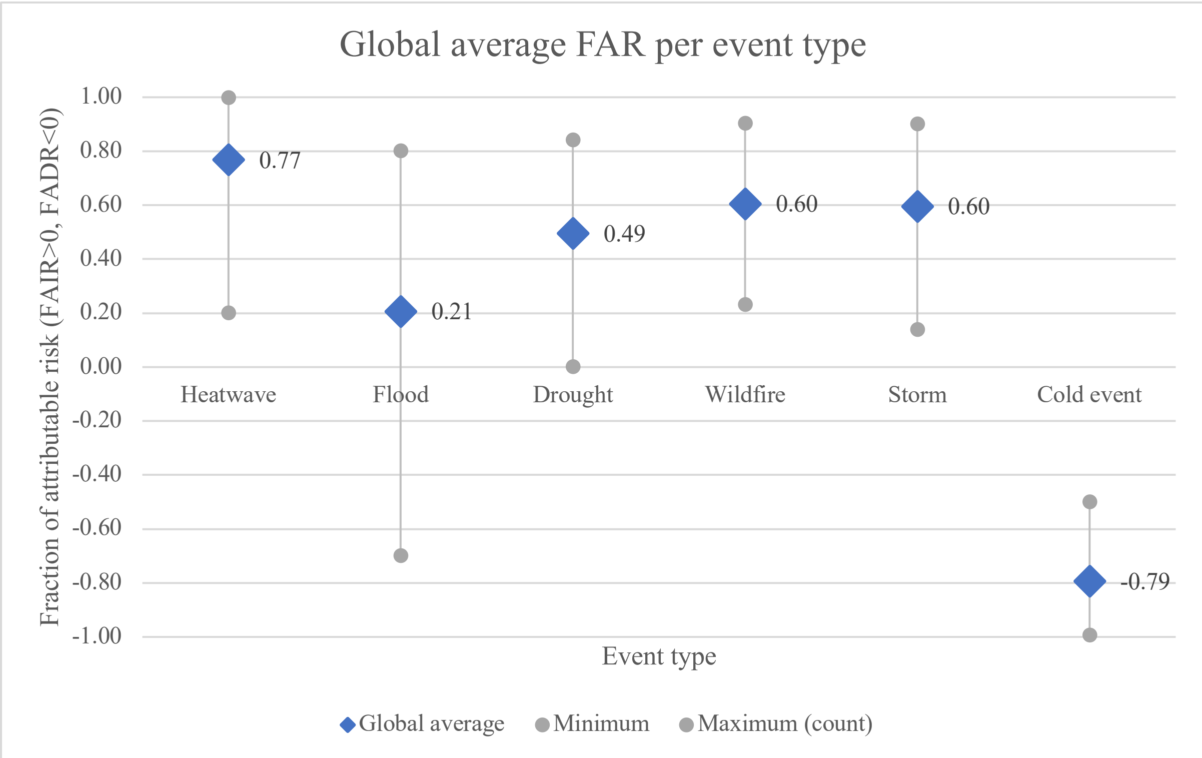

Figure 5: Global average FAR per event type, calculated using attribution results in the master database

An average FAR per-continent per-event type has also been calculated to reflect the lack of uniformity in the global climate system. Figure 6 illustrates these observations. This shows very few, or no, matched attribution results to form the basis of a regional average FAR in many continents. Due to the heavy reliance on a small number of attribution results for some event type and regional combinations, these regional averages are heavily relied on for the final results of this paper.

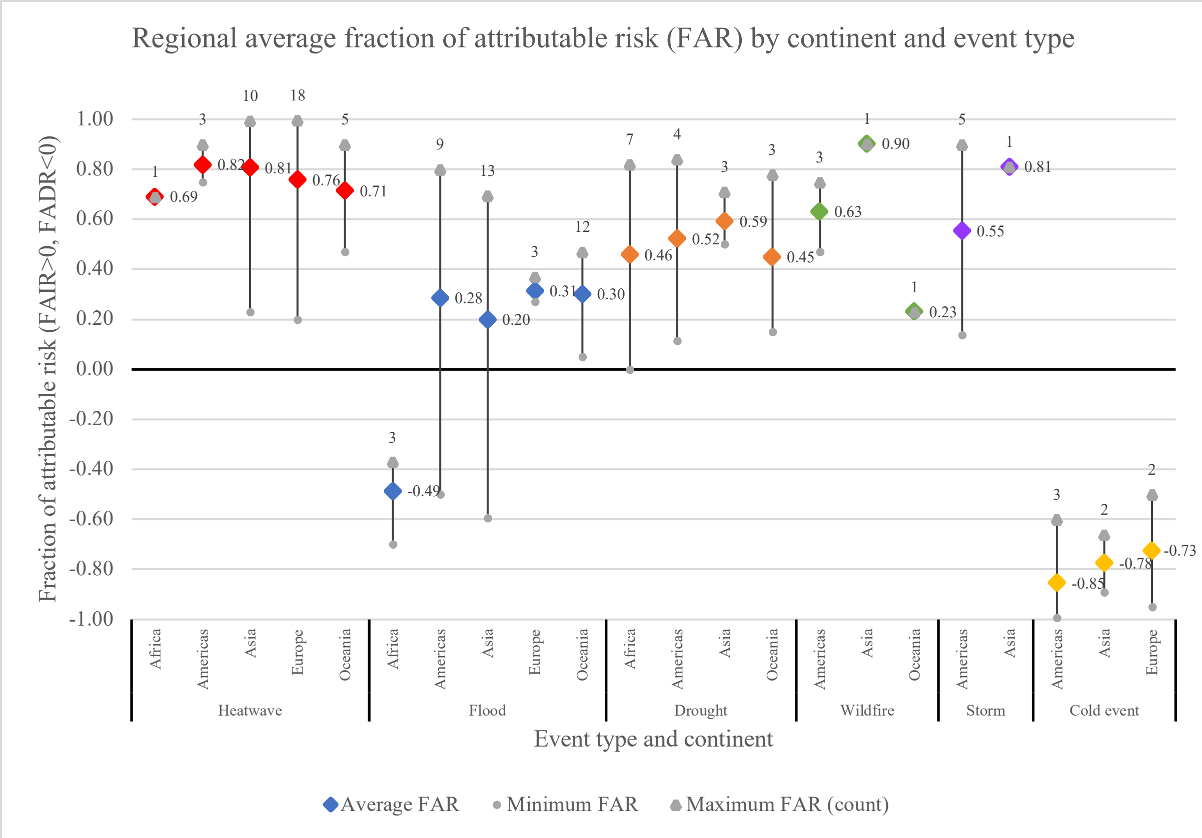

Figure 6: Regional average FAR per event type

5.2. Economic data

The following section describes the features of the economic cost data collected regarding the events in the master database.

5.2.1. Number of deaths

In the dataset, 111 of the 179 events have mortality estimates. Thirty-nine of these events are responsible for greater than (or equal to) 100 deaths, including nine events with deaths over 1,000 lives lost. Four events 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). The total number of deaths recorded from the events in this dataset is 152,727, equivalent to a statistical value of life lost of \$1.1 trillion[7].

5.2.2. Number of people affected

[7] Calculated at a SLOL of \$7.0837 million.

In the dataset, 116 of the 179 events have estimates for the number of people affected. These estimates range from 6 for a typhoon in Taiwan to 60 million estimated for two events in China, a 2009 drought and 2016 flood. The broad definition and interpretation of 'people affected' means that the economic cost of being affected is highly variable. Therefore, we cannot establish a monetary value for becoming affected, and do not include this impact variable in the results. This omission creates a limitation on the accuracy of our results, which is discussed further in Section 8.2.3.

5.2.3. Total damages

In the dataset, 110 of the 179 events have estimates for the economic damages caused. Across these 110 events, the total disaster damages stand at $435.4 billion. The event with the highest damage recorded in the master database is Hurricane Harvey in the United States, at $100.3 billion. The lowest recorded damages are $380,000 for a typhoon in Taiwan. Seventy-nine of the events have estimated damages greater than $100 million, and 7 of those are over $10 billion. These high damages are symptomatic of the bias toward conducting FAR studies on events with high economic impacts that typically occur in high-income countries where asset values are high.

5.2.4. Insured losses

A small number of events in the dataset have insured loss estimates associated with them, just 48 out of 179. The data is heavily skewed to high-income countries, notably the United States, New Zealand, Australia, and Japan, as well as China, which is upper-middle-income[8]. The restricted quality and quantity of data collection in low-income countries is one underlying reason for this. In addition, it is symptomatic of higher rates of disaster insurance 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 $31.7 billion[9].

[8] As per the World Bank classification 2020.
[9] Each assessed to have $30 billion dollars in insurance payouts, in 2017 dollars.

6. Results

The results section will examine the climate change-attributed economic cost calculations for the events in the master database; and, subsequently, the results from extrapolating findings to create a global estimate.

6.1. Attribution results for events in the master database

The first section of the results focuses on the attributed economic costs associated with the 179 events in the master database. These can be individually viewed for each event in the master database within the supplementary material (economic attribution database).

6.1.1. Deaths

From the 179 events in the dataset – a net of 60,951 total deaths are attributed to climate change. This is calculated from 75,139 deaths that occurred due to climate change increasing event probability and 14,187 deaths in events that have become less likely due to climate change. From the attributed increase in deaths, 96% have resulted from heatwaves. The net statistical value of life cost across the events in the master database is US$431.8 billion.

6.1.2. Damages

Anthropogenic climate change is responsible for $260.8 billion of extreme weather event damages in the master database. This is equivalent to 60% of the total damages recorded for these 179 events. More than 64% of the climate change-attributed damages are connected to storms, which is expected given the high damages from events such as Hurricane Harvey. Furthermore, 16% of the attributed damages resulted from heatwaves, while floods and droughts are each responsible for 10% respectively – on net. Cold events, calculated as a fall in climate change-attributed damages, are responsible for -2% of net attributed damages. Lastly, wildfires account for 2% of the net attributed damages.

6.1.3. Insured losses

Moreover, human-induced climate change is responsible for a net $78.4 billion of insured damages from extreme weather events in the master database. This is equivalent to 30% of the total climate change-attributed insurance damages in the database. 65% of the climate-attributed insured damages in the database are insurance costs related to storms. Notably, climate change-attributed insured damages from Hurricane Harvey, Hurricane Maria, and the

2012 Drought in North America combined makeup 83% of the net climate change-attributed insurance.

6.2. Total climate change-related economic costs of extreme weather events, globally

This section will focus on the results from extrapolating the attribution data across all global economic costs from extreme weather events[10]. Results from the two extrapolation methods will be compared, allowing examination of the impact of method choice on the results. Further, the globally attributed costs across time and event type will be shown.

6.2.1. Comparison of results from differing extrapolation methods

To estimate the cost of climate change from extreme weather using the attribution-based approach, the refined EM-DAT database of extreme weather events covering 2000-2019 is used. Two different approaches to extrapolation are used to attribute the costs of heatwaves, floods, droughts, storms, wildfires, and cold events over the relevant study period. The first method is the global average extrapolation method, and the second relies on regional average extrapolation[11]. Figure 8 shows how the global estimates for each event type, and impact metric, differ based on the extrapolation method used.

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[10] Restricted to heatwaves, floods, droughts, storms, wildfires, and cold events.

[11] See method section for further explanation

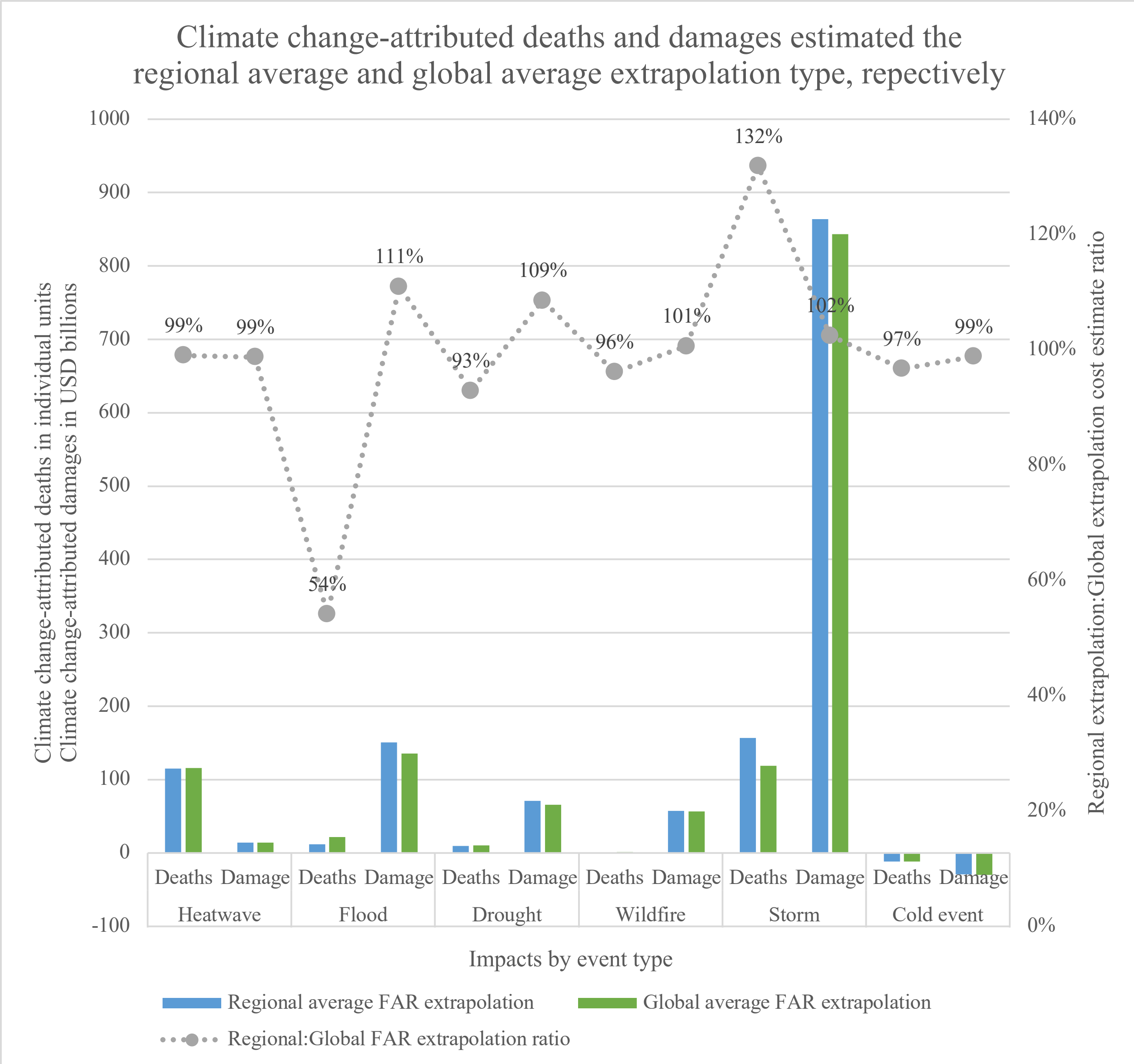

Figure 7: Comparison of the climate change-attributed economic damage and deaths between the global average and regional average extrapolation methods

The total climate change-attributed impacts, dictated by the respective extrapolation methods, have varying degrees of similarity. This is illustrated in Figure 7. 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 take on a wider range. Notably, the regional average extrapolation estimate is two percentage points higher for storm damages than the global average extrapolation estimate. This is important to note, given that storm damages contribute a lot to total attributed economic costs, making up over 60% of the total damages recorded in the EM-DAT extreme weather event dataset. There are three data comparisons where the estimates differ widely (greater than ten percentage points) between a global and continental approach: flood deaths (54%), flood damages (111%), and storm deaths (132%). These discrepancies in flood results occur because the FAR data points vary widely across attribution studies. These flood results are significantly impacted by a regional average FADR for floods in Africa 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 postivie, indicating an increase in risk resulting from climate change (FAIR). This has a relatively large impact on the regional extrapolation results as floods cause a relatively high number of deaths in Africa and a lower level of damages. Resultantly, the net global climate change-attributed deaths are estimated to be lower when using the regional extrapolation method than the global method, and the climate change-attributed damages are estimated to be higher. 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 for headline results to minimize over-reliance on a small number of attribution studies.

6.2.2. Attributed deaths

Table 1 illustrates the estimated number of deaths caused by climate change-induced extreme weather through the 2000-2019 period. It is estimated that climate change is responsible for approximately 269,200 deaths over the study period, an estimate based on the average from the two extrapolation methods.

Table 1: Climate change-attributed deaths from extreme weather events between 2000-2019

	GLOBAL AVERAGE FAR EXTRAPOLATION METHOD	REGIONAL AVERAGE FAR EXTRAPOLATION METHOD	AVERAGE
HEATWAVE	115,856	114,740	**115,298**
FLOOD	21,543	11,666	**16,604**
DROUGHT	10,510	9,763	**10,137**
WILDFIRE	913	878	**895**
STORM	118,956	156,890	**137,923**
COLD EVENT	-11,853	-11,465	**-11,659**
TOTAL	**255,925**	**282472**	**269,198**

The economic value of life lost to climate change-attributed extreme weather is highly dependent on the assumed statistical value of life. Academics and government departments have attempted to calculate this in many ways, and consequently, a wide range of values are used globally[12]. For this study, the climate change-attributed statistical loss of life using three varying VSL estimates were assessed. The first is used by the United States Department of Transportation, who use the estimate widely when assessing policy; this assumes a value of statistical life at $11.6 million (Department of Transportation, 2021). Using the global FAR extrapolation estimate for climate change-attributed deaths, at this VSL, the statistical loss of life from climate change is $2.97 trillion across 2000-2019. The second estimate used to calculate the climate change-attributed economic cost of lives lost is the United Kingdom Treasury's value of a prevented fatality, which is £2 million (USD 2020 $2.57 million) (Dolan & Jenkins, 2020; HM Treasury, 2018). Using this VSL value, climate change is responsible for $0.66 trillion of lives lost from extreme weather events in 2000-2019, using the global extrapolation method. These two values create vastly different estimates of the economic impact from mortality and embed the individual judgements of each of these respective estimates. Consequently, the last value used to calculate the statistical economic loss of life is the average of these two values, $7.0837 million per life. This middle point is the VSL that is used for the final calculations. Given this VSL, the total climate change-attributed VSL is a net $1.81 trillion from the global extrapolation method ($1.90 trillion if

[12] Refer to Section 4.3 for further elaboration.

using the average between regional and global FAR extrapolation estimate). This is equivalent to an average statistical loss of life of approximately $90.6 billion per year between 2000-2019.

6.2.3. Attributed damages

Table 2 shows the estimated total damages from extreme weather for which climate change is responsible between 2000-2019. Taking an average across extrapolation methods, climate change is responsible for an estimated $1.11 trillion in damages from extreme weather. This is primarily due to the damages caused by storms, at approximately 77% of the total climate change-attributed damages. The high incidence of damages caused by storms, relative to the small number of storm-related attribution studies (6 studies) depended upon for calculating the average FARs, limits the robustness of this result.

Table 2: Climate change-attributed economic damages (USD billions) from extreme weather events between 2000-2019

	GLOBAL AVERAGE FAR EXTRAPOLATION METHOD (USD BILLIONS)	REGIONAL AVERAGE FAR EXTRAPOLATION METHOD (USD BILLIONS)	AVERAGE (USD BILLIONS)
HEATWAVE	$14.40	$14.21	**$14.31**
FLOOD	$135.48	$150.34	**$142.91**
DROUGHT	$65.66	$71.28	**$68.47**
WILDFIRE	$56.95	$57.30	**$57.13**
STORM	$843.22	$864.12	**$853.67**
COLD EVENT	-$29.52	-$29.18	**-$29.35**
TOTAL	**$1,086.19**	**$1,128.07**	**$1,107.13**

6.2.4. Insurance of climate change-attributed damages

Table 3 shows the estimated insured losses from extreme weather events for which climate change is responsible from 2000 to 2019. These calculations are based on the global average extrapolation method. This shows that an estimated $385 billion of insurance payouts for extreme weather damages have occurred due to climate change, an average of $19.2 billion annually. This, across all extreme weather types, is 35% of total climate change-attributed damages in the EM-DAT dataset. There is a large range in the rate of insurance across event types. Notably, 86% of the insured climate-attributed damages are from storm events, and therefore the overall rate of insurance sits close to that for storms (39%). Wildfires have the highest rate of insurance payout across the event types, with over 51% of damages insured. Floods, droughts, and cold events each have an insurance payout rate of between 10-20%. There is almost a non-existent insurance payout rate for heatwaves, nearing 0%. These low rates of insurance for climate change-attributed damages are concerning, prompting questions regarding who, and how, funds the recovery from increasingly severe weather events.

Table 3: Climate change-attributed uninsured and insured damages (USD billions) from extreme weather events across 2000-2019

	UNINSURED CLIMATE CHANGE-ATTRIBUTED DAMAGES (USD BILLIONS)	INSURED CLIMATE CHANGE-ATTRIBUTED DAMAGES (USD BILLIONS)	PERCENTAGE OF CLIMATE CHANGE-ATTRIBUTED DAMAGES INSURED
HEATWAVE	$14.39	$0.01	0.07%
FLOOD	$118.20	$17.28	12.76%
DROUGHT	$54.08	$11.59	17.65%
WILDFIRE	$27.96	$28.99	50.90%
STORM	$511.68	$331.55	39.32%
COLD EVENT	-$25.17	-$4.36	14.75%
TOTAL	**701.13**	**385.06**	**35.45%**

Furthermore, it is evident in Table 4 that the distribution of insurance for climate-affected extreme weather events is not evenly distributed across the globe. In high-income countries, it is estimated that 45% of climate change-attributed damages are insured. Concerningly, damages in all other countries – including upper-middle, lower-middle, and low-income areas – are estimated to have insurance pay-outs of less than 6%[13]. For low-income countries, only 1% of damages for which climate change is responsible were covered by insurance. This shows a considerable inequity in the distribution of weather insurance globally.

[13] Excluding unclassified countries, which in the 2020 World Bank Classifications includes Venezuela.

Table 4: Rate of insurance for climate change-attributed across high to low-income countries

ECONOMIC INCOME CLASSIFICATION	PERCENTAGE OF CLIMATE CHANGE-ATTRIBUTED DAMAGES INSURED
LOW INCOME	1.0%
LOWER-MIDDLE INCOME	3.3%
UPPER-MIDDLE INCOME	5.3%
HIGH INCOME	44.6%
UNCLASSIFIED	17.7%

6.2.5. Total climate change-attributed economic costs

The estimated global cost of climate change over the 2000-2019 period is assessed using these results. These results are calculated using the global average extrapolation method, which is less sensitive to singular studies than the regional average extrapolation method. In aggregate, the climate change-attributed cost of extreme weather over 2000-2019 is estimated to be $2.90 trillion, or an average of $145 billion per year. Figure 8 is a time series plot illustrating climate change-attributed costs, including the statistical value of life lost, uninsured, and insured damages from extreme weather events between 2000-2019. The distribution of costs is highly variable by year. 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 $621.0 billion. The years in which costs reach high peaks - notably 2003, 2008, and 2010 – are predominantly pushed to high levels because of high-mortality events. The events that drive these peaks are as follows: a 2003 heatwave across Europe where climate change was responsible for 55,400 deaths; Storm Nargis in Myanmar in 2008 where climate change claimed 82,400 deaths; and a 2010 heatwave in Russia and drought in Somalia where 42,800 and 9,900 deaths are attributed to climate change, respectively.

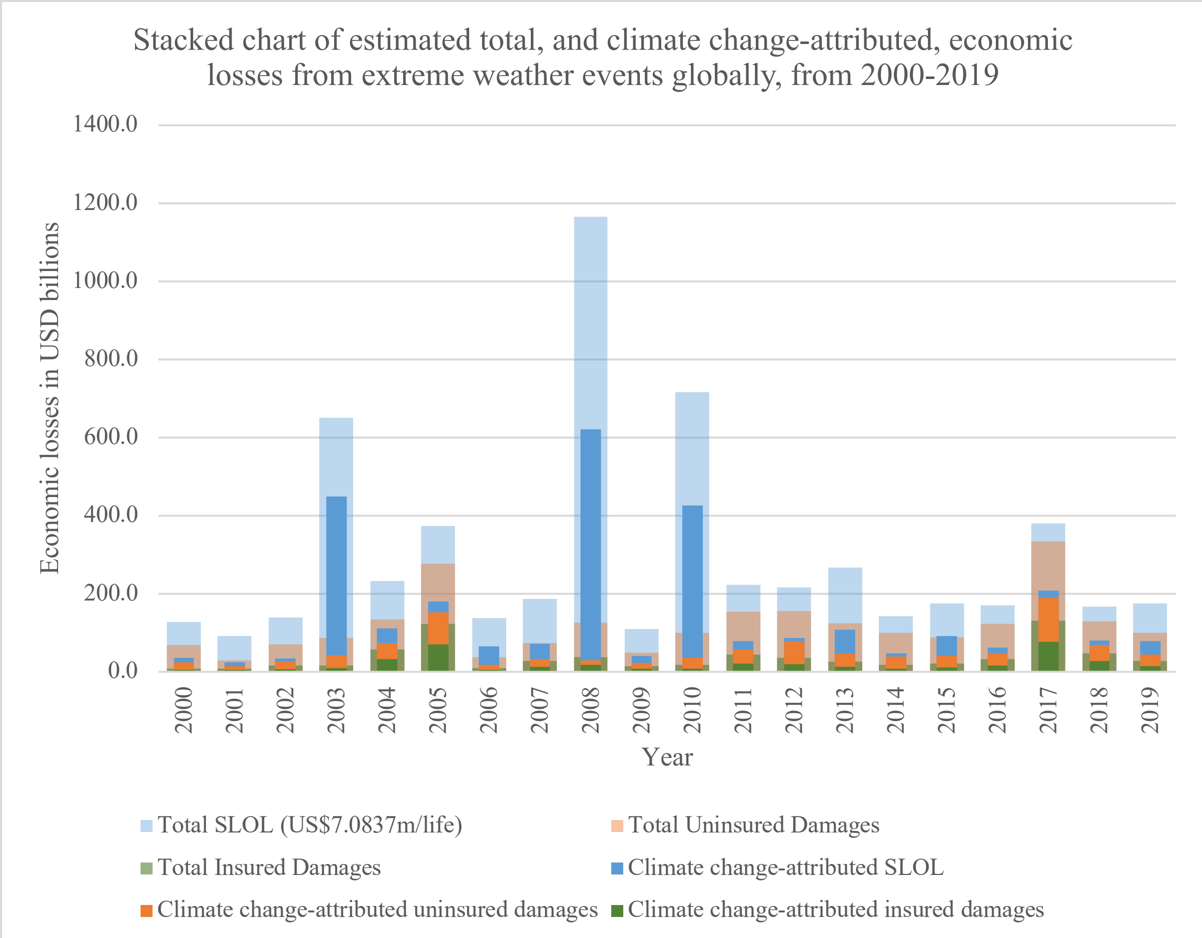

Figure 8: Time series of estimated total and climate change-attributed statistical loss of life and damages from extreme weather events across 2000-2019

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 9. The greatest peaks in monetary damages occur in 2017 and 2005. Storm events in the United States drive these. In 2005, Hurricane Katrina, Hurricane Rita, and Hurricane Wilma together caused $123 billion in climate change attributed damages. In 2017, Hurricane Harvey and Hurricane Irma saw climate change responsible for almost $96 billion in damages across the United States of America and Hurricane Maria in Puerto Rico, causing another near $43 billion in climate change-attributed damages.

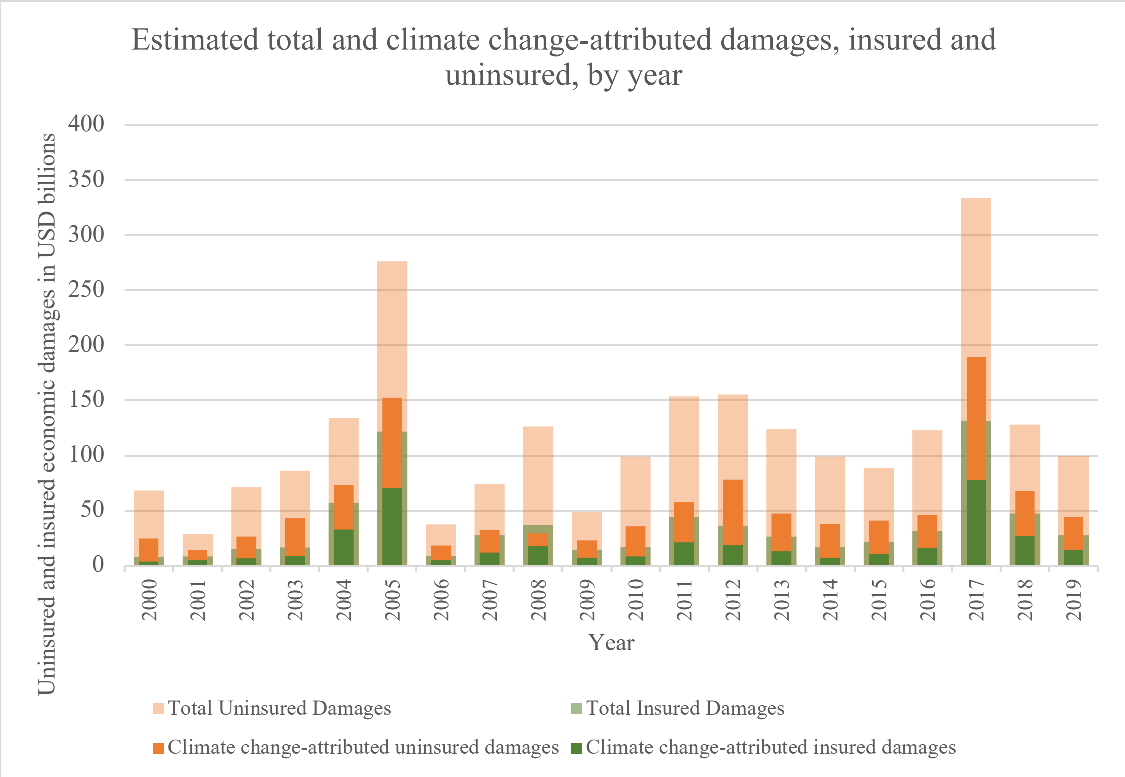

Figure 9: Time series of total and climate change-attributed uninsured and insured damages from extreme weather events between 2000-2019

Figure 10 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 countries, across the world 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 46% of the total. A few elements drive this, the first being that the United States is highly vulnerable to storms, and given the dense, high-value property in US cities, these storms induce high amounts of damage. 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. Another notable result from this analysis is that 97% of the climate change-attributed insurance for damages occurs in high-income countries, while only 0.02% occurs in low-income countries. This dramatically impacts countries' abilities to economically recover from high-impact extreme weather events.

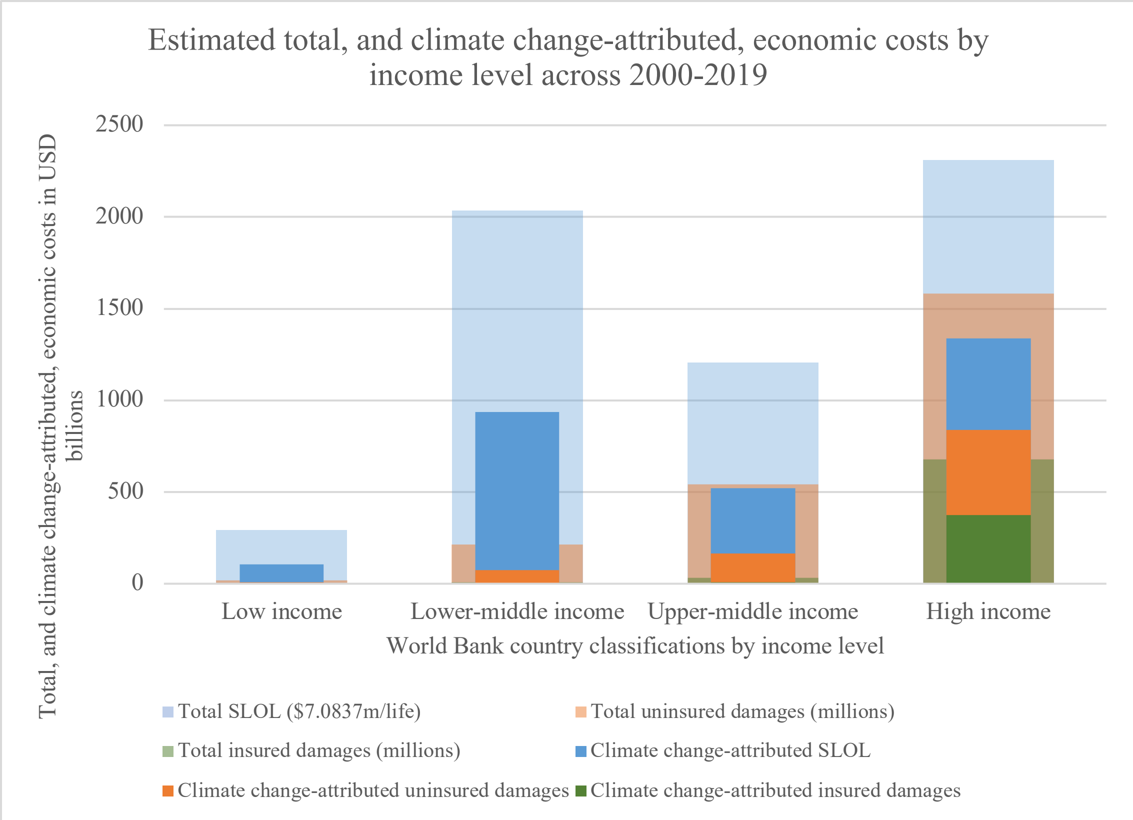

Figure 10: Total and climate change-attributed economic costs from extreme weather events across low to high-income countries between 2000-2019

These extrapolated estimates for the climate change-induced cost of extreme weather can be calculated as a proportion of GDP, as shown in Figure 14. Using the global average extrapolation method, the total economic cost inclusive of statistical loss of life, damages, and insured losses 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. With this considered, it remains interesting to view the cost of human-induced climate change relative to the size of the global economy annually. Climate change-attributed economic costs from extreme weather events vary between 0.05% to 0.82% of global GDP annually over the study period.

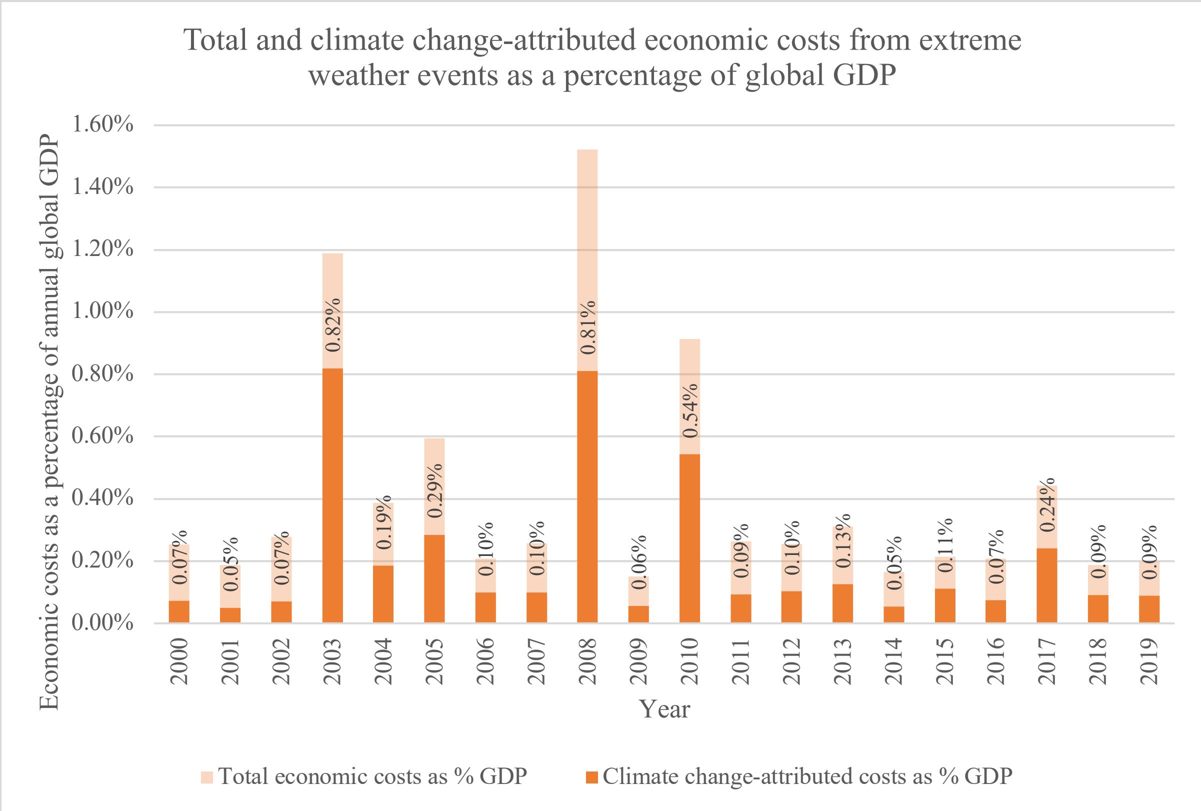

Figure 11: Total and climate change-attributed economic costs from extreme weather events as a proportion of annual global GDP, between 2000-2019

These results indicate that climate change-attributed extreme weather costs are of significant value in the study period. Given that temperatures are expected to continue rising, and the nature of extreme weather events will consequently change, we can expect that human-induced costs from extreme weather events may increase in the coming decades.

7. Discussion

Quantification of the economic cost of climate change is essential for well-informed, well-balanced decision-making. The complexity and magnitude of climate change as an economic, environmental, and social problem means that this quantification is not simple nor free of uncertainty. However, we must quantify the economic impact as accurately as possible to ensure informed decisions can be made about mitigation and adaptation measures, globally, and in specific locations. This discussion will contextualize the estimations of climate change-induced economic costs from extreme weather events; explore how this event attribution approach compares, in both the methodology and result, to economic assessments of climate change from integrated assessment models; and unpack the findings and implications concerning insurance, adaptation, and mitigation.

7.1. Comparing cost estimates from the attribution-based method and integrated assessment models

There are many different methods used to estimate the economic impact of climate change, with the attribution-based method of this research a new inclusion. The attribution-based method used is an event aggregation approach; it differs significantly from the macroeconomic method used in integrated assessment models (IAM). Comparing the results of IAM models to the results of this paper will allow an examination of how the methods differ and to what extent extreme weather events are considered in IAM. IAMs are macroeconomic models which attempt to estimate the global damages from anthropogenic climate change. Commonly this involves characterizing damages as a polynomial function of temperature (Nordhaus & Boyer, 1999; Nordhaus, 2017). One example of this is the dynamic integrated climate-economy (DICE) model, which can be used as a baseline for comparison to the results from the attribution-based approach (Nordhaus & Boyer, 1999). This model draws a simple relation between the climate and the economy, specifying that GDP falls as the average temperature rises above the pre-industrial baseline. DICE approximates the damages from climate change, as a proportion of the global economy, according to Equation 3:

Equation 3: DICE 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 sitting at 1.2℃ in 2020 (WMO, 2021A). To allow us to compare the results from attribution to those of DICE, the parameters from the DICE 2016R model have been adopted: $\varphi_1 = 0$; $\varphi_2 = 0.00236$; and temperature change, since the preindustrial baseline, between 2000-2019 was sourced from the World Meteorological Organisation State of the Global Climate Reports (2019-2015), IPCC AR5 estimates (2007-2014), and Hawkins et al. (2017) for years prior to 2006 (Nordhaus, 2017). This approach from DICE is not unique in the IAM space. The Policy Analysis of the Greenhouse Effect (PAGE) model, which was used in the well-known Stern Report (2007), also calculates economic and non-economic damages from climate change using a polynomial function. However, in PAGE, this is done using regional temperatures (Hope, 2011). Nordhaus, to his credit, has made the DICE model especially transparent by posting the model and many publications on his website, allowing nuanced comparisons to be made (Metclaf & Stock, 2015).

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 12. However, these two metrics are not directly measuring the same cost estimate, with two key differences:

1. IAM's are a measurement of economic flow (proportioned to global GDP losses) while attribution-based estimates measure loss in economic stock;
2. The attribution-based result solely estimates the economic cost of extreme weather events caused by anthropogenic activity, while IAM models attempt to estimate the overall annual cost of climate change. This, ideally, would include extreme weather costs as well as costs from changing crop yields, ocean acidification effect of fisheries, sea-level rise intrusion on assets, increased erosion, and many other impacts.

These factors limit the comparability of these two measurements. However, it is notable that extreme weather events are only one category of the damages that are, in theory, calculated by DICE. Therefore, it is of concern that results from the attribution-based method are higher than those from DICE.

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. The climate input in IAM models is the change in average temperature over the preindustrial level. This fails to capture changes in temperature extremes as they become both more frequent and severe because of anthropogenic effects. Consequently, this prevents the models from effectively including the impacts of extreme weather into the monetary estimates. Nordhaus acknowledges that these studies generally omit the impacts of some critical climate factors in his DICE 2013R user guide – including extreme weather (as well as biodiversity, ocean acidification, catastrophic climate events, and more). The solution used to account for this, admittedly large, 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[14] across 2000-2019. Relative to the climate attribution-based figure of \$2.90 trillion. This is a large undershoot that exhibits how DICE fails to accurately assess the economic impacts of climate change from extreme weather.

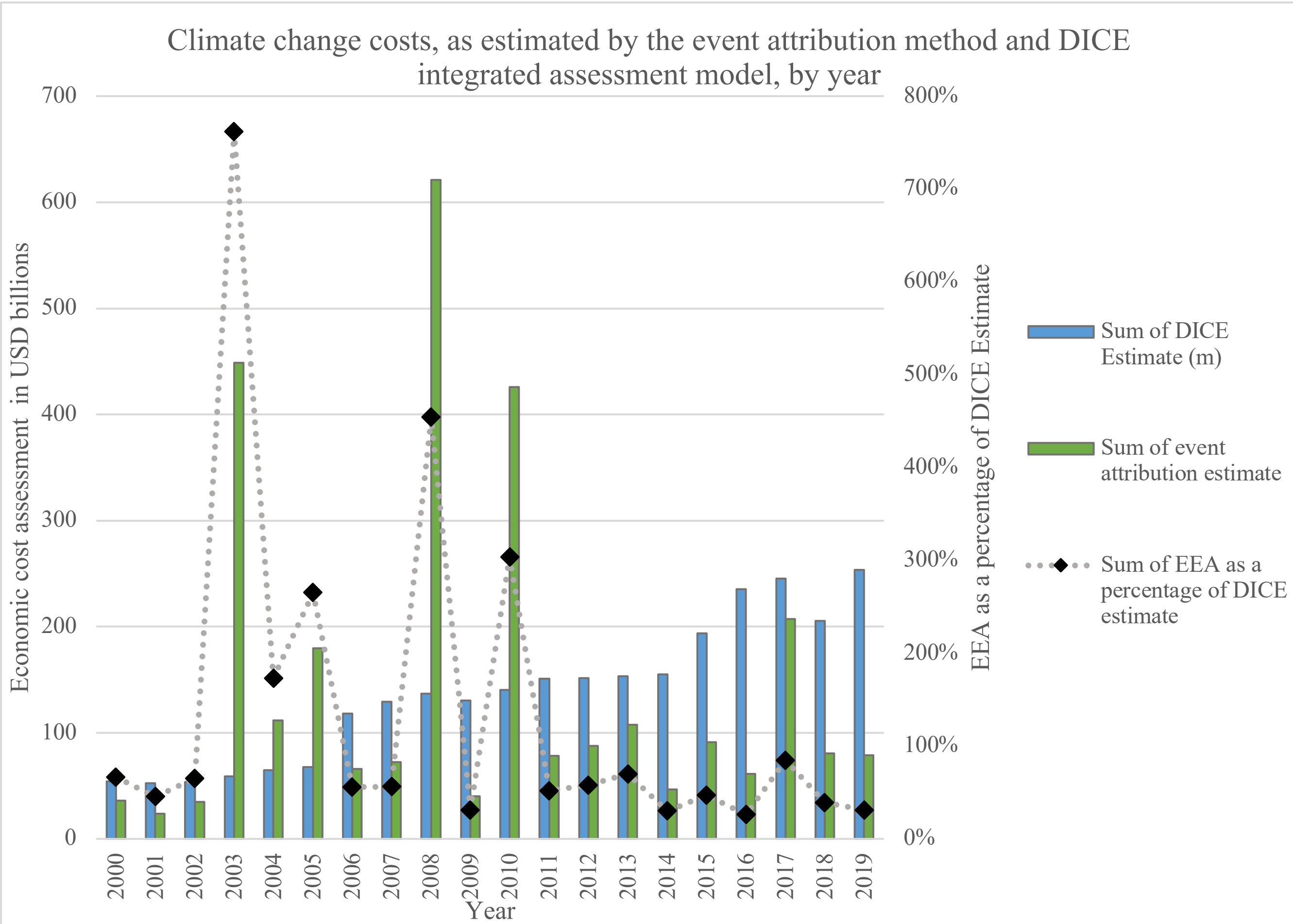

Figure 12: Comparison of the climate change cost per year as estimated by extreme event attribution and the DICE integrated assessment model

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,

[14] \$0.55 trillion would mean that extreme events account for the full value of the 25% adjustment to the DICE estimate

Rose, & Tol, 2014). The key sector of interest in FUND, for this research, is the storm sector which is the 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 Equations 4 and 5:

Equation 4: Total damages from tropical storms, FUND model

$$Total\ damage = \alpha * GDP * (\frac{y_{today}}{y_{1990}})^{\epsilon}[(1 + \delta * T)^{\gamma} - 1]$$

Equation 5: Total mortality from tropical storms, FUND model

$$Total\ mortality = \beta * population * (\frac{y_{today}}{y_{1990}})^{\eta}[(1 + \delta * T)^{\gamma} - 1]$$

Where the key inputs 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 outputs from these calculations provide interesting examples for comparison with the attribution-based results. 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 and therefore depended upon in the attribution results. 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. Further, the results estimate the average climate change-attributed mortality rate from all extreme weather events at 0.00020% per annum. These inconsistencies are illustrative of how, especially when data is lacking, it is beneficial to analyse multiple approaches to quantitative research – with these macroeconomic and event attribution techniques providing valuable contrasts.

Given the increasing frequency and severity of many extreme weather events, it is of ever-growing importance that economic cost estimates account for the costs that occur when high-impact, low-probability events eventuate. This finding is essential for policymakers, especially when considering the use of adaptation to reduce the economic and human impact of extreme weather. Ultimately, measurement tools including event attribution and IAMs should be viewed as part of a toolbox of evidence that can be drawn on by decision-makers, society, and individuals alike. Given that the limitations of all quantification approaches are presented transparently and subsequently understood by users, this gives decision-makers the best chance to make informed choices about problems that transcend the boundaries between climatic and economic issues.

7.2. Implications for climate change adaptation and mitigation

This research results rely on two elements – the level of anthropogenic emissions and their consequential effect on the climatic system (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, to ideally be below the average of $145 billion annually seen in 2000-2019, there would need to be a reduction in the FARs or economic costs we are seeing. Reducing the FARs would require climate change mitigation, i.e. reducing the volume of greenhouse gases being emitted to below net-zero allowing the stock of greenhouse gas in the atmosphere to fall. In the longer-term, economic costs will also be reduced if effective mitigation is conducted today. While in the shorter term, reducing economic costs will likely result from good adaptation policies.

Adaptation can make a considerable difference to the climate change-attributed economic impact of extreme weather events. Adaptation policies could include infrastructure development such as building flood protection or improving early warning signal systems for extreme weather events. An interesting example of this has been implemented in Europe, where a 2003 heatwave claimed upwards of 70,000 deaths, 55,400 of which were attributed to climate change in this study. 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, which allow people to regulate their temperature. This made a marked impact on the fatality of subsequent heatwaves – the French heatwave in 2019 was hotter than that of 2003, yet there were less than 1500 deaths, compared to over 19,000 across the nation in 2003. From this analysis, climate change attributed deaths in the 2019 heatwave were only 7% of those experienced in 2003 in France. This shows 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 provide an impetus to increase spending on climate change adaptation and mitigative policies. The quantification of economic costs allows us to better understand how climate change impacts different communities globally. It allows for more evidence-based policy formulation and better targeting of adaptation spending. This should ultimately help reduce climate change-attributed economic costs from extreme weather in the future.

Overall, the results from the attribution-based approach provide another valuable tool for thinking about the economic impact of climate change. It can help contextualise and contrast the findings of IAMs, and shape funding prioritization for adaptation and mitigation globally. However, it is also imperative that the limitations of these estimates are understood fully.

8. Current limitations of the attribution-based approach

This research is designed to explore the potential of an attribution-based method for estimating the human-induced cost 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 been extended to a global approximation prior to this research (Clarke, Otto, & Jones, 2021; Frame et al., 2020A; Frame, Wehner, Noy, & Rosier, 2020B). As is typical of a first attempt, 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 which must be examined. 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 better estimations in the future.

8.1. Extreme event attribution limitations

Extreme event attribution is a young, yet expanding, sub-field of climate science. Given the emerging nature of this research field, the literature is limited, methodologies are continuously being refined, and the field's development faces many challenges. Notable limitations are the uneven geographical coverage of attribution studies and the lack of attribution studies conducted on important classes of extreme weather. These lacunae are significant, given the relatively small number of attribution studies conducted overall. The sensitivity of the FAR to event definition and question framing is additionally important to consider in the interpretation of this research.

8.1.1. Geographical distribution

Extreme event attribution studies are more commonly conducted in high-income countries, with lower-income regions underrepresented in the literature. From the CarbonBrief source spreadsheet, only 8% of the attribution studies are conducted on extreme events in Africa, while over half of the events studied are in either America (31%, with 75% of these in North America) 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. 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 opposition to an economic loss threshold for study, a human-based threshold causes less bias against low-income countries where physical assets are of lesser value (Stott et al., 2015).

Despite this, low-income countries currently remain underrepresented in the literature and, therefore, in the data used to calculate results in this study. Consequently, extrapolation based on the total average FAR per event type leans over-proportionately on event probabilities from high-income regions, notably Europe and America. Comparatively, for the regional extrapolation method, there are data gaps in Africa and Oceania, resulting in over-reliance on as low as one data point in the calculation of an average FAR – or relying on an imperfect substitute (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 nation and even more locally within countries. Improved geographical coverage of event attribution studies would improve the robustness of the methodology presented, especially if this allowed for greater granularity in the extrapolation method.

8.1.2. Disaster types

The second issue with event attribution data, specifically FAR measurements, is a highly uneven spread of research across different event types. In the CarbonBrief dataset, 33% of all attribution studies analyse the role of climate change in inducing heatwaves, the best-represented category of event. Comparatively, storms, which are highly important when considering the human-induced economic cost of extreme weather, make up only 8% of the studies in this dataset. One reason behind this discrepancy is the degree of confidence, and related difficulty, associated with attributing different event classes. 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). Contrastingly, events such as droughts are caused by many compounding factors - such as precipitation, temperature, and soil moisture – making the attribution process significantly more complex. Cyclones, additionally, have high levels of complexity, which means that large-ensemble attribution studies of these storms have only become technically possible in recent years – and a high computational cost for each simulation persists (National Academies of Sciences, 2016). Resultantly, when assessing the average FAR across event types, such as storms, there are very few data points making the results subject to greater inaccuracy. This harms the robustness and increases the uncertainty of the approximation of the global cost of climate change-induced extreme weather.

8.1.3. Question framing

The question framing in an event attribution study can induce large discrepancies in how the role of anthropogenic emissions is quantified. One such example, which gained significant attention, was the 2010 Russian Heatwave. Two seemingly contradictory event attribution studies were conducted – one ruling a negligible role of human-induced climate change, and the other recording a five-fold increase in likelihood (Dole et al., 2011; Rahmstorf & Coumou, 2011). However, when reconciled, the importance of question framing became central to this difference, and it was shown that both results were scientifically sound. One of the motivating factors behind the discrepancy was that Dole et al. (2011) analysed the change in intensity, whilst Rahmstrof and Coumou (2011) analysed the change in frequency. Moreover, subtle question 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 quantification (Hannart, Pearl, Otto, Naveau, & Ghil, 2016; Otto, 2017). The dependence on existent event attribution studies embeds question framing choices into the research results. In future, greater availability of FAR metrics would allow a greater specificity around the studies used, for example, allowing only for studies that calculate the FAR based on changing event frequency. However, given the limited data, such restrictions were not made in this study.

8.1.4. Event definition

To conduct an event attribution study, the author(s) must define the event in question across a broad range of variables. Each weather event is unique by nature, natural (external and internal), and human-induced forcings must culminate in a particular place, at a particular time, to create that event and its evolution through time (Otto, 2017). An author must define the boundaries of the event being analysed to measure a FAR, including the spatial and temporal definitions. These decisions ultimately impact the final FAR calculated, which feeds into the average value used for extrapolation in this study. Commonly, the event definition will reflect the extent of the event's impacts, as the authors seek to answer what role anthropogenic climate change played in creating the economic and societal impacts (Otto, 2017). For example, calculating a FAR using 3-day rainfall levels may be used when a flood has caused devastation, as it is the short burst of intense rainfall that caused water to accumulate. For this study, attribution studies that define events based on the extent of the largest human and economic impacts are beneficial. 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 an impact-based definition. For example, it is often found that meteorological observational datasets are not extensive enough – across time or in granularity – to allow attribution to occur based at a specific locality or on a specific factor. Resultantly, the event definition must deviate from the boundaries of the actual impacts to ensure the adequacy of data records (Otto, 2017).

8.1.5. Events made less likely in the presence of climate change

This research looked at events that became more probable and less probable due to anthropogenic climate change. However, there is still an embedded underrepresentation of events that have become less likely because of human-induced climate change. This is because attribution studies are not conducted on events that have not occurred. For example, Van Oldenborgh et al. (2017) indicate that a flood that results from snowmelt has not recently occurred in England 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 has been no recent occurrence, no attribution study has quantified this. Resultantly, there is an embedded upward bias in the attribution studies conducted and consequently in the results of this research.

8.2. Economic impact data limitations

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

8.2.1. Economic data quality

The economic cost data used in this research underestimates the true costs of climate change over the study period. This is because economic cost measurements are chronically under-measured and investigated globally. There is a need for greater attention and funding practices required by public and private institutions to ensure better information keeping. Additionally, some economic costs are difficult to measure, for example, productivity losses in a heatwave: how many people are not going to work due to heat? How many tradespeople are sent home once it becomes too hot? These questions require strong monitoring and research skills to estimate the total losses from a heatwave accurately. 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 financial losses – predominantly caused by power outages and transport system disruptions. This same event recorded zero damages or insured losses in EM-DAT. Improvements in the accuracy of economic impact measurements would improve the approximated results gained through this research. This limitation is present globally, but especially in lower-income countries where economic data measurement infrastructure is severely lacking. Better measurement and data gathering practices would allow decision-makers at all levels to make more informed choices on policy.

8.2.2. Terminology

As mentioned in Section 3.2.2, this research's economic data collection process grouped all monetary costs under the 'damages' category. This was done to ensure consistency with the EM-DAT approach. However, this is a loose use of terminology relative to the true variance of economic impacts from extreme weather. To better understand the nature of economic impacts, databases and measurement practices need to be improved to reflect an accurate breakdown of costs. For example, following the terminology of the Intergovernmental Expert Working Group on Indicators and Terminology relating to disaster risk reduction, which are fully outlined in Section 1.1, would improve understanding of the types of economic impacts that are most prominent for different events and in different countries. 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). Consequently, better decisions about how to adapt in the face of increasing extreme weather would be made.

8.2.3. Economic costs associated with 'affected people'

The number of people affected is an impact datapoint recorded in EM-DAT, reflecting an economic cost resulting from an extreme weather event. From the global average extrapolation approach, it was found that climate change is responsible for 1.4 billion people being 'affected' by extreme weather between 2000-2019. Where *affected,* in line with the EM-DAT definition, means requiring immediate assistance following a disaster. This could range from an acute need for life-saving medical attention, the long-term provision of basic survival resources, or just some supply of short-term emergency provisions. This is equivalent to between 18-23%[15] of the global population, over 2000-2019, affected by climate change-induced extreme weather. Evidently, this must be related to economic costs, including healthcare costs, costs of provision of basic services such as emergency shelter, water, and food. However, given the extensive but imprecise range of costs that could be associated with someone being classed as an 'affected' party, using a singular monetary value for all affected parties would be misleading. Therefore, these costs are not included in the final calculation of global economic impact. This is an additional source of underestimation that is embedded in the results.

Additionally, people can be affected in many ways by an extreme weather event aside from requiring immediate medical assistance or basic survival needs. For example, people may suffer from ongoing mental health impacts (e.g. stress, grief), lose a period of education after the event, or lose their job if their place of employment is harmed – to name a few. These people do not count as having been affected, under the EM-DAT definition, yet suffer high economic costs due to extreme weather events. These costs are not captured accurately in the data. They, therefore, are omitted from the results of this research, making a further contribution to the underestimation of the global cost of climate change-attributed extreme weather.

The limitations of this research are extensive and demonstrate why the global approximation of the human-induced extreme weather event economic costs should not be considered robust. This research, however, provides a framework and methodology that should be built upon and improved to progress towards a more robust estimation of economic cost. Each limiting factor described above has the potential to be reduced with more research by climate scientists and economists, globally. Estimating the cost of climate change should never be the product of a singular methodology - whether that be this proposed event attribution approach, an IAM, or something different altogether. Alternatively, the knowledge produced through a toolbox of methods should be considered and scrutinized continuously. This would allow decision-makers to have a full suite of data and information that reflects the complexity and sensitivities embedded in this climate-economy research area.

[15] This estimation does not account for the possibility that one person can be affected by multiple climate-attributed extreme weather events, although this is highly likely. The available data does not allow analysis to this depth.

Conclusion

The characteristics of extreme weather events are changing because of anthropogenic climate change – some are becoming more frequent, less frequent, more intense, shorter, or longer. There are a multitude of these changes occurring globally, and they already cost the world hugely in terms of lives, direct, and indirect economic losses. This research has attempted to estimate how much economic cost climate change has been responsible for, pertaining to extreme weather events, over the last 20 years. This has been done using an attribution-based estimation method, which leans heavily on extreme event attribution studies and the subsequent calculations of the fraction of attributable risk for individual extreme events. Using the global extrapolation method, it was estimated that climate change is responsible for $2.90 trillion (US) in economic cost from extreme weather over 2000-2019 – a figure which includes economic damages and the statistical value of life. This is equivalent to an average of 0.20% of global GDP annually. In contrast, DICE, a well-recognized integrated assessment model, on average estimates climate change damages of 0.19% of annual global GDP over the same period. However, the attribution method is only approximating the climate change cost of one cost source, extreme weather events, while the DICE model attempts to create an estimate of the cost of climate change more broadly. The results suggest that climate change-related costs from extreme weather events are not well captured in IAM, contributing to a likely underestimation of the global economic impact of climate change. However, as discussed, using an attribution-based method to approximate the global cost of climate change has not been done before, and therefore many limitations to the approach are outstanding. Hence, the cost estimation, rather than being considered accurate, should be interpreted as highly approximate and a best first attempt, given the available data.

For now, more event attribution studies need to be conducted, and the geographical and event type representation of studies improved. This, in addition to better economic data, will allow the approximation of the global climate change-attributed economic cost of extreme weather to be continuously refined. Importantly, this attribution-based method provides another 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, and the CarbonBrief (2021) spreadsheet, can be accessed in the supplementary material provided alongside this report.

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