# Designing and Describing Climate Change Impact Attribution Studies: A Guide to Common Approaches

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**Key Points:**

- A small but growing number of studies estimate the observed consequences of human-caused climate change using statistically rigorous methods.
- These end-to-end impact attribution studies can ask the same question in markedly different ways, based on a small number of methodological choices.
- A common typology of impact attribution can help articulate study differences—and the strength of evidence that they can generate.

## Abstract

Impact attribution is an emerging transdisciplinary sub-discipline of detection and attribution, focused on the social, economic, and ecological impacts of climate change. Here, we provide an overview of common end-to-end frameworks in impact attribution, focusing on examples relating to the human health impacts of climate change. We propose a typology of study designs based on whether researchers choose to focus on long-term trends or specific events; whether they compare climate scenarios by estimating impact probabilities, or only focus on the difference in impact distributions; and whether they choose to split climate change attribution and impact estimation into separate analytical steps (and often, separate studies). We map four common study designs onto this typology, and discuss their relative strengths in terms of both inferential rigor and science communication potential. We conclude by discussing a handful of related and emerging approaches, and discuss how methodological innovations in impact attribution are continuing to advance our understanding of the climate crisis.


## 1 Introduction

Climate change is having a marked impact on humans and ecosystems, ranging from shifting burdens of disease to exacerbating global economic inequality and biodiversity loss (Callaghan et al., 2021; Carleton & Hsiang, 2016; Hans-Otto Pörtner et al., 2021, 2022). By 2021, over 100,000 studies had reported potential climate-driven changes in human and natural systems (Callaghan et al., 2021). Quantifying these impacts—and tracing them back to specific sources of human influence on the climate system—is a key step towards building the scientific evidence base to spur climate action, including investment in adaptation and reparative justice. This problem falls under the purview of detection and attribution, an area of climate science that has existed for decades, but remains nascent in its application to social and ecological impacts.

In this Review, we provide an overview of the different study designs that have been applied to climate change impact attribution so far, and propose a typology of these studies based on three choices that researchers make when designing their analysis. Using this typology, we consider the relative strengths and weaknesses of these approaches, and explore how future work might continue to strengthen and expand  the impact attribution literature. Throughout, we use examples from human health as a category of climate change impacts that is high-priority, readily measured, and closely connected to extreme events, making it one of the core areas explored in the impact attribution field. However, the principles we outline could be applied to many other categories of impacts on human and natural systems.

## 2 A Simple Typology

### 2.1 Defining major terms

Some of the language around detection and attribution has changed over time, and means different things to different communities, leading to some level of cross-talk and confusion. We first establish a set of common terminology that we use throughout this review.

***Detection and attribution*** refers to the area of climate science generally concerned with the detection of changes in the climate system outside of natural variability (i.e., ***climate change detection***), and their attribution to different sources of natural and human-caused (anthropogenic) influence on the climate system (***climate attribution***). Over time, this field has also expanded to include the detection of potential impacts on human and natural systems (usually called ***impact assessment***), and their attribution to observed climate change and its causes (***impact attribution***).

***Attribution science*** is broadly concerned with understanding the causes of observed climate change and its impacts. To that end, attribution studies usually contain some sort of quantitative analysis, focused on how weather and climate are influenced by ***natural forcings*** (primarily incoming solar radiation and volcanic aerosols) and ***anthropogenic forcings*** (such as greenhouse gas emissions, some aerosol emissions, and land cover change). Beyond a shared focus on these areas, and a general understanding that – due to their importance in climate policy and public understanding – these studies need to be robust to scientific scrutiny, there is no one formal methodology or evidentiary standard that defines attribution. However, many of these studies share a specific focus on understanding how today's earth and socioeconomic systems would be different in the absence of human-caused climate change. This question is often explored by comparing the world as-is to a counterfactual climate scenario, generated by a different set of forcings; for the purposes of this Review, we usually focus on counterfactual scenarios that entail a "natural" simulation of recent climates (i.e., in the absence of anthropogenic forcings), although other counterfactual scenarios are commonplace in attribution science.

In the early days, attribution science was primarily concerned with observed long-term changes in temperature and related climate variables (i.e., ***climate trend attribution***) (Santer et al., 1996). Starting with a landmark commentary about flood liability in 2003 (Allen, 2003), scientists began to consider the role of human-caused climate change in specific extreme weather events. ***Event attribution*** poses different and often more challenging problems than trend attribution, and depending on the questions being asked, different methodologies can be more informative than others. The most common approach – called risk-based (Shepherd, 2016) or ***probabilistic event attribution*** (Pall et al., 2014) – measures the effect of human-caused climate change based on the probability of a similar event's occurrence in a set of actual versus counterfactual climate simulations. These studies often summarize the effect of climate change based on either the time-to-return (e.g., a 1-in-1000 year storm might be a 1-in-10 year event in a human-altered climate, implying a 100-fold increase in risk), or the fraction of attributable risk (FAR), a statistic adapted from epidemiology that compares the probability of occurrence in the factual and counterfactual scenario, where FAR = $(P_{factual} - P_{counterfactual}) / (P_{factual})$ (e.g., in the previous example, the FAR would be estimated as 0.99). Another, newer approach called ***storyline event attribution*** takes the historical fact of the event for granted (Shepherd, 2016). In this approach, researchers simulate the event itself based on different "storylines," and compare the contribution of specific phenomena to the intensity of the event (e.g., the amount of rainfall during a specific storm). These studies also sometimes explain their findings based on probabilities: for example, a classic study estimated the change in the probability that a 2011 heat wave in Texas would have broken existing records, resulting from two phenomena of interest (an observed, natural anomaly in sea surface temperatures, versus human-caused climate change) (Hoerling et al., 2013). However, the probability of the event *itself* (i.e., the heat wave) occurring is not considered.

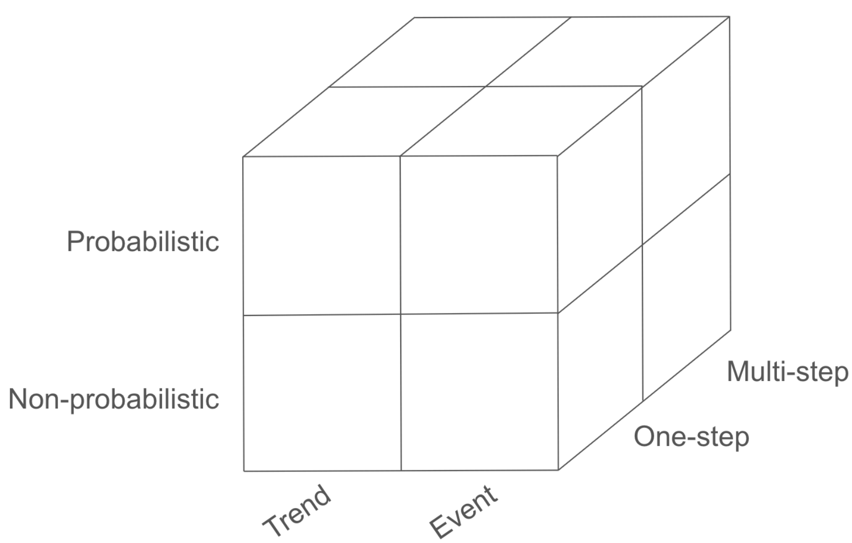
Over time, attribution science has branched out to address the downstream consequences of both long-term climate trends and extreme weather events for humans and ecosystems. To date, most research has focused on the human or ecosystem impacts of observed climate change, without explicitly isolating the anthropogenic contribution; this approach has generated most of the primary evidence used in synthesis documents like the Intergovernmental Panel on Climate Change or *Lancet* Countdown reports. However, in the last half decade, several studies have carried out analyses that connect observed impacts all the way upstream to anthropogenic influence on the climate system. For many years, the field of impact attribution has been broadly defined, in order to capture all of these studies (Ebi et al., 2017; Hegerl et al., 2010); most recently, in the sixth Intergovernmental Panel on Climate Change (IPCC) Assessment Report (AR6), the Cross-Working Group Box on Attribution stated that "Impact attribution does not always involve attribution to anthropogenic climate forcing….However, a growing number of studies include this aspect" (Hope et al., 2022).

Nevertheless, the distinction between "impacts attributable to observed climate change" and "impacts attributable to human-caused climate change" is non-trivial. The latter is often the relevant evidentiary standard for law and governance; more salient to this exercise, the methods that can be applied to the former problem are infinitely more diverse, and would probably withstand categorization into any one typology. In this Review, we therefore focus narrowly on ***end-to-end impact attribution*** studies, which we define as studies concerned with resolving and distinguishing the observed (historical or current) downstream effects of anthropogenic and natural climate forcings on humans and ecosystems. However, we acknowledge that "impact attribution" has usually been defined more broadly, and we refer readers to other excellent reviews that capture the challenges in that broader literature (Ebi et al., 2020; Stone et al., 2009).

### 2.2 Researcher choices shape impact attribution study design

Different combinations of researcher decisions can lead to radically different impact attribution study designs. In this Review, we focus on three of these decisions. The first two methodological choices are intrinsic to detection and attribution as a framework, while the third represents a decision about how to incorporate downstream impacts into climate change attribution (Stone et al., 2009). Together, these decisions create a simple parameter space, into which we here aim to categorize different kinds of study designs (Figure 1).

**Figure 1.** A typology of impact attribution study designs based on three study design decisions. Not all cells within the cube are necessarily pursued in impact attribution work.



### *2.2.1. Impacts of trends versus impacts of events*

Most climate attribution studies choose to focus either on extreme weather events (each of which can span timescales of a day to a decade), or long-term trends in climatic variables such as temperature or precipitation (usually over several decades or longer). The boundaries between the two can be blurry, and both kinds of studies are often concerned with long-run changes in the climate; however, a focus on extreme events usually requires specialized approaches, especially if researchers are interested in one specific event. The same distinction applies to impact attribution studies, which usually focus on either the impacts of extreme weather events (e.g., mortality from the 2003 European heat wave) or long-term climate trends (e.g., long-term increases in year-round mortality due to non-optimal temperatures).

### *2.2.2. Probabilistic versus non-probabilistic reasoning*

In event attribution, a distinction is made between the "probabilistic" or "risk-based" approach (which conceptualizes the impact of climate change on an event based on a change in the simulated rate of similar events over time) and the "storyline" approach (which conceptualizes the impact of climate change on an event as the contribution of anthropogenic forcings to the characteristics of the specific event itself). The same distinction can be made for event impact attribution, based on whether studies are concerned with the probability of observing an event with comparable impacts (e.g., a "heat mortality event similar to the 2003 European heat wave"), or the magnitude of the impact resulting from a specific event (e.g., "excess deaths caused by the 2003 European heat wave due to the contributions of anthropogenic forcings"). The latter category obviously captures storyline event attribution studies that include an impact-related component, but also includes other impact studies with a similar philosophy but less explicit adherence to the storyline approach (Vicedo-Cabrera et al., 2023).

For trend attribution, this distinction between probabilistic and non-probabilistic framing is less salient – and can be particularly blurry, given that a simulated distribution of impact trends can be treated as a probability distribution, a significance test, or just a range of point estimates – but a distinction can still often be made, based on study aims. For example, a probabilistic trend impact attribution study might be concerned with the long-run probability of population declines driving a species to extinction, or the probability of an infectious disease having been successfully eliminated by a particular deadline. In contrast, a non-probabilistic trend impact attribution study might focus on the contribution of human-caused climate change to the area of salt marsh inundation due to sea level rise, or to excess deaths due to non-optimal temperatures.

### *2.2.3. One-step versus multi-step analysis*

One-step impact attribution studies use a single comprehensive analysis to estimate social or ecological impacts that result from different combinations of climate forcings. In comparison, multi-step impact attribution separates the estimation of climate change impacts from the attribution of observed climate change to anthropogenic influence, often across multiple scientific studies. (Previous literature has used a confusing and inconsistent mix of terms to make this distinction, including other descriptors such as end-to-end, joint, and sequential (Ebi et al., 2017; Hegerl et al., 2010; Stone et al., 2009).)

### *2.2.4. Other kinds of methodological variation*

Our framework outlines a handful of fundamental study designs, and is not meant to capture every aspect of methodological variation among studies. Once researchers select an approach, the subsequent choices they make about implementation are often more relevant to the rigor and robustness of the analysis. For example, counterfactual scenario design – and the number of replicates used to simulate each scenario – determines how reliably studies can distinguish anthropogenic influence from natural variability. Similarly, some studies directly use data on observed outcomes of interest in the focal population (e.g., all-cause mortality records), and derive their statistical relationship to the climatic variables of interest, while others rely on prior estimates of that relationship from other populations with better data (Chapman et al., 2022; Mitchell et al., 2016). These choices are more subjective, and researchers would likely benefit from framework-specific guidelines for best practices (beyond the scope of the current Review).

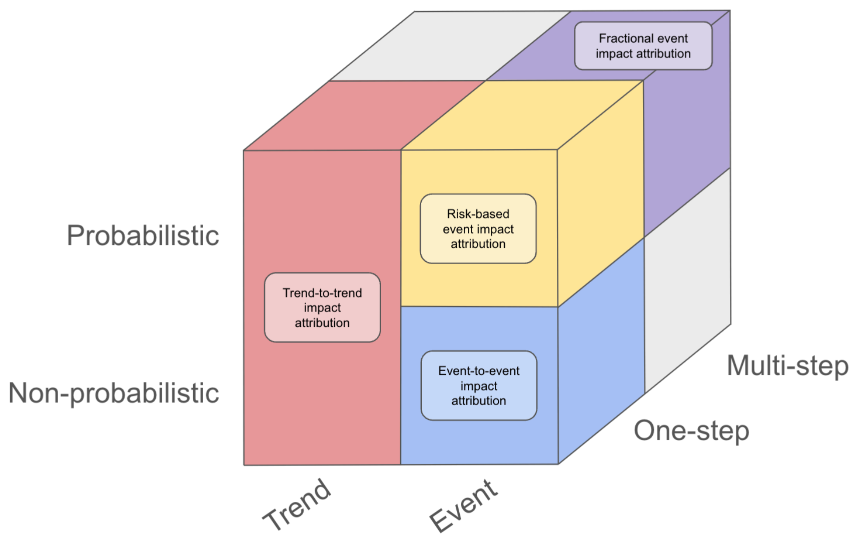
## 3 Categorizing Impact Attribution

### 3.1 The major approaches

Within our typology, we can identify at least four distinctive approaches to end-to-end impact attribution, with some amount of overlap among concepts and methods (Figure 2):

- Trend-to-trend impact attribution (one-step; trend-focused; may be probabilistic or non-probabilistic) focuses on understanding how long-term trends in the climate lead to long-term trends in human or natural systems.
- Risk-based event impact attribution (one-step; event-focused; probabilistic) focuses on how climate change reshapes the probability distribution underlying impacts on human or natural systems that result from extreme weather events.
- Fractional event impact attribution (multi-step; event-focused; probabilistic) shares the same focus as the risk-based approach, but estimates attributable impacts by multiplying the total observed impact by the estimated fraction of attributable risk for the event itself (rather than the impact), often based on an estimate from a separate study.
- Event-to-event impact attribution (one-step; event-focused; non-probabilistic) includes the storyline event attribution approach and others focused on how different forcings contribute to the impacts of a specific observed event on human or natural systems.

**Figure 2.** The same typology as in Figure 1, with four major approaches highlighted.




*3.1.1 Trend-to-trend impact attribution*

One of the most common approaches to impact attribution directly combines climate trend attribution and impact simulations in a single analysis. For example, a number of studies have examined how long-term temperature trends have led to long-term changes in heat-related mortality (Chapman et al., 2022; Stuart-Smith et al., 2023; Vicedo-Cabrera et al., 2021) and morbidity (Puvvula et al., 2022), as well as a number of issues related to child health, including preterm births (Zhang et al., 2022), low birth weight (Zhu et al., 2023), and childhood malaria (Carlson et al., 2023). Other studies have examined the contribution of human-caused climate change to global trends in poverty (Callahan & Mankin, 2022; Diffenbaugh & Burke, 2019) and food systems vulnerability (Dasgupta & Robinson, 2022; Ortiz-Bobea et al., 2021).

Trend-to-trend impact attribution studies may or may not use probabilistic framings, depending on their aims. For example, one recent study found two-to-one odds that long-term warming trends have had a positive effect on childhood malaria in Africa (Carlson et al., 2023); another study took what they called an "intensity-based" approach, focusing only on the cumulative number of excess heat-related deaths in Switzerland (Stuart-Smith et al., 2023). Both studies used an ensemble of climate models to simulate health impacts, and so generated a statistical distribution of simulated outcomes. The distinction between their framings is cosmetic, and reflects the study aims: whereas long-term temperature trends have almost certainly caused an increase in heat-related mortality, the direction of the relationship between malaria and climate change has been a point of some contention (Chaves & Koenraadt, 2010; Gething et al., 2010; Hay et al., 2002), making the probabilistic summary of trend signs a useful statistic.

Probabilistic trend-to-trend impact attribution also creates a natural home for the "third corner" of the event-trend dichotomy: cases where researchers are interested in how long-term climate trends lead to extreme "impact events," either due to intrinsic stochasticity in the impact system, or due to threshold effects in the impact-climate relationship. For example, a long-term trend in temperature might be implicated in an unprecedented epidemic of malaria or dengue fever; researchers might study these kinds of outbreaks by combining climate models with dynamical models of epidemic dynamics (Alonso et al., 2011; Ebi et al., 2020).

#### *3.1.2 Risk-based event impact attribution*

The risk-based approach to impact attribution is a direct extension of the classical approach to probabilistic extreme climatic event attribution. In addition to directly estimating the magnitude of the attributable impacts, this approach also allows estimation of relative risk or time-to-return of similar "impact events." For example, two studies have simulated the time-to-return of heat waves comparable to a specific event (the 2003 European heat wave and the 2006 London heat wave, respectively), and then layered in the mortality-temperature relationship to calculate the time-to-return of heat wave *mortality* events of a comparable magnitude (Mitchell et al., 2016; Perkins-Kirkpatrick et al., 2022). Similarly, one of these studies also used the "transfer function" between rainfall and insurance payouts to estimate the attributable financial damages of ex-Tropical Cyclone Debbie (Perkins-Kirkpatrick et al., 2022).

#### *3.1.3 Fractional event impact attribution*

As a multi-step alternative to the risk-based approach, some researchers have taken a shortcut where the attributable impact of an extreme event is estimated as the total impact of the event multiplied by an estimate of the FAR for the climate event itself; these steps are often split across separate studies, sometimes by different researchers. This approach was pioneered by a study of Hurricane Harvey (Frame et al., 2020), which was responsible for an estimated total of 476,000 life years lost; with prior estimates of the FAR converging around 80%, Frame et al. estimated that at least 357,000 lost life years were attributable to human-caused climate change. This approach has recently been used to generate a synthesis of estimated mortality and economic damages from hundreds of extreme weather events around the world since the early 2000s (Newman & Noy, 2023). This approach is most useful in cases where other approaches are prohibitive, such as when the climate-impact relationship is not very well established, could only be estimated from complex or dynamical simulations, or is multifactorial.

#### *3.1.4 Event-to-event impact attribution*

The non-probabilistic approach to event impact attribution focuses solely on how different forcings contribute to the scale of the event's observed impacts. This includes the storyline approach, which has only had limited application to impact attribution so far; for example, one recent study used this approach to examine the scale of displaced populations resulting from Tropical Cyclone Idai (Mester et al., 2022). By simulating the extent of flooding that would have resulted from the cyclone, with and without the contribution of anthropogenic forcing to the event, the authors were able to estimate that at least 16,000 additional persons were displaced. Some studies may also take a storyline-approach without explicitly using storylines to simulate the event of interest. For example, one recent study simulated mortality in Switzerland during the unusually warm summer of 2022; impact analyses based on different records of temperature observations were compared to counterfactual temperature scenarios, constructed by subtracting the estimated human contribution to long-term warming trends (Vicedo-Cabrera et al., 2023).

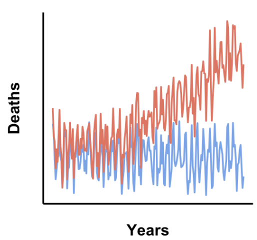
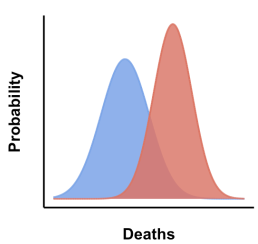
Although this study is not neatly categorized as storyline event attribution, it shares the goal of understanding the specific contribution of human-caused climate change to the unusual event.

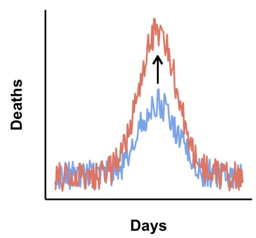
### 3.2 Strengths and weaknesses

The relative strengths and weaknesses of these different approaches depend largely on the aims of the researchers conducting a given study, or the reader making use of its findings. We identify four major goals, which are rarely specified up front, and often coexist in the same analysis.

In many cases, the goal of an impact attribution study is, simply, ***to quantify impacts***. For example, if researchers already have reason to believe that an observed impact is attributable in at least some part to human-caused climate change, the goal of an attribution study may simply be to "put numbers on" the anthropogenic component. In this light, the different approaches are somewhat interchangeable: each produces a clearly-articulated estimate of the impact, which can be communicated to policymakers and the public (Table 1). The fractional approach is particularly valuable in this context, as both a short path to a serviceable estimate, and as an option for event-impact relationships that are hard to simulate in detail (e.g., storm mortality). However, the approach also relies on the assumption that the time-to-return of event magnitude and impact magnitude scale similarly, which may be incorrect in many systems, for which the risk-based approach will produce more accurate estimates (Perkins-Kirkpatrick et al., 2022).

**Table 1.** Examples of the major impact attribution frameworks as they have been applied to the same topic: mortality due to extreme heat (Mitchell et al., 2016; Newman & Noy, 2023; Rahmstorf & Coumou, 2011; Vicedo-Cabrera et al., 2021, 2023).

| Approach | Example |
| --- | --- |
| **Trend-to-trend impact attribution**<br><br> | Vicedo-Cabrera et al. (2021) examined the effect of global temperature trends on warm season heat-related mortality in 732 locations around the world. They simulated mortality trends between 1991 and 2018, based on global climate model simulations with and without anthropogenic forcing. They estimate that annually, an average of 9,702 deaths in those 732 locations are attributable to human-caused climate change. |
| **Risk-based event impact attribution**<br><br> | Mitchell et al. (2016) attributed mortality from the 2003 European heat wave to human-caused climate change based on the probability of a particular size of "mortality event." To do so, they simulated temperatures, and the mortality that would accompany heat waves, with and without anthropogenic warming. They estimate that 506 deaths in Paris were attributable to human-caused climate change, and that "the 2003-like mortality event in Paris went from a 1-in-300-year event…to a 1-in-70-year event." |

| | |
|---|---|
| **Fractional event impact attribution**  | Rahmstorf and Coumou (2011) found that human-caused climate change made the 2010 Russian heat wave five times more likely (fraction of attributable risk = 0.80). Revisiting this event, Newman and Noy (2023) combined that statistic with a previous estimate that the 2010 Russian heat wave was responsible for 55,736 deaths, and calculated that 55,736 * 0.80 = 44,589 deaths were attributable to human-caused climate change. |
| **Event-to-event impact attribution**   | Vicedo-Cabrera et al. (2023) attributed mortality from the unusually warm 2022 summer in Switzerland to climate change, comparing mortality due to observed temperatures to an ensemble of counterfactuals derived by subtracting estimates of the overall warming trend in the region. They estimate that 623 excess heat-related deaths between June and August 2022 were the result of human-caused climate change. |

Inseparable from this first goal, some studies may also aim ***to quantify adaptation***, which is often defined as any action that either reduces adverse impacts on human and natural systems, or reduces their sensitivity to anthropogenic forcings. Evidence for adaptation is often analyzed by testing for a reduction in impact-climate relationships through time (Oudin Åström et al., 2013); researchers can then cross-project these relationships to estimate how adaptation contributed to attributable impacts. For example, one trend-to-trend attribution study estimated that adaptation to extreme heat prevented 738 deaths in Switzerland between 2004 and 2018; to do so, they estimated contemporary mortality based on the historical mortality-temperature relationship observed between 1986 and 2003 (Stuart-Smith et al., 2023). Other studies may directly account for adaptation in the impact model itself; for example, one recent event-to-event attribution study used hydrological models to test how changes in streamflow during the 'Day Zero' drought in South Africa would have been mediated by invasive alien tree clearing (Holden et al., 2022). In the special case of geoengineering, adaptation may even be addressed through the counterfactual climate scenario itself, as one probabilistic event attribution study recently did with the same drought (Odoulami et al., 2020). We suggest that any of these approaches to capturing adaptation could plausibly be used in combination with any of the one-step attribution frameworks.

In other cases, the goal may be ***to quantify uncertainty***. This need may arise from within the scientific literature, especially if the goal is to isolate small or uncertain long-term trends from internal variability in human or natural systems. For example, Carlson et al.'s recent study resolves decades of debate about the cumulative impacts of climate change on malaria in sub-Saharan Africa; their probabilistic trend-to-trend analysis concludes that it is likely (2-to-1 odds) that climate change has increased the prevalence of childhood malaria, and identifies finer-scale regions where a statistically significant trend can be isolated (Carlson et al., 2023). In other cases, the need to quantify certainty arises from real-world application: for example, for purposes related to climate litigation, the most important part of an attribution statement may be the level of certainty that a given impact was less likely or impossible in the absence of human influence.

If an extreme event is almost entirely attributable to climate change, that fact alone may be sufficient, in the absence of *any* analysis of the associated impacts; but in most cases, some sort of end-to-end analysis is usually important. To that end, risk-based and event-to-event approaches can capture complementary aspects of uncertainty, reflecting the probability of the event's occurrence or the magnitude of its impacts, respectively (just as different studies can work together to capture the same facets of an extreme event (Otto et al., 2012)).

Across any of the approaches we describe, the most significant methodological challenge is often capturing the full range of uncertainty. In a given impact attribution study, uncertainty can arise from at least eight sources: measurement error and bias in the observed weather data; biases unique to different climate models; process uncertainty in the climate system; stochasticity in climate model simulations; measurement error and bias in the observed impact data; process uncertainty and statistical uncertainty in the impact-climate relationship; and external influences on outcome variables, including both mediators (i.e., adaptation) and confounders (e.g., other environmental and social determinants of health). Some of these are easily (and regularly) addressed: for example, most impact attribution studies use at least 5-10 different climate models to capture natural climate variability and model uncertainty; many studies also report the confidence bounds of the estimated impact-climate relationship; and ideally, uncertainty is propagated across these two steps. Fewer studies address error and bias in the observational data for weather (e.g., by reproducing analyses using multiple reanalysis-based datasets) or impacts (e.g., by bootstrapping the data and re-running statistical analyses). Similarly, very few studies explore process uncertainty (e.g., by testing impact models that are estimated from different populations, or that use entirely different methods, such as statistical versus dynamical models of disease dynamics). These could be important gaps to fill in the impact attribution literature, but any individual study cannot address every source of uncertainty. As the layers of replication increase multiplicatively, propagating error across three or four of these sources can easily require hundreds of thousands of simulations, which may be computationally prohibitive for some researchers. Pushing to capture the fullest range of uncertainty possible may also benefit one aspect of scientific rigor at the expense of others (e.g., identifiability) (Rising et al., 2022), or may dilute the clarity of the findings, undermining the study's initial purpose (Maslin, 2013).

A final goal of impact attribution might be ***discovery***. We speculate that this has been a relatively rare objective in the literature published to date: impact attribution remains an effort-intensive scientific problem, and most studies have been motivated by negative impacts on human and natural systems that are already strongly believed or known to be the result of human-caused climate change. However, as these studies become more commonplace, their methods become better documented, and the computational barrier to entry becomes lower, we anticipate that more future work will use attribution science to explore poorly-understood or speculative impacts of climate change. Whereas impact attribution has mostly focused on substantiating claims about the adverse consequences of human activities, the broader field of detection and attribution is deeply connected with other parts of climate science, and often leads to advances in the understanding of complex weather phenomena or geophysical mechanisms. It seems plausible that trend-to-trend or event-to-event impact attribution studies could begin to move in similar directions, especially if machine learning helps estimate impact-climate relationships that would otherwise be challenging to resolve from first principles (Brown et al., 2023).

## 4 Emerging Approaches

Our proposed typology is focused primarily on end-to-end attribution of observed changes in human and natural systems to climate change and its causes. However, a handful of other adjacent approaches lie within the impact attribution space, and are worth noting.

## 4.1 Literature-based approaches

Previous impact attribution reviews often identify two additional study designs (Table 2), which rely on reanalysis of published literature instead of a new end-to-end quantitative analysis. We describe both given their importance in the evolution of the field, but note that both reflect a conflicting use of the term "attribution," which is most often applied to quantitative studies.

**Table 2.** Examples of how literature-based attribution frameworks could be applied to heat and mortality (Berrang-Ford et al., 2021; Callaghan et al., 2021; Ebi et al., 2020; Yiou et al., 2020).

| | |
|---|---|
| **Descriptive impact "attribution"**  | Yiou et al. (2020) estimated that a 2018 heat wave in Scandinavia was up to 100 times more likely due to human-caused climate change. Ebi et al. (2020) note that this heat wave caused hundreds of excess deaths, and that the true health impacts of the event were likely much broader than mortality alone. Notably, this descriptive approach does not quantify the specific health impact attributable to human-caused climate change. |
| **Synthesis impact "attribution"**  | Berrang-Ford et al. (2021) used machine learning to identify over 15,000 studies that identify relationships between climate and human health. Mortality-temperature relationships are among the top phenomena documented in this literature. These studies are likely a significant fraction of the broader evidence base for climate change impacts, which Callaghan et al. (2021) document in an analysis of over 100,000 studies (presumably including some focused on human health outcomes); they show these are closely correlated with the geography of attributable changes in the climate. Future work might bridge the two approaches, and directly show that evidence of excess heat mortality is clustered in the fastest warming parts of the world. |

### *4.1.1. The descriptive approach*

Some reviews describe a "sequential" (Stone et al., 2009) or "multi-step" (Ebi et al., 2017, 2020) approach to attribution, which consists of *post hoc* subjective interpretation of existing evidence that (1) an impact is connected to specific climate variables, and separately, that (2) changes in those variables are attributable to human-caused climate change. The descriptive approach is qualitative, and generates descriptive statements about the strength of available evidence. This approach has several limitations, including the potential for mismatch between climate change attribution and impact studies (e.g., use of climate data with different biases, or at different timescales or spatial resolutions); the lack of insight into natural variability, resulting in a high risk of Type I error; and other problems with subjective expert opinion. However, it may be the only way to address poorly understood impacts (for example, if the ecology of an impact is too complex to simulate), or it may simply be a precursor to more detailed analyses.

### *4.1.2. The synthesis approach*

Variously called "joint" or "synthesis" attribution (Rosenzweig et al., 2008; Stone et al., 2009), attribution mapping (Callaghan et al., 2021), consistency analysis (Bannister-Tyrrell et al., 2015), or impact fingerprint analysis (Parmesan & Yohe, 2003), what we term the synthesis approach extends the descriptive approach to a much broader scale (though the two approaches obviously exist on a continuum). Synthesis studies draw on hundreds or thousands of studies (increasingly with the help of machine learning), and examine either (1) correspondence between observed impacts and expected impacts of human-caused climate change (e.g., are species' ranges non-randomly shifting towards the poles?), or (2) correspondence between observed impacts and observed climate change that has been attributed to anthropogenic influence (e.g., are more species ranges expanding to higher elevations in hotspots of human-caused temperature increases?). In one recent example, Callaghan et al. examined over 100,000 climate change impact studies, and suggested that "Where studies documenting impacts associated with changes in temperature or precipitation co-occur with attributable trends in those variables, we claim that there is at least preliminary evidence for attributable impacts in these areas" (Callaghan et al., 2021). This kind of preliminary evidence is important, given that impact assessment studies currently outnumber end-to-end impact attribution studies by several orders of magnitude.

## 4.2 Bridging the past, present, and future

Although attribution science is generally concerned with the present or recent past, a growing set of related approaches also grapple with possible futures over the near and long term. These techniques could also be applied to social and ecological impacts—though again, this methodological space is currently under-explored.

### *4.2.1 Forecast attribution*

On the climate side of attribution science, many studies have started to take advantage of large ensembles of weather forecasts as the basis for attribution (Haustein et al., 2016). In the same way as most attribution studies use global climate models, forecast attribution studies compare weather forecasts based on actual and counterfactual climate scenarios. This approach can be used to hindcast extreme events that are challenging to attribute, such as hurricanes (Patricola & Wehner, 2018), or used more simply to reduce modeled meteorological biases (Thompson et al., 2023). Forecast attribution studies can even be run before an event occurs, in order to make advance predictions about how human-caused climate change will shape an event that is about to unfold (e.g., before a storm makes landfall) (Reed et al., 2020).

In cases where impact-climate relationships have been robustly quantified, it might be possible to incorporate forecasted impacts into these studies; this could be a new way to ground the messaging in (already often high-visibility) rapid assessments of extreme weather. Recent advances in longer-term weather forecasting, up to decadal scales, could also be relevant as a future-facing complement to trend attribution and longer-term projection studies (Dunstone et al., 2022), especially if short-term forecasts of mortality, economic damage, or biodiversity loss can better compel policymakers to action (on both mitigation and adaptation) than projections of the more "distant" impacts facing future generations.

### *4.2.2 Projection or "reverse" attribution*

Although many studies make a high-level distinction between attribution (understanding of past or present human-caused climate change) and projection (exploration of possible future scenarios for human-caused climate change), the boundary between the two is necessarily blurry. For example, as a complement to an existing trend-to-trend impact attribution analysis, researchers can also run forward-facing projections under different future emissions pathways through mid- or end of century (Carlson et al., 2023; Chapman et al., 2022; Puvvula et al., 2022). Similarly, a growing number of probabilistic event attribution studies already include a third projection scenario (often the policy-relevant targets of 1.5 or 2 °C of warming); this can be a valuable tool for framing risk, especially if the probability of event occurrence accelerates at higher levels of warming (i.e., a "rare" event in today's human-altered climate may be common under future warming levels). Bridging the gap between trend impact and event impact attribution might lead to a fuller understanding of total future impacts: for example, projections of future mortality from non-optimal temperatures are likely substantial underestimates, given that most climate models probably underestimate the future frequency of extreme heat waves (Mitchell, 2021).

## 5 Conclusions

Scientific advances across the "generations" of climate science often follow a schedule set by the IPCC assessment cycles. Between AR5 and AR6, the science of extreme event attribution advanced in leaps and bounds. Now, at the start of the seventh assessment cycle, it seems likely that impact attribution—and an increasingly explicit priority on end-to-end studies—will be a key area for scientific advancement. The real-world relevance of this scholarship also cannot be understated, given the ways that evidentiary gaps currently undermine climate litigation (Stuart-Smith et al., 2021), as well as the need for scientific input into the allocation of the Loss and Damage Fund established in 2022 (King et al., 2023; Noy et al., 2023).

We recommend that, as impact attribution continues to grow, researchers continue to pursue ambitious work that addresses the impacts of human-caused climate change, rather than just impacts of observed climate change—and that studies should be careful to self-identify their work in light of this distinction. We also recommend that future assessments carefully consider impact attribution studies along the axes of study design we identify here, and develop ways to synthesize the strength of evidence across studies using different approaches. Finally, as approaches continue to proliferate, we suggest that a continuing effort should be made to standardize terminology, as we have aimed to do in this review; and that, once specific methods become commonplace, researchers should develop standard guidelines for their implementation (like the World Weather Attribution protocol for extreme event attribution (Philip et al., 2020)). All of these will help produce a stronger and more intercomparable body of scientific evidence.

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