Detection and Attribution of Climate Change Impacts on Human Health

A Data Science Framework

Image: Lushanga, Matobo District, Zimbabwe. A pregnant woman stands in a field beside crops damaged by the drought that the region is currently suffering, linked to the El Niño cycle.

Photographer: Sven Torfinn

Front Matter

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Foreward

The 2021 "Great Texas Freeze" plunged temperatures to an alarming 40 degrees below zero, leaving in its wake a billion-dollar weather disaster. Millions were left without power, food and water, and the event resulted in the deaths of over 200 people.

Disasters of this magnitude seem to be an ever-growing occurrence. The critical question is: can we attribute these events and their subsequent health impacts to climate change caused by human activities?

This is where climate attribution research steps in, attempting to unravel this complex issue. Amidst a highly politicised climate debate, robust statistical evidence is crucial to convince the public and policy makers of the health impacts of climate change. Such evidence can shape climate adaptation policy, guide resource allocation and prioritisation, and increasingly, help to determine liability in loss and damage cases.

However, as this new report illustrates, the field of *health impact attribution* is nascent, fragmented and in urgent need of significant investment to meet today's needs.

The authors examined nearly 4,000 peer reviewed studies and found only 13 studies since 2013 that rigorously tackled health impact attribution. The majority of these focussed on the direct effects of heat, with only one study each covering a climate-sensitive infectious diseases – malaria, and a non-communicable disease – pre-term birth.

When compared to the suspected climate-sensitive burdens of zoonotic, tick-borne, water-borne, food-borne, cardiovascular, chronic kidney and mental health illness, there are huge voids in our knowledge of their climate-attributable health impacts.

The report also highlights important technical challenges holding back health impact attribution research, such as the limited availability of health and climate data. These data often demand sophisticated computational resources to work with, and need to be high-resolution, spatially referenced and available over time.

As leaders in one of the world's largest philanthropic foundations focussed on human health, we welcome and endorse this report. We appreciate the careful, collaborative efforts of the authors from multiple disciplines, who clearly set out the problem, survey the field and identify opportunities for action.

We urge you to engage with the report's findings and recommendations.

Alan Dangour
Director of Climate and Health

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Head of Data for Science and Health

Executive Summary

The purpose of this project was to define the current state-of-the-art in the detection and attribution of human health impacts of human-caused climate change, sometimes shortened as **health impact attribution**. As this interdisciplinary field of research has emerged over the last decade, the numbers of deaths from extreme heat, storms, floods, many climate-sensitive infectious diseases, and some other climate change-related risks has increased markedly. Health impact attribution has the potential to bring to light these growing costs of climate inaction—but only if the field can catch up to the rapidly-evolving crisis.

This report provides an overview of the field as it stands today, including reflections on the history of its evolution out of climate science; an overview of the aims and approaches of the current body of literature; a deep dive on the data and tools that have been applied to the problem so far; and suggestions on how the field could progress in the future. Throughout, we reflect on four key areas—data, tools, talent, and policy—at the heart of the Wellcome Trust's strategy on data science for climate change and health, and we highlight opportunities in each of these areas that could help advance health impact attribution.

In the last decade, over a dozen studies have demonstrated that human-caused climate change has made the adverse health outcomes of heat waves and other natural disasters more likely or more severe, and, in some cases, increased the burden of childhood diseases and pregnancy complications. These studies only account for a small percent of published research on the health impacts of climate change, but they provide some of the best-supported evidence for contemporary impacts, and will play an important role in climate policy, including loss and damage financing and litigation.

Future work could help scientists catalogue more of the key health impacts of climate change (e.g., infectious diseases, malnutrition, and mental illness), especially in the frontline communities where investment in adaptation could make the most difference. Strategic investments in data science could help health impact attribution meet its full potential:

1. Several regions and risks are understudied due to limited high-resolution data on health outcomes across space, time, and high-risk populations. Creating new software interfaces to leverage governmental and commercial health data and enhancing efforts to mine data from published literature and historical records, could put new health impacts of climate change on the map.
2. A growing number of projects are developing and openly sharing climate models that can support impact attribution research, but processing these data requires technical expertise. Sharing more pre-processed datasets with a health focus in mind or developing open software to automate steps like bias correction, could lower the barrier to entry.
3. Few researchers are formally trained in every step of the attribution workflow and in different attribution techniques, and best practices in climate science are rapidly evolving but rarely documented. Supporting interdisciplinary teams with Global South leadership, developing standardised protocols for study design and reporting, and embracing open science practices like code sharing could build a better community of practice with the required data science expertise.

Chapter 1

Chapter 1: Project Overview

Between February and October of 2023, our team – led jointly out of Georgetown University (USA) and the University of Cape Town (South Africa) – met virtually to explore issues in the field of health impact attribution, interviewed more than two dozen experts, and conducted a systematic review of over 3,000 peer-reviewed studies.

This report provides a synthesis of our findings, and aims to:

- capture the current state of health impact attribution as a scientific field
- identify gaps, limitations, and barriers, especially as they relate to data science
- identify work in adjacent fields that could shape the future of health impact attribution
- identify the global community of experts leading the field's development
- identify their priorities, key experiences, and challenges faced in their work
- make a set of recommendations for future research and funding efforts.

In **Chapter 2** of this report, we establish key definitions, and provide a brief history of health impact attribution, including its context in the broader field of detection and attribution. (A glossary is also available in **Chapter 6**.)

In **Chapter 3**, we describe a systematic literature review of health impact attribution studies, as well as relevant work in adjacent areas of epidemiology and climate science. Out of 3,677 studies we reviewed, we identified 13 that met several basic criteria for health impact attribution. We report the findings of these 13 studies; analyse their research effort in terms of geographic area, climate risk, and health impact of interest; examine the data and methodologies they use, and the data science practices they follow; explore the community of practice responsible; and identify key gaps for future work to address.

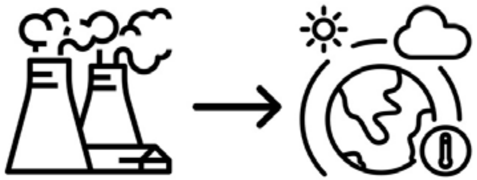
In **Chapter 4**, we describe the results of the expert elicitation process. We identified 72 experts in health impact attribution and three overlapping areas of expertise (climate change and health; detection and attribution; and global health practice). A total of 25 experts from 10 countries agreed to be interviewed in depth about their outlook on health impact attribution, including their active areas of research, the barriers they face, and where they believe funders could make a difference, with a particular focus on data science and related solutions.

Informed by both the systematic literature review and expert elicitation, we conclude in **Chapter 5** by making recommendations for how the field could progress in the next 5-10 years, with a particular focus on how research funding can use data science as a touchstone to organise more comprehensive, impactful, rigorous, and equitable research.

Chapter 2

Chapter 2: Introduction

Climate change is already having a marked impact on humans and ecosystems, with dramatic physical, social, ecological, and economic impacts (Pörtner et al. 2022; Callaghan et al. 2021; Carleton and Hsiang 2016; Pörtner et al. 2021). The human health impacts of climate change are increasingly apparent, as more of the world's population is regularly exposed to intensive heat waves, catastrophic storms and floods, and unprecedented surges of dengue fever, cholera, and other infectious diseases. Quantifying those impacts—and tracing them back to greenhouse gas emitters—is a key step towards building the evidence base to spur climate action, including adaptation and reparative justice. This is the purview of **health impact** attribution, a quantitative field at the intersection of climate science and public health.



A Guide to Health Impact Attribution

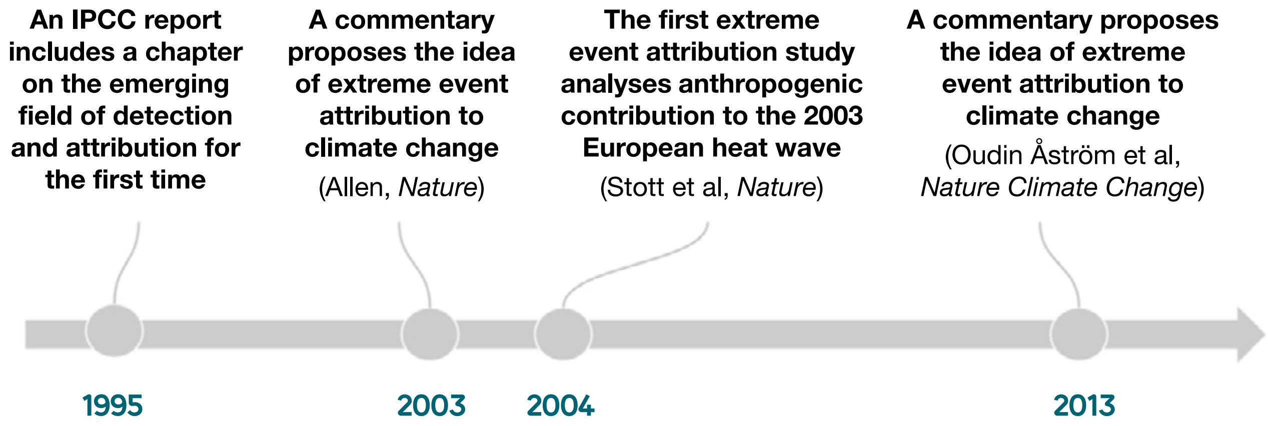
Detection and Attribution

Climate scientists frequently grapple with the twin issues of causation and uncertainty. In the earlier days of the climate crisis, the most significant scientific questions revolved around the level of certainty that humans were the root of the problem. Today, there is little doubt that recent climate change is outside the realm of normal **natural variability** in the climate system, that natural factors in the earth system cannot sufficiently explain the observed changes, and that anthropogenic influences are responsible for roughly 1.2 °C of global warming at the time of writing. However, plenty of questions remain about the role of **human-caused climate change** in specific trends or extreme weather events, and their impacts on humans and ecosystems.

The field of **detection and attribution** grapples the core challenges of:

1. detecting changes in the planet's climate
2. distinguishing these changes from natural internal variability (noise)
3. attributing these changes to the relative contribution of various anthropogenic sources (including anthropogenic sources like greenhouse gas emissions, some aerosol emissions, and land cover change) and natural forcings (primarily incoming solar radiation and volcanic aerosols)
4. understanding how today's earth system (and impacts on humans and ecosystems) would be different if recent climate change had excluded certain radiative forcings (usually those of anthropogenic origin).

Figure 2.1
A brief and incomplete history of detection and attribution



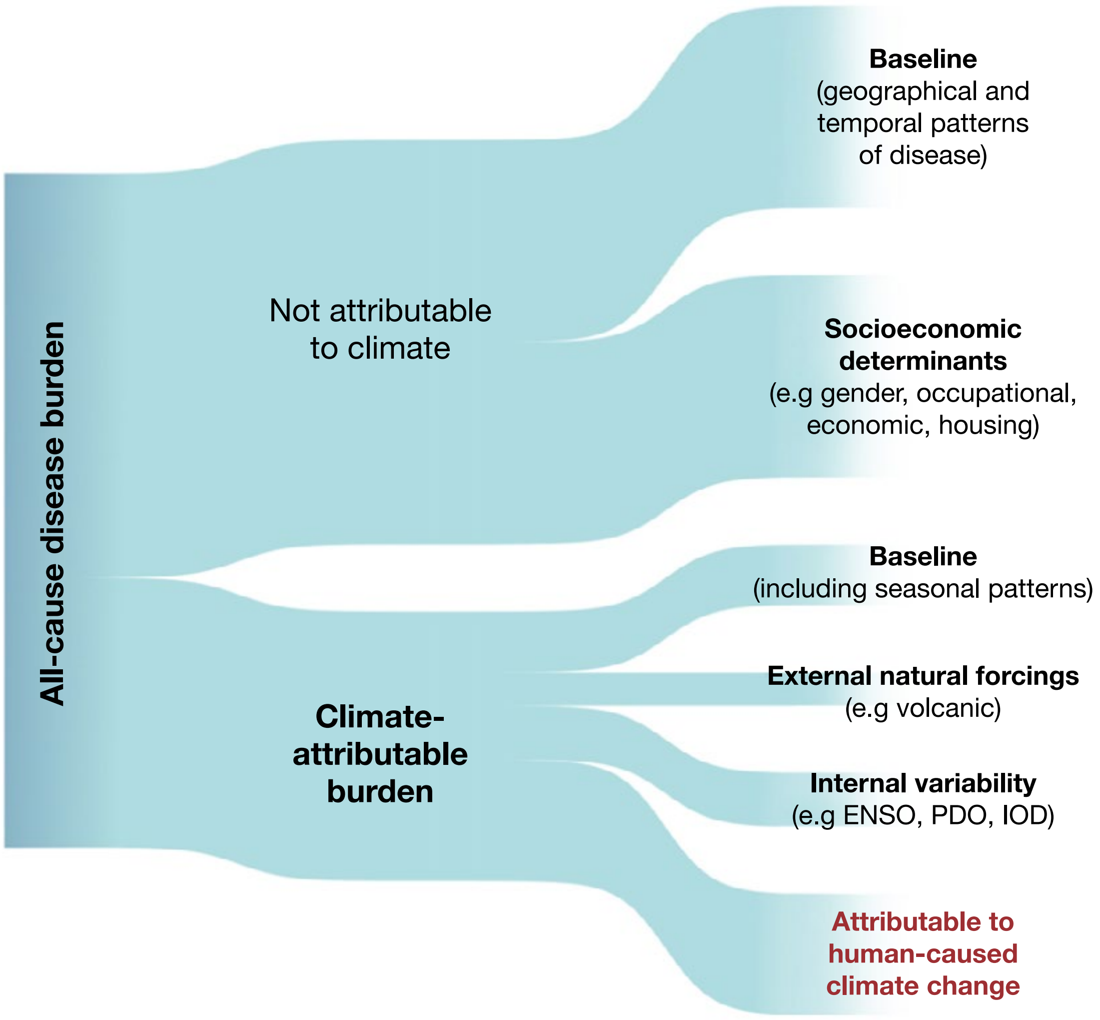
This final challenge has shaped the most recognisable methodology found in most attribution work: the simulation of a **counterfactual scenario** that captures a "natural climate" in the absence of anthropogenic forcings, and its comparison with historical or present-day climate.

As these methods have been refined, they have been applied to progressively more complex problems (Figure 2.1). In the 1990s, most work was focussed on **trend attribution**—specifically, the attribution of long-term changes in temperature and related variables to human activities (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**). As the field continues to grow, scientists are now turning their attention to the downstream consequences for humans and ecosystems, and grappling with whether the same frameworks can be used to trace these impacts all the way back to ultimate causes (for example, the burning of fossil fuels) (**impact attribution**).

Impact Attribution and Impact Assessment

Many of the tools and frameworks that were developed for the detection and attribution of human influence in the global climate system can also be used to understand the resulting impacts, including consequences for human health. However, this causal inference problem requires a much broader view of drivers: disease burdens are shaped not only by climate, but other environmental influences, as well as social, economic, and political determinants of health. As such, researchers must both separate the influence of climate from these other factors, and subsequently separate human influence from other sources of climate variability (Figure 2.2).

Figure 2.2
Drivers and sources of variation in all-cause disease burden



(ENSO: El Niño-Southern Oscillation; PDO: Pacific Decadal Oscillation; IOD: Indian Ocean Dipole.)

This problem falls under the banner of **impact attribution**, an emerging area of detection and attribution research focussed on isolating and quantifying the causal role of human-caused climate change on specific social or ecological outcomes (Figure 2.3). Importantly, these studies only capture a subset of the "**climate-attributable**" burden of disease—specifically, the component that can be traced back to anthropogenic influences like greenhouse gas emissions.

Impact attribution studies also fall under the broader umbrella of **impact assessment**, the sub-field of climate change research concerned with quantifying and explaining these impacts, and projecting future impacts, feeding into work that identifies strategies for adaptation.

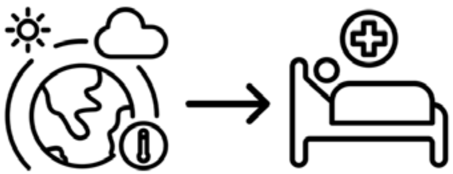
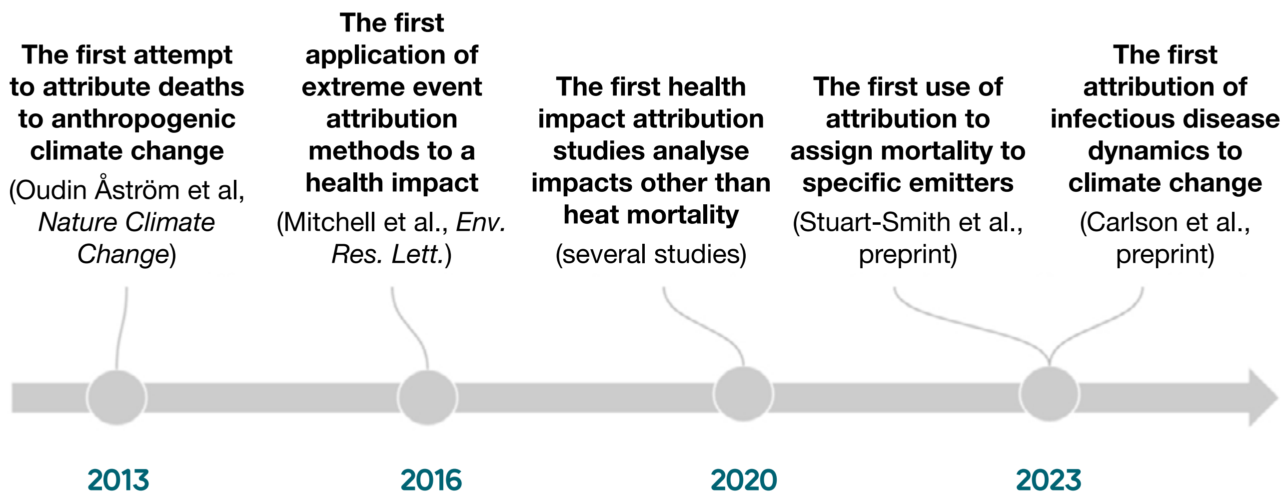


Figure 2.3
A brief history of health impact attribution



Impact assessment is a diverse field, drawing on a mix of quantitative and qualitative methods, as well as expertise from several climate-related fields, including hydrology, ecology, economics, public health, and geography. For example, research on the relationship between climate change and dengue fever could include any of the following:

- Developing a forecasting model of weekly case counts across districts of a city, based on land cover, weekly temperature and rainfall, and household income—and piloting an early warning system in partnership with local communities and the health ministry.
- Testing the impact of temperature in communities at the United States-Mexico border, and explaining differences in vulnerability using participatory mapping of mosquito-borne disease risk factors (e.g., containers with standing water; no screens on windows).
- Estimating the relationship between temperature and transmission risk based on a laboratory experiment with the mosquito vector, and projecting future global populations at risk of epidemics under different scenarios for greenhouse gas emissions reduction.
- Simulating an unusually-large dengue fever epidemic that occurred during an El Niño year, comparing to a counterfactual scenario for the same El Niño event without human influence on the climate system, and taking the difference between simulations to estimate the excess cases attributable to anthropogenic climate change.

Each of these studies would be a different form of impact assessment, but only the last would be considered impact attribution (by the definitions used in this report).

Impact assessment is a thriving field of research, with a sizable global community of practice: one recent study estimated that between 2013 and 2019, there were nearly 16,000 studies on the health impacts of climate change alone (Berrang-Ford et al. 2021). As we show in Chapter 3, attribution studies are a very small and specialised subset of this body of work.

Box 2.1 Disambiguating attribution

Like climate science, epidemiology commonly grapples with causal inference problems, and uses attribution-related terms to describe causation. For example, a study might estimate the number of tuberculosis cases attributable to air pollution, or estimate the attributable fraction of diarrhoea in children under 5 that is caused by a rotavirus infection. In the context of climate change, public health experts are increasingly aware of the need for "attribution," but may use the term as a catch-all for impact assessment, unrelated to the specific methodological criteria that climate scientists use to define detection and attribution. This can lead to cross-talk between experts and confusion about semantics versus real evidence gaps (see Chapter 4). Here, we adhere to language from climate science as much as possible, distinguishing between health risks that are "climate-attributable" and "attributable to anthropogenic climate change," and using impact assessment as the term for research on climate change impacts on health that does not meet the specific methodological criteria of detection and attribution.

Why Does Health Impact Attribution Matter?

Health impact attribution studies are the most statistically rigorous way of measuring the health burden of human-caused climate change, and as such, play a key role in informing the public health response to climate change. More practically, these studies are anticipated to play an increasingly important role in climate policy, including wrongful death litigation and international financing mechanisms for loss and damage.

Some of the earliest and most dramatic impacts of climate change have been felt in the health sector, including excess deaths, increased disability, and loss of years of life. However, not every weather-related injury or death is the result of (or was made more or less likely by) human-caused climate change. For example, the "Great Texas Freeze" of 2021 killed over 200 people, and was widely discussed in the media as an example of "climate weirding," but the event itself may not have been outside the range of natural climate variability (Doss-Gollin et al. 2021). In other cases, the degree of anthropogenic influence depends on the question being asked. For example, the 2010 Russian heat wave and wildfires was the second deadliest heat wave on record, with over 50,000 estimated excess deaths. The role of climate change was a key problem in the early attribution literature, with studies concluding that an event of its kind was more likely due to human-caused climate change, but the severity of the event itself was within the normal range of climate variability (Otto et al. 2012).

Without the use of attribution science, these debates can last for decades. For example, the involvement of human-caused climate change in the resurgence of malaria in the east African highlands has been hotly debated since the late 1990s, with some malaria experts even calling the hypothesis "hot air" and "dangerous pseudoscience" in some early commentaries (Hay et al. 2002; Carlson et al. 2023). Through the years, the debate has touched on problems like whether a temperature trend was actually detectable (Malakooti, Biomndo, and Shanks 1998; Shanks et al. 2002; Omumbo et al. 2011; Stern et al. 2011), which is now a matter of settled science; whether malaria transmission has returned to baseline due to a temporary post-2000 global warming 'hiatus' (Rodó et al. 2021), an idea that has fallen out of favour in climate science; and whether natural sources of variability like the Indian Ocean Dipole (Hashizume, Terao, and Minakawa 2009; Hashizume, Chaves, and Minakawa 2012) or the El Niño-Southern Oscillation (Lyon et al. 2017) might have more explanatory power. In cases like these, impact attribution studies are likely to be the only way to confidently resolve the relationship between anthropogenic climate change and the health outcome of interest (Carlson et al. 2023).

A Typology of Health Impact Attribution

Over the last two decades, several terms have been introduced to describe different kinds of attribution frameworks (Table 2.1), but no universal classification exists, even just for health impact attribution studies. Here, we propose a typology that is informed by these definitions, as well as specific features of the studies that we explore in Chapter 3.

Table 2.1
Previously-introduced terminology in the detection and attribution space

Source	Terminology introduced
(Allen 2003)	Fraction of attributable risk
(Rosenzweig et al. 2008)	Joint attribution End-to-end attribution
(Stone et al. 2009)	End-to-end analysis Sequential analysis Meta-analysis Synthesis analysis
(Hegerl et al. 2010)	Single-step attribution Multi-step attribution
(Pall, Wehner, and Stone 2014)	Probabilistic extreme event attribution
(Bannister-Tyrrell, Harley, and McMichael 2015)	Consistency analysis
(Shepherd 2016)	Risk-based approach Storyline-based approach
(Ebi et al. 2017)	Single-step attribution Multi-step attribution Synthesis and meta-analysis
(Stuart-Smith et al. 2023)	Intensity-based approach

Adapting several existing definitions, we first highlight a few key axes of methodological variation in the broader field of detection and attribution:

- Some studies focus on a long-term trend in the climate system and its downstream impacts on health, while others focus on the impact of extreme events. (Some studies might eventually focus on the attribution of extreme health "events" linked to gradual climate trends, such as unusually-large infectious disease outbreaks linked to rising temperatures, but this methodological space is under-developed).
- Probabilistic studies conceptualise attribution based on the probability or likelihood of observing a particular impact. For extreme events, this approach (i.e., **probabilistic event attribution**) grapples with the frequency of occurrence or time to return of a comparable event, and the relative risk between the two scenarios (e.g., if a 1-in-1000 year event has become a 1-in-10 year event in a human-altered climate, a study might say the event was 100 times more likely due to climate change, or simply, that it was extremely unlikely to occur in the absence of climate change).
- One technique that is common in probabilistic attribution studies (but is adapted from epidemiology) is the calculation of a **fraction of attributable risk (FAR)**, defined based on the relative probability of an event as ($P_{factual}$ - $P_{counterfactual}$) / ($P_{factual}$). (For example, in the previous hypothetical, the fraction of attributable risk would be 99%, indicating that climate change could be thought of as almost entirely responsible for the event and its impacts.) This approach has recently been subject to conceptual critiques (Perkins-Kirkpatrick et al. 2022; Brown 2023).
- Some approaches are based on a non-probabilistic framing. **Storyline event attribution** takes the existence of a specific historical or contemporary event for granted (rather than considering the probability of its occurrence), and – through "nudged" climate models that produce the weather scenario of interest – focuses on how the event would have differed with and without anthropogenic influence (Shepherd et al. 2018).
- Most impact attribution studies use climate models to estimate impacts with and without human-caused climate change. This framework, variously called "one-step" or **end-to-end** analysis, is labour-intensive and computationally-intensive, but allows researchers to capture uncertainty at every step: uncertainty in the observational climate data, climate model uncertainty, and statistical model uncertainty. However, sometimes researchers split this effort across multiple analyses (a "multi-step" or sequential analysis), and sometimes, split those analyses across multiple studies.

Table 2.2
A typology of impact attribution studies

	Long-term trends in impacts		Impacts of extreme weather events	
	Probabilistic	Non-probabilistic	Probabilistic	Non-probabilistic
End-to-end (one-step)	“Trend-to-trend”		“Risk-based”	“Event-to-event”
Sequential (multi-step)			“Fractional”	
	(“Descriptive”)			

Based on these axes of variation, and the observed methodologies found in our systematic literature review (see Chapter 3), we propose a simple typology of five major study designs (Table 2.2). We categorise the major approaches to health impact attribution as:

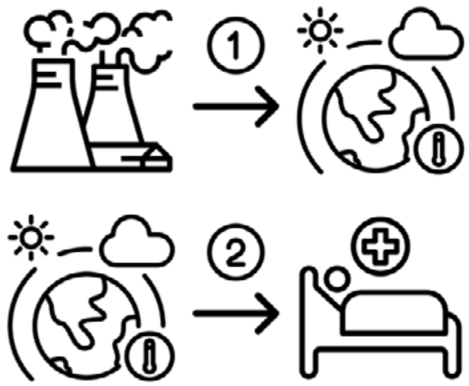
- **“Trend-to-trend”**: An end-to-end approach that examines a long-term trend in both the climate system and a related health outcome. Within this category, some studies are more explicitly probabilistic in their reasoning, estimating the odds of a particular trend sign as a form of significance testing; for example, Carlson et al. report that they “find two-to-one odds that human-caused climate change has increased the overall prevalence of childhood malaria across sub-Saharan Africa since 1901” (Carlson et al. 2023). Other studies focus on the magnitude of the observed health impact and the accompanying confidence interval (Vicedo-Cabrera et al. 2021), which has recently been described as an “intensity-based” interpretation (Stuart-Smith et al. 2023). Although the two framings have obvious parallels with probabilistic- versus storyline-based extreme event attribution, for trend attribution, these differences are mostly cosmetic, and reflect different choices about how to interpret the distribution of simulated outcomes.
- **“Event-to-event”**: An end-to-end event impact attribution approach that focuses not on the probability of the event occurring, but on the way that anthropogenic influence on the event shaped its impacts. For example, Vicedo-Cabrera et al. (2023) examined mortality in Switzerland during the unusually warm summer of 2022, compared to a counterfactual based on observed temperatures minus estimated warming due to climate change. (In its construction of a counterfactual, this approach also shares features with some trend-to-trend studies, but we classify it as event-to-event given that the methodology allows the summer of 2022 to be anomalously warm even in the absence of human influence.) This approach would be most rigorously implemented by studies following the storyline event attribution framework (i.e., actually simulating weather phenomena of interest with different forcings, rather than deriving counterfactuals by detrending observations), but we found no such studies that examined a health outcome (see Chapter 3).
- **“Risk-based”**: An end-to-end analysis that directly attaches probabilistic event attribution to a simulation of the resulting health outcomes. Estimated health impacts can be presented several ways, such as a point estimate and confidence interval, the fraction of attributable risk, or the return period of a particular “health event.” For example, Mitchell et al. conclude that due to “the 2003-like mortality event in Paris went from a 1-in-300-year event…to a 1-in-70-year event” (Mitchell et al. 2016).
- **“Fractional”**: A sequential analysis that revisits an independent probabilistic event attribution study, and multiplies the previously estimated fraction of attributable risk by a known health impact to estimate an attributable health impact. For example, Hurricane Dorian caused 356 deaths in the Bahamas in 2019; with an estimated fraction of attributable risk of 0.14 (Reed et al. 2021), approximately 50 of those deaths could be attributed to human-caused climate change (Newman and Noy 2023). This approach can be used when the relationships between health impacts and specific climate variables are hard to quantify, such as for storm-related mortality (Frame et al. 2020); however, its simplicity has attracted some scrutiny (Perkins-Kirkpatrick et al. 2022).
- **“Descriptive”**: A two-step qualitative framework that relies on *post hoc* subjective interpretation of observational evidence that (1) an emerging impact is connected to climate variables, and (2) changes in those variables are attributable to human-caused climate change. This approach has been widely discussed in previous literature on health impact attribution but is problematic in several ways (see below).

These approaches are not mutually exclusive or neatly defined, and some studies could be considered edge cases or fall into multiple categories; for example, studies examining the return period of a particular kind of event over a long interval could also be considered a type of trend attribution. We discuss these categories in more depth in Chapter 3, with at least one study that exemplifies the major features of each (except for the descriptive approach).

What We Excluded from this Report

Land Cover and Land Use Change

While greenhouse gas emissions are the most visible source of human influence on the climate system, other forcings—due to anthropogenic aerosol emissions and land use change—are also important in detection and attribution research. The latter of these poses a definitional problem, given the extensive literature on how land cover mediates excess mortality and other health burdens associated with climate—most notably, through the urban heat island effect (J. Wang et al. 2021; Heaviside, Vardoulakis, and Cai 2016; Jandaghian and Akbari 2021). The first health impact attribution study ever published explicitly tests how urbanisation mediates excess mortality driven by anthropogenic global warming (Oudin Åström et al. 2013), and many other studies discussed in this report use global climate models that include land cover as a source of anthropogenic forcings. However, we exclude studies that examine anthropogenic influence on health outcomes *only* due to land cover from our definition of health impact attribution, instead, we group these studies under the umbrella of health impact assessment.



Descriptive Synthesis

As we show later in this report, health impact attribution is a very new field, and so far, captures only a small proportion of the health impacts that are suspected to result from climate change. For scientists, the existence of detection and attribution as a field—and its widespread perception as the final word in confidence statements—creates a conundrum: how can these mostly "un-attributed" impacts be discussed confidently in reports like the Intergovernmental Panel on Climate Change (IPCC) assessment reports or the *Lancet* Countdown reviews?

One answer to this problem is the descriptive approach to attribution (sometimes referred to as "consistency analysis," or "multi-step" or "sequential" attribution, though as we note above, those terms apply to multiple methods). The descriptive approach is a two-step process for identifying and describing climate change impacts that relies on expert assessment of the literature, and posits that a health outcome can be attributed to human-caused climate change:

1. Specific changes of interest in the climate system have been confidently and consistently attributed to anthropogenic climate change, and
2. Methodologically rigorous analyses (of any kind) show that the same climate variables have caused the observed impacts on humans or ecosystems.

These steps may be spread across multiple studies, and the attributability of a particular impact is generally established after the fact. For example, two of the most widely referenced reviews on health impact attribution (Ebi et al. 2017, 2020) discuss a handful of examples:

- The geographic range expansion of ixodid ticks that transmit Lyme disease has been facilitated by higher temperature (step 2), which has increased due to human-caused climate change in eastern Canada and the northeastern United States (step 1).
- Increased incidence of vibriosis (a water-borne infection with non-cholera *Vibrio* spp. bacteria) in the Baltic Sea is driven by sea surface temperatures (step 2), which are increasing due to human-caused climate change (step 1). Moreover, six major heatwaves between 1994 and 2014 each reportedly triggered vibriosis outbreaks in the Baltic Sea, though no event-specific attribution is cited.
- The 2018 heat wave in Scandinavia caused hundreds of excess deaths (step 2). An event of that intensity and duration was estimated to be between 4 and 100 times more likely due to climate change (step 1).

As these examples highlight, there are several limitations to descriptive attribution. For example, *post hoc* syntheses are prone to unnoticed or unavoidable methodological misalignment between studies: climate variables that are attributed to anthropogenic influence may or may not be the same as those with a demonstrated impact on the health outcome, or the same variables may be analysed at different spatial and temporal resolutions or scales. Moreover, without a fractional or end-to-end framework, researchers cannot isolate the specific health impact that is the result of human-caused climate change—sometimes leading researchers to imply the whole health burden is "attributable." Most importantly, by adding a step involving post hoc synthesis and argumentation, this approach introduces significant subjectivity about evidentiary strength into the process, undermining the unique value proposition of detection and attribution.

As such, the multi-step approach remains a useful way to discuss and synthesise the health impacts of climate change, but end-to-end and fractional attribution studies will contribute more to the growth of the health impact attribution field. In this report, we therefore excluded the "descriptive" framework, treating it more as a framework for evidence synthesis than attribution.

"Reverse" Attribution

Detection and attribution research often grapples with fundamental questions about the types of events and phenomena that are associated with anthropogenic climate change. In some cases, those questions about mechanism and possibility may be easier to ask in broad terms (*Is this kind of phenomenon a likely result of climate change?*) rather than specific historical terms (I*s this specific observation an observed impact of climate change?*). While event attribution normally seeks to understand how the characteristics of an event are different in the current climate, as compared to a counterfactual present-day world without climate change, there is a growing approach that does the same, but uses the future climate state as its counterfactual.

Adapting the same techniques, with similar methodological challenges, the "reverse attribution" approach asks "how will," rather than "how has," human induced climate change alter the characteristics of a specific event. For example, projecting how future sea level rise would affect flooding from a comparable event can make the link between human-caused climate change and storm mortality, displacement, and economic costs (Mitchell et al. 2022). As in the classic detection and attribution approach, the questions are driven by understanding causation, rather than predicting the future.

In some cases, the connections are more explicit: for example, the "Half a degree additional warming, prognosis and projected impacts" model intercomparison project (HAPPI) was developed in parallel to the attribution-oriented Climate of the 20th Century + Detection & Attribution (C20C+) project. While the HAPPI MIP experiments consider future impacts of 1.5 and 2 °C warming compared to a recent baseline, they are also designed for maximum comparability with C20C+ models (Mitchell et al. 2017), allowing researchers to easily address historical and future change in the same study (Shiogama et al. 2020).

These approaches highlight that the distinction between attribution and projection is not always well defined, and that studies of future climate change can help inform efforts to understand attributable impacts. However, we exclude this approach in this report, both to simplify our core definition of health impact attribution (which starts from a focus on historical or contemporary observations), and because the boundaries and strengths of this "reverse" attribution approach are far less defined in the impact space than in climate science.

Chapter 3

Chapter 3: Literature Review

Our Aims

The purpose of this chapter is to provide an overview of published literature in health impact attribution and adjacent fields. Based on a systematic literature review, we identified 13 studies that have quantitatively estimated the health impacts attributable to human-caused climate change. We structure our analysis of these studies around the stages of the research cycle:

1. The community generating research
2. The scientific questions being asked
3. The data that researchers use
4. The methods and software tools used to analyse those data
5. The open science strategies used to disseminate findings.

We conclude with a detailed discussion of major findings and data science frameworks in the closest related areas of research, including the broader field of health impact assessment, other kinds of impact attribution, and related detection and attribution work in climate science.

Our Methodology

The Ideal Study

The criteria by which we identified health impact attribution studies were necessarily subjective: the field is relatively new, and studies vary significantly in scope and methodology. We therefore used five features to guide our search, noting that the ideal study would have all five, but some exceptions might be made due to variation in study design (Figure 3.1):

1. Self-identification as an attribution study
2. A clear focus on distinguishing anthropogenic climate change and natural variability
3. A robust counterfactual climate scenario
4. A clear focus on health outcomes of climate change
5. A robust statistical analysis of health-climate relationships

Although this was not part of the inclusion criteria, several studies also re-used the same core statistical model from their attribution analysis for other aims as well. We paid special attention to four key aspects of study design that maximised these studies' policy relevance (Figure 3.2):

1. Focusing on vulnerable populations
2. Testing for any effect of adaptation to climate risks
3. Translating health impacts to financial cost
4. Projecting future impacts

Figure 3.1
Five core criteria that define a health impact attribution study

1 

Did the study describe itself as attributing a health outcome to human-caused climate change

2 

Did the study try to distinguish the effects of natural variability from anthropogenic climate change?

4 

Did the study identify a specific and measurable health outcome of interest

3 

Did the study's analysis use climate models with a robust counterfactual scenario

5 

Did the study include a statistical analysis of observational health and climate datasets that tests their relationship?

Figure 3.2
Four criteria that make health impact attribution studies more policy relevant

1 

Did the study look for disproportionate impact on specific populations?

2 

Did the study test for the health impact of adaptation to climate over time?

3 

Did the study estimate the financial cost associated with health impacts?

4 

Did the study predict health impacts under scenarios for future climate change?

Search Methodology

We considered the health impacts of climate change as broadly as possible, adapting categories proposed by previous work (Haines et al. 2021):

- **Direct impacts of weather on human health**: direct morbidity and mortality due to extreme heat, extreme cold, and other extreme weather events (e.g., storms, floods, droughts, etc.), including injuries.
- **Indirect impacts on the burden of non-communicable disease**: malnutrition; maternal and child health, including general causes of childhood mortality or disability (e.g., diarrhoeal disease, stunting, miscarriages); and non-communicable diseases, including cancer, diabetes, and cardiovascular disease.
- **Indirect impacts on the burden of infectious disease**: vector-borne diseases (e.g., malaria, dengue or yellow fever, Lyme disease); food-borne diseases; water-borne diseases (e.g., cholera) and other diseases that spread to humans primarily through the environment (e.g., coccidioidomycosis); respiratory and other directly-transmitted diseases (e.g., influenza); and diseases that spread largely through climate-sensitive modes of animal-to-human transmission (e.g., leptospirosis, Lassa fever, hantavirus).
- **Indirect impacts on well-being and mental health**: suicides; mental illness, including depression and anxiety; and health impacts of migration, displacement, and conflict.

To identify relevant literature, we searched PubMed on July 21, 2023, setting no limits on search dates and using a keyword set that aimed to capture relevant methodologies but as wide a range of health impacts as possible (see **Annex 1** for the full keyword set). This search generated a list of 2,259 abstracts to review; of these, 458 studies were relevant to the broad topic of climate change and health, and their full text was reviewed. We also searched Web of Science on September 11, 2023, but we found that these keywords generated significantly more off-topic results, and so narrowed our search of Web of Science to studies with these keywords in the title or abstract. After de-duplicating the search results that were already captured by the PubMed search, we were left with 1,418 abstracts to screen; we again narrowed our protocol slightly, and limited our review to studies that documented an observed impact of climate or weather on a historical or present-day health outcome (95 studies).

In total, we systematically screened 3,677 abstracts, and reviewed the full text of 552 studies in depth. In the second stage of screening, we noted several reasons to exclude studies (Box 3.1):

- Not primary research (i.e., reviews, commentaries, and meta-analyses) (n = 13).
- No explicit health outcome being measured or data included (n = 17).
- Health impacts were analysed in relation to temperature, but not in a framework that related temperature changes to human-caused climate change (n = 301).
- Health impacts were analysed in relation to other climatic drivers (i.e., rainfall, humidity, extreme weather events, etc.), sometimes in addition to temperature; but not in a framework that related those drivers to human-caused climate change (n = 110).
- The study generated projections of future climate change impacts, but not present-day impacts of climate change (even if historical data were used to calibrate a statistical model that might otherwise be eligible) (n = 66).
- An observed trend or health impact was measured, and statistical analysis suggested a relationship with weather or climate, suggesting a possible observed health impact of human-caused climate change, but no counterfactual scenario was used (n = 39).

These categories are not mutually exclusive, and each study was (subjectively) assigned the most relevant reason, but many studies met two or more criteria for exclusion.

After excluding studies based on these criteria, we found a total of three eligible studies from our PubMed search (Vicedo-Cabrera et al. 2021; Puvvula et al. 2022; Y. Zhang et al. 2022); and another three eligible studies in our Web of Science search (Oudin Åström et al. 2013; Mitchell et al. 2016; Vicedo-Cabrera et al. 2023). Given the limitations of the systematic review, we also conducted a manual search of Google Scholar using similar keyword sets, as well as focusing on the publication record of experts identified during the expert elicitation: this led to the identification of another three studies (Perkins-Kirkpatrick et al. 2022; Chapman et al. 2022; Frame et al. 2020). Finally, we conducted a manual search of five preprint servers (arXiv, medRxiv, bioRxiv, ResearchSquare, and SSRN) with heavily simplified keyword sets (e.g., “detection attribution climate change health” and “DAMIP health”), and a cutoff date of September 1, 2023. This led to the identification of four additional studies (Newman and Noy 2023; Carlson et al. 2023; Stuart-Smith et al. 2023; Zhu et al. 2023), one of which was published while the report was being prepared.

Box 3.1
What's not detection and attribution?

Despite significant discussions around definitions, terminology, and the outer limits of detection and attribution, we did not find a significant misuse of terminology or many peer-reviewed studies that miscategorised their approach. Only one relevant study in our sample that self-identified as detection and attribution (criterion 1) was excluded: (Wu 2016) examined evidence that geographic range shifts in Asian bats are consistent with expectations given climate change, a finding that could be relevant to the emergence of zoonotic diseases (Carlson et al. 2022). We excluded this study based on the criteria we specified above, but note that we are aware of no species geographic range shift studies that would meet our criteria, and causal inference to explain biodiversity change is an open challenge (Gonzalez, Chase, and O'Connor 2023). Future work should be careful to ensure consistent and careful use of terminology, and we have aimed here to provide a common and up-to-date source of definitions relevant to impact attribution and assessment.

The Eligible Studies

Based on the result of our systematic literature review, we identified a total of 13 studies—ten peer-reviewed publications and 3 preprints, collectively spanning a decade of work (2013 to 2023)—that attributed observed health impacts to human-caused climate change. Whereas systematic literature review studies are often treated as a non-comprehensive sample of hundreds or thousands of peer-reviewed xfpapers, the field of health impact attribution is small enough that we believe our findings represent a nearly-comprehensive, if not full, picture of the relevant body of work at the time of writing. Nevertheless, the list could become incomplete fairly soon, as interest in attribution continues to grow rapidly.

Table 3.1
Study mapping onto nine methodological criteria for eligibility

Criteria for eligibility	1	2	3	4	5	6	7	8	9
(Oudin Åström et al. 2013)	Blue	Blue	Orange	Blue	Blue	Orange	Blue	Orange	Orange
(Mitchell et al. 2016)	Blue	Blue	Blue	Blue	Yellow	Orange	Orange	Orange	Orange
(Frame et al. 2020)	Blue	Blue	Blue	Blue	Blue	Orange	Orange	Blue	Orange
(Vicedo-Cabrera et al. 2021)	Blue	Blue	Blue	Blue	Blue	Orange	Orange	Orange	Orange
(Chapman et al. 2022)	Blue	Blue	Blue	Blue	Yellow	Blue	Yellow	Orange	Blue
(Perkins-Kirkpatrick et al. 2022)	Blue	Blue	Blue	Blue	Blue	Orange	Orange	Orange	Blue
(Puvvula et al. 2022)	Blue	Blue	Blue	Blue	Blue	Orange	Orange	Orange	Blue
(Y. Zhang et al. 2022)	Blue	Blue	Blue	Blue	Blue	Orange	Orange	Blue	Orange
(Vicedo-Cabrera et al. 2023)	Blue	Blue	Yellow	Blue	Blue	Blue	Orange	Orange	Orange
(Newman and Noy 2023)	Blue	Blue	Blue	Blue	Blue	Orange	Yellow	Orange	Orange
(Carlson et al. 2023)	Blue	Blue	Blue	Blue	Blue	Blue	Orange	Orange	Blue
(Stuart-Smith et al. 2023)	Blue	Blue	Blue	Blue	Blue	Orange	Blue	Orange	Orange
(Zhu et al. 2023)	Blue	Blue	Blue	Blue	Blue	Yellow	Orange	Orange	Orange
Total number of studies	**13**	**13**	**11**	**13**	**11**	**2**	**2**	**3**	**3**
(Total number of edge cases)			(2)		(2)	3)	(2)		

(Key: 1: Study self-description; 2: Focus on human-caused climate change; 3: Use of a counterfactual climate scenario; 4: Focus on a human health impact; 5: Statistical analysis of health data; 6: Focus on impacts on specific populations; 7: Test for, or inclusion of, adaptation in statistical analysis; 8: Estimation of financial losses; 9: Future projections. Blue shows studies that fully meet a criterion; yellow indicates partial implementation or similar approaches; orange indicates that a criterion was not met by that study.)

All but one of the studies we identified met all five core criteria, and 2 to 3 studies each adopted a mix of the additional four (non-essential) approaches (Table 3.1). A handful of methodological edge cases were adjudicated:

- **Use of counterfactual scenarios (criterion 3)**: Two studies used counterfactuals that could only partially resolve human versus natural influence on the climate system. While Oudin Åström et al. describe their mortality estimates as attributable to anthropogenic climate change, their approach predates the more widespread use of natural forcing only climate scenarios in impact attribution studies, and relies instead on comparison between the present day (1989-2009) and a reference period (1900-1929). By today's standards, this methodology would be insufficient for attribution, and in our systematic literature review, we excluded several other studies that use time-period comparison, but make more limited claims about attribution to anthropogenic influence. More recently, Vicedo-Cabrera et al. (2023) simulated a natural climate counterfactual scenario for temperatures in Switzerland in 2022 by using a detrending process, which assumed that recent warming is mostly due to anthropogenic climate change. We excluded a small number of other studies that took a similar but less robust approach (see discussion of (Alonso, Bouma, and Pascual 2011) later in this chapter).
- **Analysis of health data (criterion 5)**: Two studies (Mitchell et al. and Chapman et al.) used an approach that estimated temperature-related mortality from all-cause mortality based on parameters derived in other studies. As such, these studies skip a key step of end-to-end attribution: the formal derivation of response functions from the health data being used for the analysis. Nevertheless, both studies do analyse real observational data on a health outcome – in contrast to similar studies that estimate health impacts attributable to climate change based only on models (Silva et al. 2013).
- **Disproportionate impacts on specific populations (criterion 6)**: Zhu et al. estimated how response functions differed between several major geographic regions, but these differences are not aligned with specific social or economic risk factors.
- **Consideration of climate adaptation (criterion 7)**: Chapman et al. included long-term declines in all-cause mortality in their analysis, and noted that this reflects a type of adaptation, but did not test interactions with climate vulnerability. Newman & Noy compare heat waves in France from 2003 and 2019, and suggest that observed differences in mortality are reflective of adaptation, but conduct no statistical analysis.

We nevertheless include each of these studies given their overall framing and objectives. In the following sections, we discuss these 13 studies in greater depth.

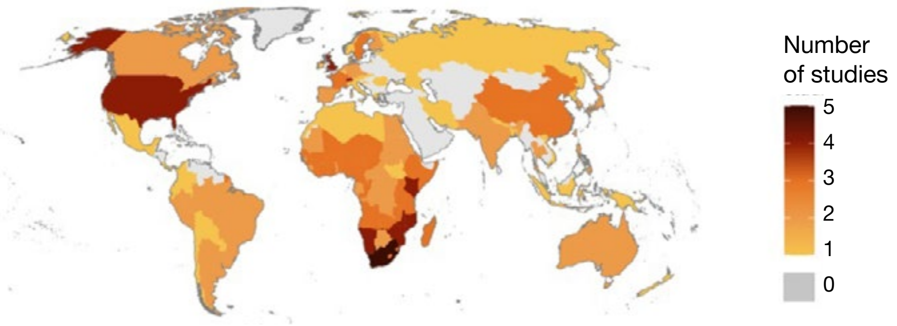
The Community of Practice

Study authors hailed from every continent (Figure 3.3), and only one study (Zhu et al. 2023) was noticeably missing authors from a focal continent examined in their study (Africa). Almost all co-authors from low- and middle-income countries were in middle authorship positions, even on work specific to their part of the world. The only exceptions were in two studies led by China-based teams, and one study with a senior author from South Africa.

These observations may speak to limited capacity in some regions, but also highlight power and funding imbalances found across both climate science and global health (Overland et al. 2022; Abimbola 2019), and indicate an opportunity for improved representation from low- and middle-income countries (LMICs) in attribution research.

Figure 3.3
Geography of study scope and author affiliation

Geographic focus of health impact attribution studies



Lead or senior authorship only

Authorship of health impact attribution studies

The Scientific Questions

Roughly two-thirds of the work conducted on health impact attribution to date is focussed on the direct health impacts of heat (Table 3.2). A small number of studies have also explored mortality from other kinds of extreme weather, impacts on maternal and child health, and most recently, climate-sensitive infectious diseases (malaria) and non-communicable diseases (asthma and diabetes); to date, no health impact attribution studies have explicitly focussed on mental health and well-being. In three cases, we grouped studies with their closest area of interest, but the study addressed multiple categories of health impacts: Chapman et al. focussed on heat-related childhood mortality (mortality due to non-optimal temperatures and child health); Zhang et al. predicted neonatal mortality (mortality due to non-optimal temperatures) and secondary cases of asthma and diabetes (non-communicable disease) resulting from preterm births (child health) due to extreme heat; and finally, Carlson et al. tested the effects of floods and droughts (extreme weather) on childhood malaria (infectious diseases and child health).

The most commonly used health variable of interest was all-cause mortality (8 of 13 studies), but other studies did also examine a handful of other health-related variables, including years of life lost, incidence of low birth weight and asthma, or prevalence of childhood malaria.

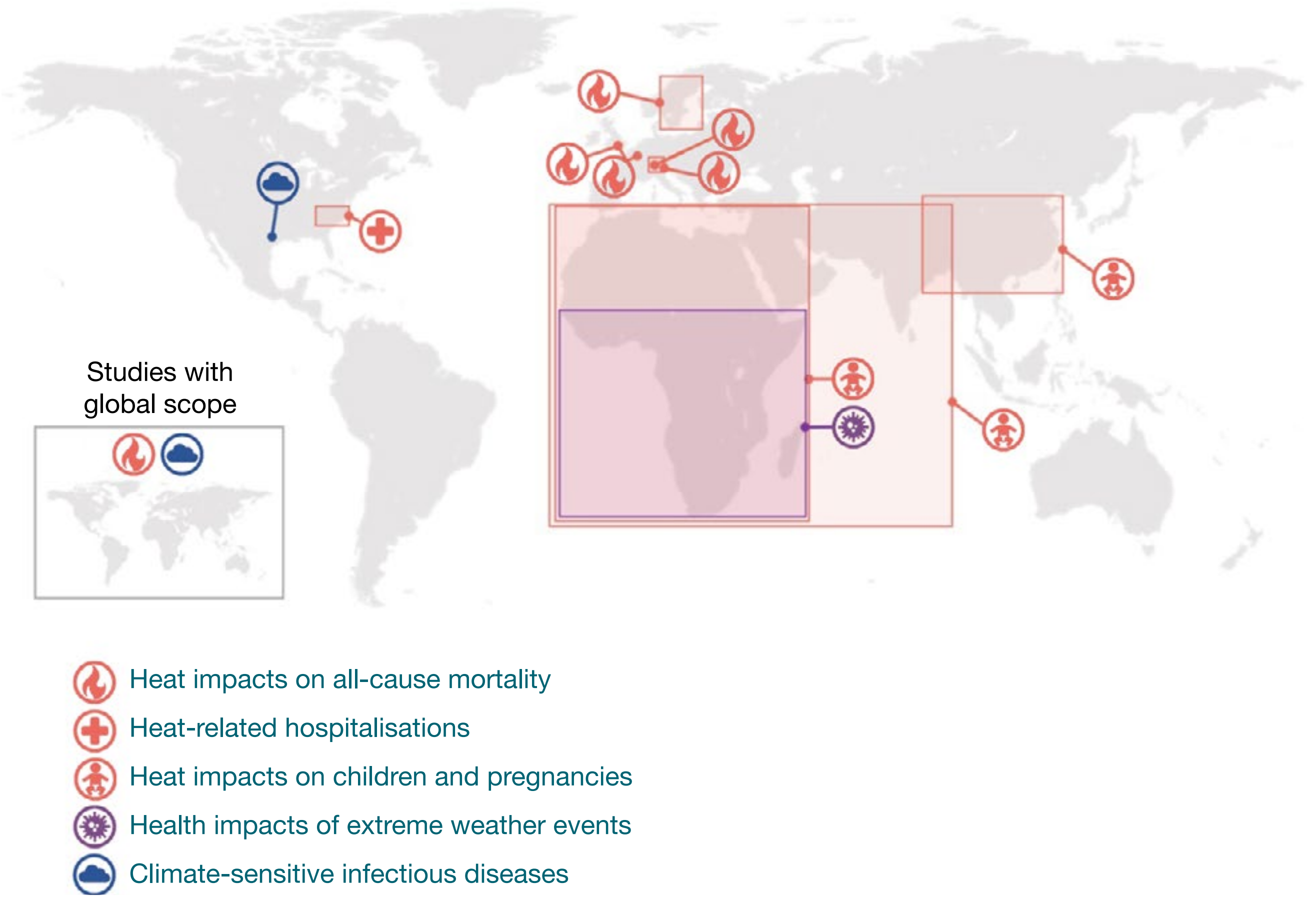
Only a small number of studies (2 of 13) examined datasets with a global extent, but with the notable disclaimer that both have substantial gaps, and neither could fully capture the global impacts of climate change across every region. Of those that were region specific, almost half focussed on western or northern Europe (Figure 3.4); a small handful of studies examined health impacts in Asia, Africa, or the United States. We found no region-specific studies focussed on Australia, Latin America and the Caribbean, or north and central Asia. All five studies that focussed on a specific city or state were restricted to Europe and North America.

Most studies examined long-term trends in climate-related health risks, including the long-term health impacts of rising temperatures. Four studies focussed on specific, individual events: three heat waves (the 2003 heat wave in London and Paris; the 2006 heat wave in London; and the 2022 heat wave in Switzerland) and one storm (Hurricane Harvey in 2017).

Table 3.2
Distribution of research effort by health outcomes of interest

Health impact of climate change	Studies (■)
Non-specific burden of mortality due to non-optimal temperatures	■■■■■■■■
Burden of heat illness and injury due to non-optimal temperatures	■
Burden of mortality from other extreme weather events	■■■
Burden of non-communicable diseases	■
Burden of climate-sensitive infectious diseases	■
Burden on maternal and child health	■■■■
Burden on mental health and well-being	

Figure 3.4
Geographic scope and health impact of the 13 core studies



Understudied Health Impacts

Given the current distribution of research effort, it seems likely that significant health burdens have not yet been formally attributed to human-caused climate change (Box 3.2).

Proportional to both their burden and broader research effort, the most conspicuous gap we identified surrounds climate-sensitive infectious diseases. In the broader climate change impact assessment literature, infectious diseases – especially mosquito- and tick-borne diseases – are one of the best-studied categories of health impacts (Berrang-Ford et al. 2021), but only a single study examined attributable burdens of malaria; no studies focussed on respiratory, water-borne, food-borne, or zoonotic disease burdens. This area is even recognised as a priority for attribution research, with one review discussing a multi-step attribution framework for Lyme disease (Ebi et al. 2017), and another setting out the steps required for a hypothetical trend attribution focussed on the 2019 global surge of dengue fever epidemics (Ebi et al. 2020).

Among the non-communicable diseases, we only found a single study: based on their estimates of attributable preterm births, Zhang et al. (2022) also estimated the resulting burden of childhood asthma, type I and II diabetes, and neurodevelopmental disorders, as well as the economic cost of each. Cardiovascular disease, chronic kidney disease, malnutrition, and mental illnesses and their impacts all also remain notably absent.

Box 3.2
The global burden of climate change

The total health impact was first estimated two decades ago by a pair of reports (McMichael et al. 2003, 2004), which estimated that as of the year 2000, roughly 166,000 deaths a year (and 925,350 disability-adjusted life years (DALYs) lost) should be expected due to five categories of climate change-related health risks: malaria, diarrhoeal disease, floods, malnutrition, and cardiovascular disease driven by non-optimal temperatures. Of these five categories, three—malaria, floods, and heat-related deaths—have now been formally assessed by impact attribution studies. However, so far, no studies have focussed on malnutrition or diarrhoeal disease; both will be key priorities for future work.

Table 3.3
The 2004 McMichael et al. study's global estimates of the health burden of human-caused climate change, broken down by risk.

Health impact	Deaths	DALYs	Region of highest burden
Malnutrition	77,000	2,846,000	South Asia
Diarrhoeal disease	47,000	1,459,000	South Asia
Malaria	27,000	1,018,000	East Africa
Cardiovascular disease	12,000	–	South Asia
Floods	2,000	193,000	Latin America (non-Andes)

Though they predate the first health impact attribution study by a decade, and their estimates were derived through projection methods, the McMichael studies represent an important landmark in the evolution of this field, and have several lessons for future work:

- Most of the health burden of climate change is concentrated in the low- and middle-income countries that are least responsible for the crisis.
- The greatest health burdens of climate change may not just be region-specific, but will likely disproportionately affect specific populations, such as children or the elderly.
- The burden of disability-adjusted life years lost to climate change may be far more dramatic than the apparent mortality cost, and should be estimated where possible.
- Infectious disease represents a key area where climate change impacts could be dramatic but hard to fully capture.

No up-to-date estimate has been published to replace the McMichael study, and given the high degree of methodological heterogeneity of the attribution studies we examined—and the significant time investment and data needs required to generate each—it seems unlikely that the next iteration will be fully based on impact attribution work. Thousands of impact assessment studies have been published since 2003 that could form the basis of a more comprehensive re-assessment; in the meantime, attribution studies may be more useful as a scalpel than a dragnet, untangling the most complicated long-term trends in climate-related health impacts, and estimating the most significant burdens caused by extreme events.

Understudied Climate Phenomena

A number of categories of health-related climate hazards may be important for future work, both to capture new impacts and to better understand well-studied ones:

- Despite the overwhelming focus on the mortality costs of non-optimal temperature, more complex phenomena are understudied. The health effects of extreme cold were the best represented: three of our studies respectively examined trends in cold-related mortality, fractional mortality due to cold waves, and the effects of extreme cold on low birth weight (Oudin Åström et al. 2013; Newman and Noy 2023; Zhu et al. 2023). Oudin Åström et al. also examined the interaction between climate change and the urban heat island effect, but no other attribution studies have since. Only one of our 13 studies examined heat-humidity interactions (Mitchell et al. 2016), and none examined the disproportionate health impact of compound extremes across consecutive days and nights (J. Wang et al. 2021; He et al. 2021). Each of these topics could be an important facet for future attribution work to consider.
- The nexus of extreme precipitation, flooding, and sea level rise is severely understudied relative to their potential impacts. One study examined flood- and storm-related mortality (Newman and Noy 2023), while another examined their mediating effect in malaria transmission (Carlson et al. 2023). Future work should consider these effects in more depth, as well as more complex related phenomena, like shifting monsoon intensity.
- The health impacts of drought are similarly poorly understood. As with floods, two studies examined their direct mortality cost and impact on malaria transmission (Newman and Noy 2023; Carlson et al. 2023). Future work should explore the effect of droughts on malnutrition and related health outcomes like stunting, particularly in relation to the severe drought and resulting humanitarian crisis that has been ongoing in the Horn of Africa since 2020. Future work could also explore the knock-on effects of drought on water insecurity, which in turn increases the risk of diarrhoeal disease (P. Wang et al. 2022), and, due to water storage behaviours, mosquito-borne diseases like dengue fever (Pontes et al. 2000).
- Wildfires were only represented in one fractional study (Newman and Noy 2023). Though attribution can be a key challenge given how many interacting processes drive their frequency, severity, and characteristics, wildfires should be a key priority for future work, given their impacts on mortality, mental health and well-being, and – through the air pollution they generate – chronic cardiopulmonary and respiratory infectious diseases (X. Zhou et al. 2021; Reid et al. 2016).
- Like wildfire smoke, dust storms cause significant direct morbidity and are a risk factor associated with both chronic cardiopulmonary and respiratory infectious diseases (Schweitzer et al. 2018; Aghababaeian et al. 2021). Among the regions where their impacts on human health are a concern (Aghababaeian et al. 2021), climate change is likely increasing the frequency of dust storms in North America and Australia, while trends in east Asia, the Middle East, and the Mediterranean are less clearly resolved (Masson-Delmotte et al. 2021); future attribution studies could prioritise these regions.

The Data

The Health Data

Many studies used public health data sources maintained by government agencies, such as the UK Office for National Statistics (ONS) (Mitchell et al. 2016), China's National Maternal Near Miss Surveillance System (NMNMSS) (Y. Zhang et al. 2022), Switzerland's Federal Office of Statistics (Vicedo-Cabrera et al., 2023), and the North Carolina Disease Tracking and Epidemiologic Collection Tool (NC DETECT) (Puvvula et al. 2022). Sources like these may not be as immediately open to all researchers or the public, but likely contain a significant volume of unique health data that will be essential for future work.

A smaller number of studies also accessed data curated by academic consortia such as the Multi-Country Multi-City (MCC) Collaborative Research Network and the Integrated Public Use Microdata Series (IPUMS). The data in these projects are not openly available, but can sometimes be obtained through, for instance, approval of proposals from steering committees, and ensuring their involvement in the research. Finally, a small number of studies took advantage of open epidemiological datasets that had been directly shared by prior publications (e.g., a compendium of malaria prevalence published by (Snow et al. 2017) was reused by (Carlson et al. 2023); (Y. Zhang et al. 2022) reused data on preterm births in China previously published by (Chen et al. 2019) and (Deng et al. 2021).

The Observational Climate Data

Studies relied on a small handful of sources for observational climate data: for example, four studies used data from the University of East Anglia's Climatic Research Unit (CRU) project (Harris et al. 2020), and a fifth used the European Centre for Medium-Range Weather Forecasts (ECMWF)'s ERA5 reanalysis project (Hersbach et al. 2020). Several studies also used weather station data from global sources like the National Oceanic & Atmospheric Administration (NOAA)'s Global Historical Climatology Network (Menne et al. 2018), or national data sources, like the Swedish Meteorological and Hydrological Institute (smhi.se), the British Atmospheric Data Centre (rdamsc.bath.ac.uk), and MeteoSwiss (meteoswiss.admin.ch).

The Climate Simulations

For global climate models (historical climate models and counterfactual simulations), studies reported that they used data from freely-available sources like the Detection and Attribution Model Intercomparison Project (DAMIP; 4 studies), the Coupled Model Intercomparison Project phase 6 (CMIP6; 3 studies), and the World Climate Research Programme's Climate of the 20th Century + Detection & Attribution (C20C+) project (1 study). Only one study specifically used a climate model to simulate a counterfactual scenario that was targeted towards a specific research question: Mitchell et al. used the software weather@home (Massey et al. 2015) – as did Perkins-Kirkpatrick et al., but only for a separate analysis on financial damages (Perkins-Kirkpatrick et al. 2022; Mitchell et al. 2016).

Studies varied substantially in terms of their approach to counterfactual scenarios. Studies that used data sources like DAMIP or C20C+, or generated simulations using weather@home, all used counterfactual scenarios that fully capture natural variability in the climate system. However, a handful of studies derived their counterfactual scenarios by statistically processing (i.e., some manner of detrending) observational or simulated data themselves (Oudin Åström et al. 2013; Vicedo-Cabrera et al. 2023; Stuart-Smith et al. 2023). These *ad hoc* approaches are generally less robust, and can be harder to evaluate, given how they vary across studies.

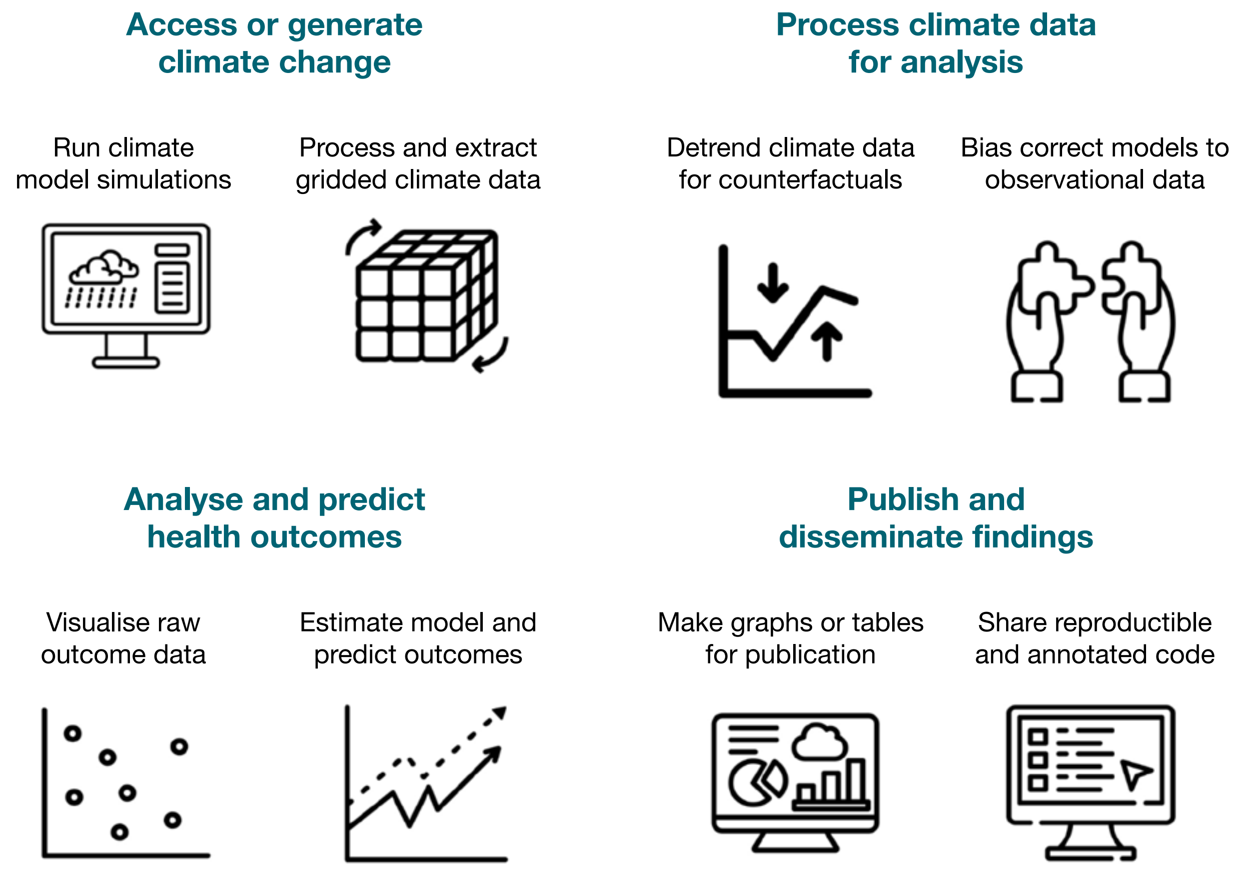
The Methodological Frameworks

Workflow and Software

No two studies followed the exact same methodology. However, each study followed a workflow that involved accessing and processing climate data, accessing and processing health data, deriving the relationships between the two, and predicting, summarising, and visualising outcomes of interest. As such, many studies face the same data science challenges (Figure 3.5), such as working with climate data stored in netCDF files (a compressed format uncommon in other fields), **bias correcting** climate models to observational data (a set of procedures that reduce error and increase the interoperability of the observational and simulated data), or simulating outcomes across space, time, and the full range of uncertainty.

All five studies that reported working with any specific programming languages used the open statistical software R, which has one of the most active communities of practice for academic data science, especially in fields like ecology and epidemiology. Many studies used R packages that implement specific statistical methods, some of which have arisen partly due to needs in the climate-health research space—most notably, the ‘dlnm’ package for distributed lag linear and non-linear regression models (Gasparrini 2011), which are widely used in studies of temperature-related mortality (Gasparrini and Leone 2014). No studies reported using any software packages dedicated to detection and attribution analyses, and it is unlikely that an all-purpose, end-to-end attribution workflow could be well captured by one piece of software, given variation among study designs. However, some of the software pipelines developed for these studies could probably be similarly containerised, and reused for commonly-encountered purposes (e.g., all-cause mortality based on temperature time series for specific locations), feeding into open science initiatives like living studies and real-time attribution.

Figure 3.5
Common data science tasks in a health impact attribution study



The Typology

We classified each study into four broad categories of impact attribution (Figure 3.6). Even in this small sample, we found each of the four main methodologies of impact attribution represented at least once, with most studies falling into the trend-to-trend attribution category. Extreme event-focussed studies were comparatively surprisingly under-represented.

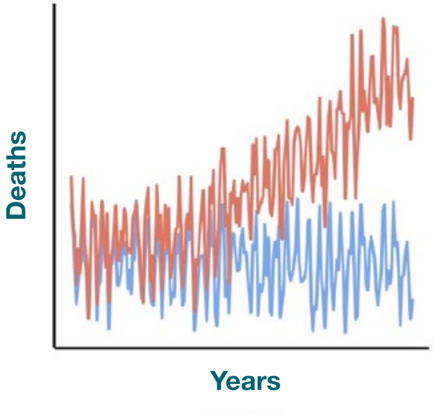
A handful of studies also extended their analyses to address questions with specific relevance to public health. For example, Vicedo-Cabrera et al. (2023) disaggregated estimates within the study population, finding that women over the age of 65 experienced the greatest mortality rate during a 2021 heat wave in Switzerland. Similarly, two studies tested for evidence of adaptation: whereas Oudin Åström et al. found no evidence of adaptation to heat waves in Stockholm between 1980 and 2019, Stuart-Smith et al. found that up to 700 heat-related deaths in Zürich between 1969 and 2018 were averted by adaptation. Stuart-Smith et al. also borrowed a methodology from the more climate litigation-relevant areas of detection and attribution work, and estimated the numbers of deaths attributable to specific fossil fuel suppliers.

A key area for future methodological reflection is how different studies have handled various forms of uncertainty. While studies using the fractional approach are particularly limited in this area, most end-to-end studies reported the uncertainty of their estimates in some detail, with six of the 13 studies' abstracts reporting at least some of their key findings with a confidence interval. Most studies acknowledged two main sources of uncertainty: the statistical uncertainty inherent to the estimation of health-climate relationships, and the compounding uncertainty introduced at the prediction stage by variation among climate models. Handling of the latter source varied between studies: six studies used at least 10 global climate models, and one used 25 (Vicedo-Cabrera et al. 2023), but some recent studies also used fewer models (Zhu et al. 2023; Stuart-Smith et al. 2023), and one used just a single model (Perkins-Kirkpatrick et al. 2022). (We note, however, that the study's aim was to illustrate methodological challenges, rather than produce a robust estimate of mortality.)

A third source of uncertainty that was barely discussed across all 13 studies arises from observational climate data: one study used multiple observational datasets to generate a range of counterfactual scenarios (Vicedo-Cabrera et al. 2023), but no studies examined how sensitive estimates were to different observational data. For health outcomes that have a monotonic positive relationship with temperature, this source of uncertainty might not jeopardise the robustness of inferred trends; for those that display a non-linear relationship or threshold behaviour, differences between observational datasets could be consequential, especially in regions with poor weather station coverage (e.g. central and southern Africa, the Arabian peninsula, the Amazon basin, and Patagonia). Future studies could consider exploring this in more detail, although fully incorporating multiple observational climate datasets into an end-to-end pipeline will require additional effort (due to bias correction) and computing resources (as the number of simulations increases several-fold).

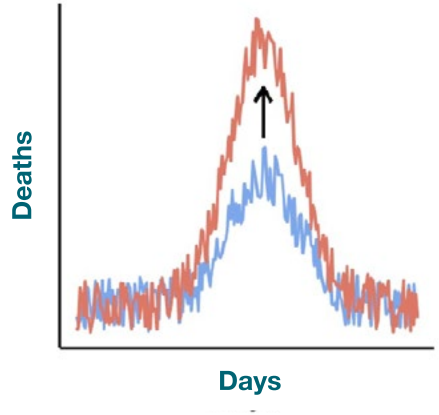
Figure 3.6
Distribution of studies by category

Trend-to-trend



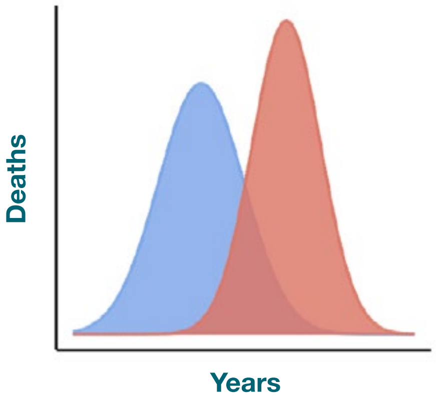
(Oudin Åström et al. 2013; Vicedo-Cabrera et al. 2021; Chapman et al. 2022; Puvvula et al. 2022; Y. Zhang et al. 2022; Carlson et al. 2023; Stuart-Smith et al. 2023; Zhu et al. 2023)

Event-to-event



(Vicedo-Cabrera et al. 2023)

Risk-based



(Mitchell et al. 2016; Perkins-Kirkpatrick et al. 2022)

Fractional

(Frame et al. 2020; Newman and Noy 2023)

One study

Underutilised Methodologies

Published health impact attribution studies show a surprising degree of methodological diversity considering the novelty of the field and the small number of publications. However, some newer approaches are still under-represented. In particular, storyline attribution may be particularly useful for not just future extreme event attribution work, but as a framework for dissecting the anatomy of extreme *outbreaks* as well, such as the unprecedented surges of dengue fever in 2019 or the massive cholera outbreak in Mozambique that followed Cyclone Freddy in 2023. As with extreme climate events, many such events might be well within the range of "natural" variability between epidemics; studies that estimate the contribution of climate change to intensity, severity, duration, or spatial extent of epidemics might better address the core issues that policymakers and the public are interested in understanding.

Future work may also take advantage of newer methodologies for estimating response functions. Most work to date has used tools that are popular for estimating heat-related mortality, such as distributed-lag non-linear regression models; other approaches from climate econometrics, like "fixed-effects" panel regression (S. Hsiang 2016), may be valuable especially in cases where social, economic, and ecological confounders have a comparable or larger influence on disease dynamics than climate. Similarly, machine learning-based analyses might be useful for understanding complex emergent phenomena (Brown et al. 2023).

Another important methodological step will be connecting attribution methods to compartmental epidemic modeling approaches: while some studies have come close (e.g., (Alonso, Bouma, and Pascual 2011)), we found no studies that have fully combined the two methods—or indeed, any approach combining natural and anthropogenic sources of variability in the climate system with the variability in disease processes captured by stochastic, dynamical simulation. Bridging that gap will require substantial computational investment: capturing the full space of uncertainty could require millions of simulations, even before accounting for parameter uncertainty in the epidemiological process. Advances in software tools for epidemic simulation and optimisation will go a long way to make this kind of work possible.

A final challenge we identified for future work is the extension of existing approaches to be maximally relevant to real-world problems. We identified five such approaches in our 13 studies:

1. Estimating disproportionate impacts on specific populations
2. Estimating the benefits of adaptation
3. Estimating the financial cost of health impacts
4. Projecting future impacts under different mitigation scenarios
5. Attributing health burdens to individual emitters.

Developing tools to make these approaches easier to incorporate would go a long way to increasing the relevance of the health impact attribution literature, especially if these approaches can be combined to answer questions like "How many lives could adaptation efforts save in the coming century?" or "What is the cumulative loss and damage due to an unusually deadly cyclone for which each major emitter of greenhouse gasses is responsible?

The Publication & Translation Process

Major Findings

Every study identified a health impact that could be attributed with reasonable certainty to human-caused climate change (Table 3.4). To some degree, this reflects selection bias and publication bias (as well as the limitations of the fraction of attributable risk approach, which is predisposed to identifying non-zero health impacts). However, the attribution statements made by these studies speak strongly to climate change as a public health emergency.

Table 3.4
Health impacts that have been attributed to human-caused climate change

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable impact attribution statement(s)
Non-specific burden of mortality due to non-optimal temperatures	
Heat-related mortality in Stockholm, Sweden (Oudin Åström et al. 2013)	"[T]he number of deaths attributable to climate change over the past 30 years due to excess heat extremes in Stockholm is estimated to be 288." "Not accounting for urbanisation and the urban heat island effect would yield a net reduction of 12 cold spells and 33 lives saved owing to fewer cold extremes. The increase of the number of heat extremes would be even more remarkable with 273 excess heat extremes occurring in 1980–2009, resulting in 447 excess deaths attributable to changes in the frequency of heat extremes." "Mortality from heat extremes in 1980–2009 was double what would have occurred without climate change."
Mortality due to the 2003 heat wave in London, UK and Paris, France (Mitchell et al. 2016)	"In summer 2003, anthropogenic climate change increased the risk of heat-related mortality in Central Paris by ~70% and by ~20% in London, which experienced lower extreme heat. Out of the estimated ~315 and ~735 summer deaths attributed to the heatwave event in Greater London and Central Paris, respectively, 64 deaths were attributable to anthropogenic climate change in London, and 506 in Paris."
Heat-related mortality in 732 populations in 42 countries (Vicedo-Cabrera et al. 2021)	"Across all study countries, we find that 37.0% of warm-season heat-related deaths can be attributed to anthropogenic climate change and that increased mortality is evident on every continent." "The overall estimate that 0.58% of all warm-season deaths are attributable to climate change translates to an average of 9,702 deaths across the 732 locations."

Table 3.4
Health impacts that have been attributed to human-caused climate change (continued)

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable impact attribution statement(s)
Non-specific burden of mortality due to non-optimal temperatures	
Mortality due to the 2006 heat wave in London, UK (Perkins-Kirkpatrick et al. 2022)	"[A]nthropogenic climate change has increased the number of deaths associated with a 1-in-4 year event in London by ten deaths." "[W]hen interested in an event class question, 37%–50% of deaths are attributable to anthropogenic climate change when the mortality rate is at least 60, but if we are interested in the event itself, 17% (10 deaths out of 60) are attributable to the anthropogenic influence on the climate."
Heat-related childhood mortality in Africa (Chapman et al. 2022)	"By 2009, heat-related child mortality was double what it would have been without climate change; this outweighed reductions in heat mortality from improvements associated with development."
Mortality due to the 2022 heat wave in Switzerland (Vicedo-Cabrera et al. 2023)	"2.1% of the all-cause mortality in the summer of 2022 would have been avoided in absence of anthropogenic climate change. This corresponds to 370 deaths and 60% of the observed burden between June and August 2022. As in the observed burden, 60% of heat-related deaths attributed to climate change happened in females (220 vs. 150 in males), and 90% in older adults (330 vs. 39)."
Heat-related mortality in Zürich, Switzerland (Stuart-Smith et al. 2023)	"[O]ver 1,700 deaths attributable to anthropogenic temperature increases in the Canton of Zürich (Switzerland) over 50 years. Changing exposures and vulnerabilities to heat, including due to adaptation, avoided over 700 deaths." "Across the full analysis period, heat-related mortality attributable to climate change was 1.4% of all-cause mortality." "[A]n average of 19 heat-related deaths attributable to anthropogenic climate change occurred each summer in 1969-1985, rising to 48 per summer since 2004....cumulative greenhouse gas emissions of each of the top six highest-emitting investor and state-owned companies caused, on average, at least one additional death per summer in Zürich since 2004." **Note: this study has not been peer reviewed, and quotes are subject to change.**

Table 3.4
Health impacts that have been attributed to human-caused climate change (continued)

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable impact attribution statement(s)
Burden of heat illness and injury due to non-optimal temperatures	
Heat-related hospitalisations in North Carolina, USA (Puvvula et al. 2022)	"Over 4 years (2011, 2012, 2014, and 2015), we observed a significant decrease in the rate of HRI assuming natural simulations compared to the observed. About 3 out of 20 HRI visits are attributable to anthropogenic climate change in Coastal (13.40%) and Piedmont (16.39%) regions."
Burden of mortality from other extreme weather events	
Mortality due to Hurricane Harvey (2017) in Texas, USA (Frame et al. 2020)	"[A]bout 476,000 life-years were lost as a direct damage of Hurricane Harvey with almost 80% of the loss associated with the monetised damages to physical assets. For life-years, we therefore estimate that it is likely that at least 148,000 life-years, with a best estimate of 357,000 life-years, lost were directly attributable to anthropogenic climate change."
Mortality due to 185 extreme weather events in 52 countries (Newman and Noy 2023)	"From the 185 events in the dataset – a net of 60,951 deaths are attributable to climate change – 75,139 deaths that occurred due to climate change in events that became more likely and 14,187 deaths in events that have become less likely due to climate change. The net statistical value of life cost attributed to climate change across the 185 events in the master database is… US$431.8 billion."
Burden of mortality from other extreme weather events	
No studies	
Burden of climate-sensitive infectious diseases	
Childhood malaria in sub-Saharan Africa (Carlson et al. 2023)	"[W]e find two-to-one odds that human-caused climate change has increased the overall prevalence of childhood malaria across sub-Saharan Africa since 1901" "[B]y 2014, human-caused climate change was responsible for an average of 84 excess cases of malaria per 100,000 children ages 2 to 10, with higher elevation and cooler regions in southern and east Africa having greater increases." **Note: this study has not been peer reviewed, and quotes are subject to change.**

Table 3.4
Health impacts that have been attributed to human-caused climate change (continued)

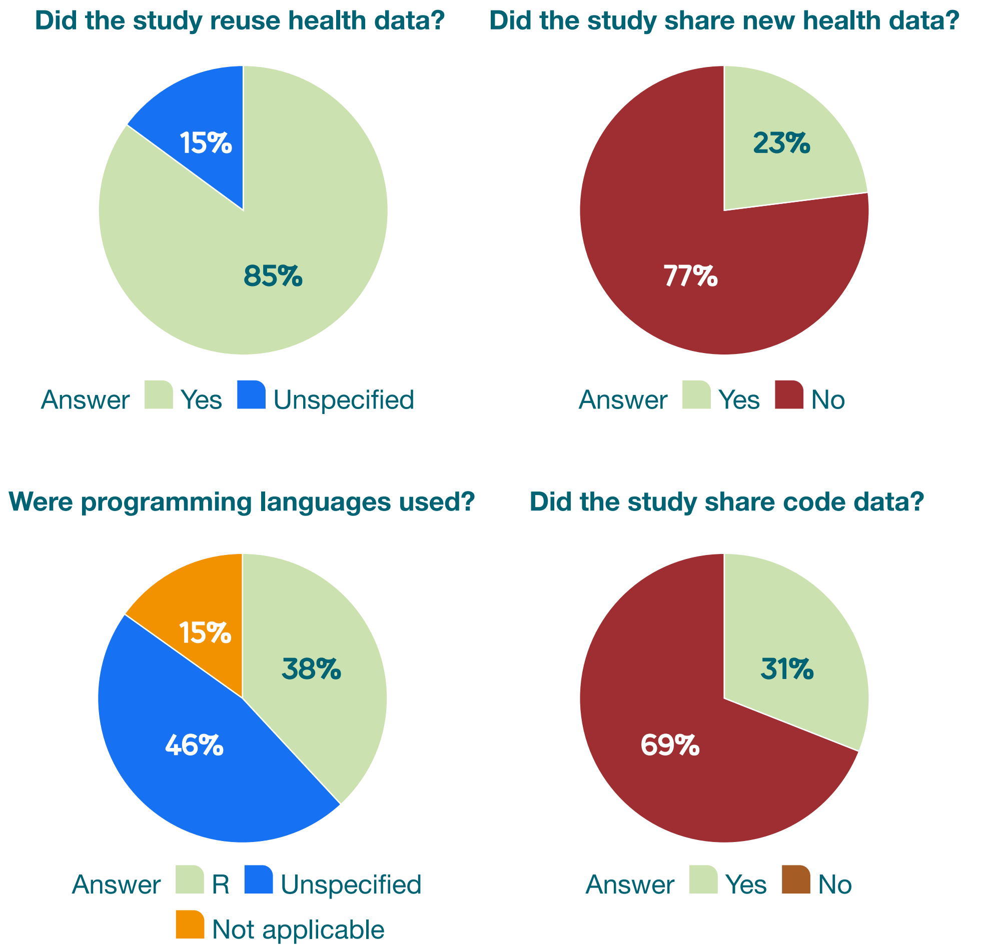
(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable impact attribution statement(s)
Burden on maternal and child health	
Preterm births due to heat waves in China (Y. Zhang et al. 2022)	"[D]uring 2010-2020, an average of 13,262 PTBs occurred annually due to heatwave exposure in China….25.8% of heatwave-related PTBs per year on average can be attributed to anthropogenic climate change, which further result in substantial human capital losses, estimated at over $1 billion costs."
Low birth weight in 31 countries in Africa and south Asia (Zhu et al. 2023)	"Anthropogenic climate change contributed approximately 68.05%, 86.41%, and 76.79% of extreme heat-related LBWs in Southern Asia, Western Africa, and Eastern Africa, respectively, whereas it reduced extreme cold-related LBWs in Central, Eastern, and Southern Africa." **Note: this study has not been peer reviewed, and quotes are subject to change**
Burden on mental health and well-being	
No studies	

Open Science

Five of the studies we identified were originally shared on preprint servers, reflecting the uptake of open science principles in both climate science and public health (particularly after the Covid-19 pandemic, which radically increased use of preprint servers in epidemiology). This is an important step towards community-building: by sharing research findings on preprint servers, researchers invite constructive scrutiny from a broader community than is possible through conventional peer review alone, thereby enhancing the quality and robustness of their findings. Preprints also allow researchers to share policy-relevant findings months to years earlier than they otherwise might, which is especially important for studies focussed on the health impacts of extreme weather events or other time-sensitive topics (e.g., major infectious disease outbreaks). Although this can create opportunities for flawed research to shape public conversations or policymaking, the Covid-19 pandemic has significantly increased public and journalistic literacy about preprints and the need to be cautious about their conclusions.

Figure 3.7
Use of software tools and uptake of open science principles



Once studies were published, many lacked key methodological details needed to independently reproduce their workflow, and only 4 of the 13 studies shared the code to reproduce their analyses in a public Github repository (Figure 3.7); one study also deposited code in a university-specific repository (the University of Bern BORIS repository; boris.unibe.ch). Moreover, studies rarely shared sufficient data to independently reproduce their analyses, reflecting two parallel problems. First, most climate change impact studies point to the source of their climate data but do not reshare the specific files, due to their size (and the resulting cost of depositing data on sites like DataDryad that can support large file sharing). Second, almost all studies reported using and processing external datasets on health outcomes, but very few shared these datasets alongside the publication; for some of these studies, but not all, this is likely due to restrictions on sharing government data.

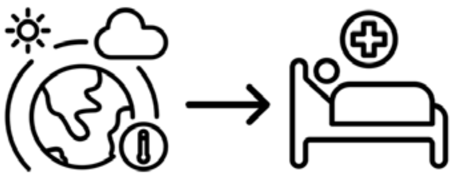
The limited adoption of code and data sharing practices is a significant barrier to replicating and verifying study findings, and creates a non-trivial opportunity for undetected errors, particularly given the complexity of some code pipelines used in these studies. Given public scrutiny on climate science, and relevance to sensitive issues like litigation, reproducibility is fundamental to the integrity and credibility of the field, and represents an important area for problem solving, especially around data sharing platforms and restrictions.

The Adjacent Fields

In addition to our systematic review of health impact attribution studies, we also examined the published literature in several adjacent fields, including broader research on climate change and health, and other areas of detection and attribution research. There are significant opportunities to learn from these fields, especially in terms of scientific gaps and emerging approaches.

Health Impact Assessment

Impact attribution is a small and specialised field of research—and only a small fraction of the broader field of impact assessment. Thousands of studies have measured health impacts attributable to climate and weather, but not necessarily human-caused climate change.



For example, two recent studies estimated global mortality attributable to non-optimal temperatures (Table 3.5). These studies help contextualise exposure to extreme temperatures as a health risk, but they only estimate the health impacts of weather and climate patterns, in general, and do not isolate the health impacts specific to human-caused climate change.

Table 3.5
Major recent estimates of global temperature-attributable mortality

Study	Timescale	Estimated mortality attributable to non-optimal temperatures:
(Zhao et al. 2021)	2000–2019 (averaged)	5,083,173 deaths per year (95% CI: 4,087,967–5,965,520)
(Burkart et al. 2021)	1990	1,224,000 deaths per year (95% CI: 1,132,000–1,312,000)
	2019	1,686,000 deaths per year (95% CI: 1,515,000–1,826,000)

Of the studies that passed our first round of screening, we found that 55% (n = 301 studies; 8% of all search results) did analyse health impacts attributable to temperature, and an additional 20% of excluded abstracts (n = 110 studies; 3% of all search results) addressed health impacts attributable to other climatic variables, such as rainfall, humidity, or extreme weather. Studies in this category collectively address a much broader set of health impacts than our 13 studies, and often address related topics like adaptation and differential vulnerability (Table 3.6).

Table 3.6
Example health impact assessment studies that set the stage for attribution

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable findings
Non-specific burden of mortality due to non-optimal temperatures	
The 2008 cold wave in China (M. G. Zhou et al. 2014)	"The 2008 cold spell increased mortality by 43.8% compared to non-cold spell days with the highest effects in southern and central China. The effects were more pronounced…for females more than for males, and for the elderly aged ≥75 years old more than for younger people. Overall, 148,279 excess deaths were attributable to the 2008 cold spell."
Heat and air conditioning in 311 populations in 4 countries (Sera et al. 2020)	"Excess deaths due to heat decreased during the study periods from 1.40% to 0.80% in Canada, 3.57% to 1.10% in Japan, 3.54% to 2.78% in Spain, and 1.70% to 0.53% in the USA. However, increased air conditioning explains only part of the observed attenuation, corresponding to 16.7% in Canada, 20.0% in Japan, 14.3% in Spain, and 16.7% in the USA.… Our findings are consistent with the hypothesis that air conditioning represents an effective heat adaptation strategy, but suggests that other factors have played an equal or more important role in increasing the resilience of populations."
Burden of heat illness and injury due to non-optimal temperatures	
Injury in China (Hu et al. 2023)	"For per 1 °C increase in daily mean temperature, the cumulative excess risk (CER) of unintentional injury increased by 0.40%. Specifically, drowning (CER = 2.06%) had much higher mortality risk than transport injury (CER = 0.59%) and mechanic force (CER = 0.82%).... However, we also found a negative relationship between temperature and the mortality risk of accidental suffocation (CER = −1.24%) and poisoning (CER = −1.53%)." "Populations living in Western China, people aged 15–69 years, and male may suffer more injury mortality burden from increased temperature caused by climate change."
Stroke, globally (Bo et al. 2023)	"The global burden of stroke attributable to high temperature had an increase trend from 1990 to 2019.… Globally, in 2019, an estimated 0.048 million deaths and 1.01 million DALYs of stroke were attributable to high temperature.…Stroke burden due to high temperature has been increasing, and a higher burden was observed in people aged 65–75 years, males, and countries with a low [socio-demographic index]."

Table 3.6
Example health impact assessment studies that set the stage for attribution (continued)

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable findings
Burden of mortality from other extreme weather events	
Covid-19 mortality and smoke from the 2020 wildfires in the USA (X. Zhou et al. 2021)	"[W]e found that a daily increase of 10 μg/m3 in $PM_{2.5}$ for 28 subsequent days was associated with an 8.4% increase in COVID-19 deaths." "[W]e found a very large estimate of the percentage of total COVID-19 deaths attributable to PM2.5 levels on the wildfire days (77.6%), even after having accounted for many potential confounders. This is due to the fact that 77% (17 of 22) of the total number of COVID-19 deaths occurred during or near wildfire days with very high levels of $PM_{2.5}$."
Global mortality from tropical cyclones (Huang et al. 2023)	"Tropical cyclone exposure was associated with an overall 6% increase in mortality in the first 2 weeks following exposure. Globally, an estimate of 97,430 excess deaths per decade were observed over the 2 weeks following exposure to tropical cyclones, accounting for 20.7% of excess deaths per 100,000 residents (excess death rate) and 3.3 excess deaths per 1000 deaths (excess death ratio) over 1980–2019….From 1980–99 to 2000–19, marked increases in tropical cyclone-related excess death numbers were observed globally, especially for Latin America and the Caribbean and south Asia."
Burden of non-communicable diseases	
Premature mortality due to air pollution, globally (Silva et al. 2013)	"[A]t present, 470,000 premature respiratory deaths are associated globally and annually with anthropogenic ozone, and 2.1 million deaths with anthropogenic $PM_{2.5}$-related cardiopulmonary diseases (93%) and lung cancer (7%).... Uncertainty in [concentration response functions] contributes more to overall uncertainty than the spread of model results. Mortality attributed to the effects of past climate change on air quality is considerably smaller than the global burden: 1,500 deaths yr–1 due to ozone and 2,200 due to $PM_{2.5}$."
Hospitalisation related to chronic kidney disease in China (F.-L. Wang et al. 2023)	"With a 1°C increase in daily mean temperature, the cumulative relative risks (RR) over lag 0–7 d were 1.008 for nationwide. The attributable fraction of [chronic kidney disease (CKD)] hospitalisations due to high temperatures was 5.50%. Stronger associations were observed among younger patients and those with obstructive nephropathy. Our study also found that exposure to heatwaves was associated with added risk of hospitalisations for CKD compared to non-heatwave days (RR = 1.116) above the effect of daily mean temperature."

Table 3.6
Example health impact assessment studies that set the stage for attribution (continued)

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable findings
Burden of climate-sensitive infectious diseases	
HIV in Africa (Burke, Gong, and Jones 2014)	"[I]nfection rates in HIV-endemic rural areas increase by 11% for every recent drought, an effect that is statistically and economically significant. Income shocks explain up to 20% of variation in HIV prevalence across African countries."
Antibiotic resistant bacteria in the USA (MacFadden et al. 2018)	"[I]ncreasing local temperature as well as population density are associated with increasing antibiotic resistance (percent resistant) in common pathogens. We found that an increase in temperature of 10 °C across regions was associated with an increases in antibiotic resistance of 4.2%, 2.2%, and 2.7% for the common pathogens *Escherichia coli, Klebsiella pneumoniae* and *Staphylococcus aureus*."
Burden on maternal and child health	
Post-typhoon infant mortality in the Philippines (Anttila-Hughes and Hsiang 2013)	"[U]nearned income and excess infant mortality in the year after typhoon exposure outnumber immediate damages and death tolls roughly 15-to-1…and additional findings—that only female infants are at risk, that sibling competition elevates risk, and that infants conceived after a typhoon are also at risk—indicate that this excess mortality results from household decisions made while coping with post-disaster economic conditions. We estimate that these post-typhoon "economic deaths" constitute 13% of the overall infant mortality rate in the Philippines." **Note: this study has not been peer reviewed, and quotes are subject to change.**
Stillbirths in the USA (Ha et al. 2017)	"Approximately 17–19% of stillbirth cases were potentially attributable to chronic whole-pregnancy exposures to local temperature extremes. This is equivalent to ~1,116 cold-related and ~1,019 hot-related excess cases in the United States annually…. This incidence translates to ~4 additional stillbirths per 10,000 births for each 1°C increase."

Table 3.6
Example health impact assessment studies that set the stage for attribution (continued)

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable findings
Burden on mental health and well-being	
Suicides in India (Carleton 2017)	"[H]igh temperatures increase suicide rates, but only during India's growing season, when heat also reduces crop yields…[W]arming temperature trends over the last three decades have already been responsible for over 59,000 suicides throughout India."
Outpatient visits for depression in Chongqing, China (Y. Zhou et al. 2023)	"[D]epression outpatient visits were significantly associated with extremely high humidex (≥40)…. [F]emales and the elderly (≥60 years) appeared to be more susceptible to extremely high humidex. The attributable numbers (AN) and fraction (AF) of extremely high humidex on depression outpatients [between 2014 and 2019] were 1709 and 1.10%, respectively."

Studies like these may share several key features with impact attribution studies:

- Similar aims (quantifying health risks of climate change)
- Similar language ("attribution" or "attributable")
- Similar reporting (attributable fraction of risk; total attributable deaths or cases)
- Similar methods (e.g., distributed lag non-linear regression models)
- Hypothesis-testing or estimation of adaptation through time
- Projection of impacts under future climate change scenarios

As such, it can be difficult to distinguish some of these studies from health impact attribution work without close inspection with the criteria used here. However, these points of overlap also suggest that perhaps dozens of statistically-rigorous studies already contain some of the key components required for an impact attribution study, and that their existing statistical models could be readily applied to historical and natural climate counterfactual scenarios (satisfying criterion 2 and 3; see Figure 3.1). In some cases, studies have already begun developing their own counterfactual climate scenarios that approximate that aim, but these techniques are insufficient to fully separate anthropogenic climate change from other variability (see below).

Although non-attribution impact studies will likely continue to be the majority of primary literature in climate epidemiology, the evidence base that these studies comprise is much more extensive, making them an ongoing source of invaluable data for synthesis efforts and policymakers.

The Edge Cases

We found that a handful of methodological frameworks toe the line between impact assessment and attribution—especially when common methods already rely on counterfactual scenarios.

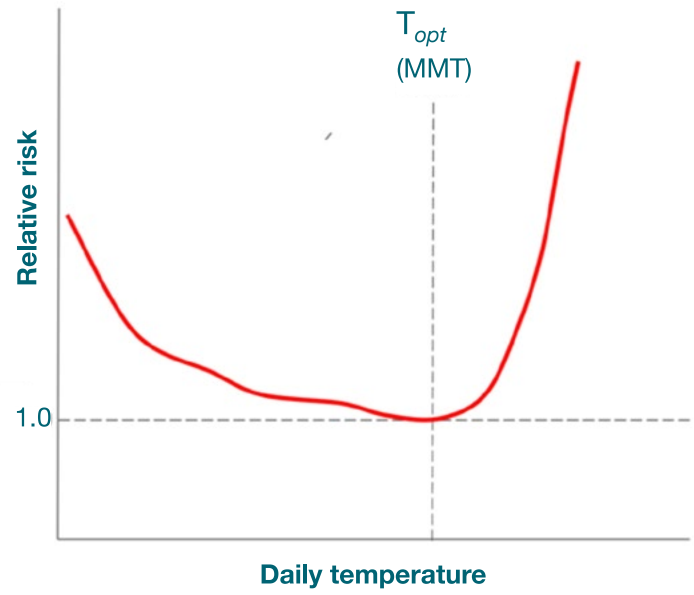
For example, in environmental health research, the most common method for studying mortality-temperature relationships is to:

1. estimate the mortality-temperature curve (Figure 3.8) using a distributed lag non-linear model or similar regression framework,
2. identify the minimum mortality temperature (MMT, or T_{opt}), and recenter the model with the MMT as the reference temperature, such that relative risk at $T_{opt} = 1.0$, and
3. estimate excess mortality due to non-optimal temperatures, by comparing observed mortality to a counterfactual scenario where temperature is fixed at the MMT.

Even without following the methods used in detection and attribution studies, this framework can speak to the health effects of climate change; for example, many studies apply these statistical models to predict mortality under future climate change scenarios (Gasparrini et al. 2017; Lüthi et al. 2023), or test for adaptation by examining how minimum mortality temperatures have shifted through the recent past (Huber et al. 2022). Some studies even use framing developed for the detection and attribution space: for example, one recent study used time-to-return methods to show that once-a-century heat mortality events in a 2000 climate became 1-in-10 to 20 year events by 2020 (Lüthi et al. 2023). We excluded this and some similar studies (Kysely and Kim 2009) from our definition of health impact attribution, given our search parameters (specifically criterion 3), but highlight the convergence in aims and methods, and suggest that in cases like these, the boundaries of detection and attribution are relatively subjective.

In a handful of other cases, we found that health impact assessment studies captured by our literature search had developed detailed counterfactuals for long-term warming trends or extreme events, and used these scenarios to tell a compelling story that was suggestive of climate change impacts. Studies like these highlight the ease with which formal attribution methods (and specifically, models from sources like DAMIP) could be introduced into existing efforts, leading to much stronger inference about attributability.

Figure 3.8
An example analysis of mortality due to non-optimal temperatures



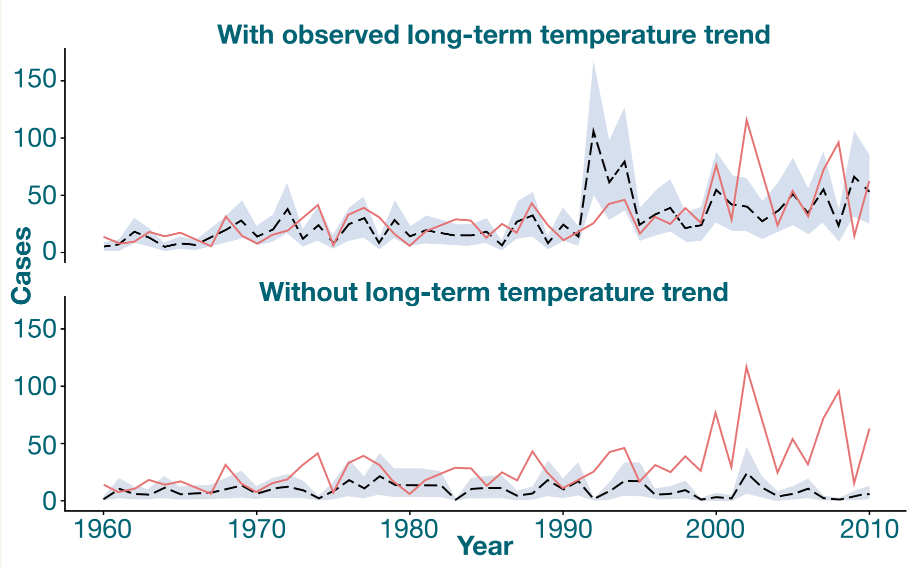
Case Study 1.

Malaria in the east African highlands is driven by rising temperatures.

The early 1990s witnessed a gradual resurgence of malaria in the east African highlands—and the involvement of human-caused climate change has been a hotly debated topic. Alonso et al. developed a compartmental model of human and mosquito population dynamics, and applied it to a long-term dataset capturing malaria incidence at a tea plantation in Kericho, Kenya (Alonso, Bouma, and Pascual 2011). By simulating the same dynamics without a long-term positive trend in temperature (Figure 3.9), they demonstrated that seasonal peaks were eight times higher due to the temperature trend, and that the resurgence was likely implausible without climate change—but they also noted that the observed trend was larger than these simulations could account for, suggesting the involvement of other factors as well.

By some definitions, this could be considered the first health impact attribution study. However, we excluded it here due to the construction of the counterfactual climate scenario, which draws temperatures randomly from observations during the 1970s and applies these to the whole interval. This approach demonstrates an effect of long-term climate change in the region—and those changes are now widely agreed to be driven by human-caused climate change—but the study's design is unable to separate the role of anthropogenic and natural climate variability.

Figure 3.9
Simulated malaria dynamics in Kericho with and without rising temperatures.



(Adapted from Figure 3 in (Alonso, Bouma, and Pascual 2011).
Not real data; only for illustration purposes.
Dashed lines: "simulations"; red line: "observations.")

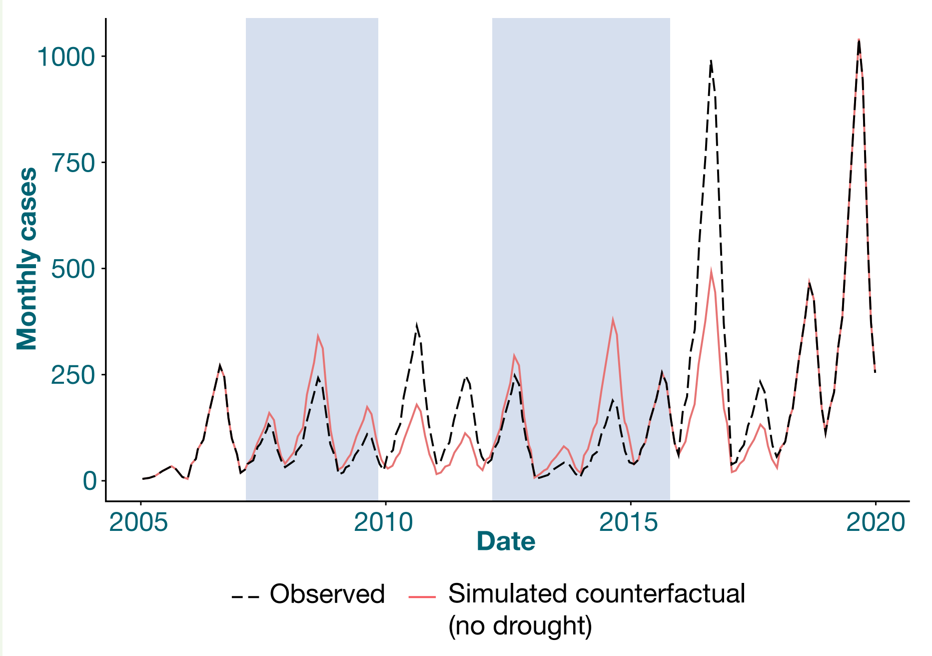
Case Study 2.

Valley fever in California is driven by extreme droughts

Coccidioidomycosis, or valley fever, is a soil-persisting fungal pathogen that has become a growing problem in the western United States. Head et al. investigated simulated epidemic dynamics as a function of temperature and rainfall, and examined the influence of the North American megadrought by simulating the same dynamics in the absence of the 2007-9 and 2012-15 droughts in California (Head et al. 2022). During these droughts, an estimated 1,234 cases and 2,323 cases were averted respectively, but these were offset by an estimated 1,467 and 2,649 drought-attributable excess cases (again, respectively) in the following two years (Figure 3.10).

Although the counterfactual scenario constructed by Head et al. does not distinguish between anthropogenic influence and natural variability, several other studies have attributed long-term increases in drought frequency in California to human-caused climate change, or demonstrated anthropogenic involvement in the severity of the 2012-15 drought (Griffin and Anchukaitis 2014; Diffenbaugh, Swain, and Touma 2015; Swain et al. 2014; Williams et al. 2015).

Figure 3.10
Major droughts mediate valley fever transmission in California



(Adapted from Figure 4 in (Head et al. 2022).
Not real data; only for illustration purposes. Red line: “simulations”; black line: “observations.” Blue boxes show periods of drought.)

Other (Non-Health) Impact Attribution Studies

Deaths resulting from heat waves and storms have been some of the highest-profile early impacts of climate change. As a result, health has always been at the forefront of detection and attribution research. However, impact attribution work in adjacent fields like agriculture, economics, ecology, and geography can offer useful insights into health-relevant impacts (Table 3.7), and can help plan the public health response to the climate emergency.

Table 3.7
Other health-relevant impacts attributed to human-caused climate change

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable impact attribution statement(s)
Impact of anthropogenic climate change on global economic inequality (Diffenbaugh and Burke 2019)	"We find very high likelihood that anthropogenic climate forcing has increased economic inequality between countries. For example, per capita gross domestic product (GDP) has been reduced 17–31% at the poorest four deciles of the population-weighted country-level per capita GDP distribution, yielding a ratio between the top and bottom deciles that is 25% larger than in a world without global warming."
Global desertification of drylands (Burrell, Evans, and De Kauwe 2020)	"We found that, between 1982 and 2015, 6% of the world's drylands underwent desertification driven by unsustainable land use practices compounded by anthropogenic climate change. Despite an average global greening, anthropogenic climate change has degraded 12.6% (5.43 million km^2) of drylands, contributing to desertification and affecting 213 million people, 93% of who live in developing economies."
Longer allergy seasons due to pollen in North America (Anderegg et al. 2021)	"We find widespread advances and lengthening of pollen seasons (+20 d) and increases in pollen concentrations (+21%) across North America, which are strongly coupled to observed warming. Human forcing of the climate system contributed ~50% of the trend in pollen seasons and~8% of the trend in pollen concentrations." "[H]uman forcing of the climate system has substantially exacerbated North American pollen seasons, particularly for pollen season duration and spring pollen integrals."
Global impact of climate change on agricultural productivity growth (Ortiz-Bobea et al. 2021)	"[Anthropogenic climate change] has reduced global agricultural [total factor productivity] by about 21% since 1961, a slowdown that is equivalent to losing the last 7 years of productivity growth. The effect is substantially more severe (a reduction of ~26–34%) in warmer regions such as Africa and Latin America and the Caribbean."

Table 3.7
Other health-relevant impacts attributed to human-caused climate change (continued)

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable impact attribution statement(s)
Global impact of heat waves on poverty (Callahan and Mankin 2022)	"We find that human-caused increases in heat waves have depressed economic output most in the poor tropical regions least culpable for warming. Cumulative 1992–2013 losses from anthropogenic extreme heat likely fall between $5 trillion and $29.3 trillion globally. Losses amount to 6.7% of Gross Domestic Product per capita per year for regions in the bottom income decile, but only 1.5% for regions in the top income decile."
Severe food insecurity in 83 countries (Dasgupta and Robinson 2022)	"[F]or every 1°C of temperature anomaly, severe global food insecurity has increased by 1.4% in 2014 but by 1.64% in 2019. This impact is higher in the case of moderate to severe food insecurity, with a 1°C increase in temperature anomaly resulting in a 1.58% increase in 2014 but a 2.14% increase in 2019."
Populations displaced by cyclone Idai (2019) in Mozambique (Mester et al. 2023)	"[C]limate change has increased displacement risk from this event by approximately 3.1 to 3.5%, corresponding to 16,000-17,000 additional displaced persons."
Economic loss and damage imposed by individual emitters (Burke et al. 2023)	"CO_2 emissions in the US since 1990 have caused ~$2T in global damage through 2020, with India ($293B) and Brazil ($167B) being harmed the most."

These studies share many conceptual features with health impact attribution, struggle with similar methodological challenges (e.g., reliance on generating *ad hoc* counterfactuals), and experiment with similar policy-oriented framings (e.g., attribution of impacts to individual emitters). They generally rely on similar datasets (e.g., the CRU and ERA5 observational climate datasets) and software tools (e.g., the 'nlme' and 'RNetCDF' R packages (Michna and Woods 2013; Pinheiro et al. 2013)), but some problems also require bespoke approaches: for example, to simulate storm-related flooding, Mester *et al*. use the standalone software GeoClaw (Berger et al. 2011) and several named algorithms (Mester et al. 2023). Similarly, we found that studies related to agriculture and ecosystems often grappled with both climate change and land use change as co-occurring causal factors, and used unique algorithms to distinguish their influence (e.g,. TSS-RESTREND; (Burrell, Evans, and Liu 2017)). Given growing awareness of the human health impacts of deforestation and other kinds of land use change, these methods might be directly applicable to some health impact attribution problems (MacDonald and Mordecai 2019; Wolff et al. 2018; Mahon et al. 2022; Potts et al. 2018; Santika et al. 2023).

Future impact attribution studies could continue to offer useful insights into key areas such as:

- **Economic losses**: Extreme heat, cold, and precipitation events have been shown to impact poverty (Hallegatte and Rozenberg 2017; Arga et al. 2020) as well as aggregate economic growth (Kotz, Levermann, and Wenz 2022), with hypothesised channels including agricultural output declines, labour productivity losses, and health impacts, among other mechanisms. Natural disasters influenced by climate change, such as hurricane and tropical cyclone activity, have been linked to long-running economic growth (S. M. Hsiang and Jina 2014; Strobl 2011) and to tax revenues (Ouattara and Strobl 2013), among other economic outcomes.
- **Livestock and wildlife health**: Extreme heat, wildfires, and other climate-related risks can cause sudden waves of mortality in livestock, causing extreme economic losses and potentially acute food shortages (North and Ouweneel 2020). Broader impacts will also ripple through wildlife, leading to unpredictable impacts on ecosystem function and infectious disease dynamics (Carlson et al. 2022; Mahon et al. 2022).
- **Ecosystem and biodiversity change**: Climate-driven geographic range shifts can bring along new diseases with their hosts (Carlson et al. 2022). Biological invasions have been identified as one of the major drivers of human and animal disease risk (L. Zhang et al. 2022; Mahon et al. 2022). Some taxa, such as bats, rodents, migratory birds, and mosquitoes may pose a more direct risk to human health, through pathogens that range from chronic burdens like malaria, to pandemic threats like influenza.

Advances in each of these areas will contribute to the broader mission of understanding the risks climate change poses to global public health.

Health-Relevant Climate Change Attribution Studies

Impact attribution studies may not always be possible, reliable, or necessary. In some cases, it may be easiest to focus research efforts on “direct” attribution of extreme weather events or climate trends that have an obvious relevance to human health (Table 3.8); this approach is particularly useful if health data are limited, or health impacts are difficult to quantify (e.g., poor mental health or stress related to extreme weather). In other cases, detection and attribution studies may find limited or no anthropogenic influence on weather and climate phenomena with notable health impacts, circumventing the need for an end-to-end impact attribution study.

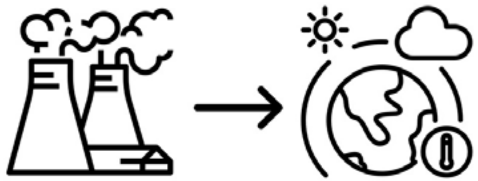


Table 3.8
Example detection or attribution studies focussed on climate phenomena with relevance to human health outcomes

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable detection or attribution statement(s)
Hurricane Sandy in the USA (2012) (Magnusson et al. 2014)	“[T]he [sea surface temperature (SST)] anomaly had a small effect on Sandy’s track in the forecast, but the forecasts initialised with the warm SST anomaly feature a more intense system in terms of the depth of the cyclone, wind speeds, and precipitation.”

Table 3.8
Example detection or attribution studies focussed on climate phenomena with relevance to human health outcomes (continued)

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable detection or attribution statement(s)
Heat waves in the Central Valley, California, USA (Mera et al. 2015)	“[A]nthropogenic greenhouse gas emissions doubled the chances that California’s Central Valley experienced the heat extremes [above 40 °C] observed during the 2000s.”
Attribution of Syrian drought to anthropogenic climate change (Kelley et al. 2015)	“[A]nthropogenic forcing has increased the probability of severe and persistent droughts in this region, and made the occurrence of a 3-year drought as severe as that of 2007−2010 2 to 3 times more likely than by natural variability alone. We conclude that human influences on the climate system are implicated in the current Syrian conflict.”
The 2015 heat wave in Egypt (Mitchell 2016)	“[O]ver Egypt the event was made 69% more likely due to anthropogenic climate change, and this was a similar value of 67% when only Cairo was considered.”
Major tropical cyclones (Patricola and Wehner 2018)	“[R]elative to pre-industrial conditions, climate change so far has enhanced the average and extreme rainfall of hurricanes Katrina, Irma and Maria, but did not change tropical cyclone wind-speed intensity.”
Impact of 2015-like El Niño events on drought, fire, and air pollution (Shiogama et al. 2020)	“There are no significant increases in the chances of burned area and CO_2 and $PM_{2.5}$ emissions exceeding the 2015 observations due to past anthropogenic climate change.” “Historical anthropogenic drying has increased the probability of exceeding the observed values of the burned area (from 5 % to 23 %), CO2 emissions (from 5 % to 23 %), and PM2.5 emissions (from 2 % to 24 %), but these changes are not statistically significant due to the large uncertainties.”
The 2021 Texas, USA cold wave (Doss-Gollin et al. 2021)	“Although specific locations experienced very intense (> 100 year return period) temperatures, we find that for most locations in Texas the temperatures recorded during the February 2021 cold snap had precedent in the historical record.”
2020 heavy monsoon rain in Vietnam (Luu et al. 2021)	“[W]e find that the 2020 event, occurring about once every 80 years (at least 17 years), has not changed in either probability of occurrence (a factor 1.0, ranging from 0.4 to 2.4) or intensity (0%, ranging from −8 to +8%) in the present climate in comparison with early-industrial climate. This implies that the effect of human-induced climate change contributing to this persistent extreme rainfall event is small compared to natural variability.”

Table 3.8
Example detection or attribution studies focussed on climate phenomena with relevance to human health outcomes (continued)

(Note: some quotes are edited to remove parentheticals with uncertainty ranges.)

Study scope	Notable detection or attribution statement(s)
The 2019-2020 Australian bushfire season (van Oldenborgh et al. 2021)	"[C]limate change has induced a higher weather-induced risk of such an extreme fire season. This trend is mainly driven by the increase of temperature extremes." "We find that the probability of extreme heat has increased by at least a factor of 2. We do not find attributable trends in extreme drought, neither on the annual timescale nor for the driest month in the fire season, even when mean precipitation does have drying trends in some models. Commensurate with this we find a significant increase in the risk of fire weather as severe or worse as observed in 2019/20 by at least 30%. Both for extreme heat and fire weather we think the true change in probability is likely much higher due to the model deficiencies."
The 2021 Pacific coast heat wave in Canada and the USA (S. Y. Philip et al. 2021)	"The observed temperatures were so extreme that they lay far outside the range of historical temperature observations. This makes it hard to state with confidence how rare the event was…. [W]e found that such a heat wave event would be at least 150 times less common without human-induced climate change. Also, this heat wave was about 2 °C hotter than a 1-in-1000-year heat wave would have been in 1850–1900, when global mean temperatures were 1.2 °C cooler than today."
Impact of climate change on extreme wildfire growth in California (Brown et al. 2023)	"So far, anthropogenic warming has enhanced the aggregate expected frequency of extreme daily wildfire growth by 25%, on average, relative to preindustrial conditions. But for some fires, there was approximately no change, and for other fires, the enhancement has been as much as 461%."
Days over 50 °C in the Middle East and Mediterranean (Christidis, Mitchell, and Stott 2023)	"[A]t all locations, temperatures above 50 °C would have been extremely rare or impossible in the pre-industrial world, but under human-induced climate change their likelihood is rapidly increasing. At the hottest locations we estimate the likelihood has increased by a factor of 10–103, whereas by the end of the century such extremes could occur every year. All selected locations may see 1–2 additional months with excess thermal deaths by 2100."

These studies use many of the same climate model sources and tools (e.g., DAMIP, C20C+, weather@home) and observational datasets (e.g., ERA5 and CRU) as the impact attribution studies we describe above. Perhaps unsurprisingly, they also engage with a much wider range of data sources, including other observational datasets, such as BerkeleyEarth (Rohde and Hausfather 2020), or national-scale datasets curated by governments (Luu et al. 2021); other modeling projects oriented towards attribution, such as EUCLEIA (eucleia.eu) and EUPHEME (jpi-climate.eu/project/eupheme); and other modeling projects aimed at other purposes such as higher-resolution predictions, such as PRIMAVERA and HighResMIP (Haarsma et al. 2016). Across almost all of these sources, climate data are shared openly and without restriction.

One notable development in these studies is the emerging application of machine learning, which is commonly used in multiple areas of climate change impact assessment, but has historically been under-utilised in detection and attribution studies. For example, one recent analysis used random forests and neural networks to simulate the relationship between climate change and wildfire risk (Brown et al. 2023). Approaches like these are well-suited for complex and multi-causal phenomena like wildfires, and could be equally valuable for understanding complex health risks of climate change—provided that models are mechanism-informed and the community follows best practices for interpretable and reproducible machine learning.

The Future of the Field

The published literature on health impact attribution is growing in real-time. While this report was being prepared, a fourteenth study was uploaded to a preprint server: a trend-to-trend attribution of the global health burden, including both non-communicable and infectious disease outcomes, due to $PM_{2.5}$ air pollution due to wildfires (Park et al. 2023)—a major advance compared to previous work (Silva et al. 2013). Studies like Park et al.'s highlight how much scientific territory remains uncharted in health impact attribution, and the potential for each new study to be both a significant advance and a critical jumping off point for future work.

Chapter 4

Chapter 4: Expert Elicitation

Our Aims

To gain a broad understanding of the researcher community and stakeholders involved in health impact attribution, we conducted semi-structured interviews with experts in the climate-health field, identified through a collaborative process in our team. These experts included researchers in several academic fields, as well as other climate-health stakeholders and decision-makers.

Our Methodology

The Interviews

An interview guide was developed to facilitate a semi-structured interview process, with open-ended questions to allow for a broad range of possible responses. We sought to assess:

- Level of knowledge about, and involvement in, existing research on detection and attribution broadly and its application to human health.
- Perceived barriers to detection and attribution work on health, including data availability for health outcomes, climate data tractability, open source code and software availability, funding availability, and other areas identified through the process.
- Whether gaps in attribution research are responsible for any limitation or distortion of the existing evidence base for climate change as a public health crisis.
- Perceived benefits of detection and attribution language and an underlying scientific evidence base as they might help communicate the health impacts of climate change and thereby motivate social and policy action.
- Priority areas for future research and opportunities for coordination of effort.
- Opportunities for future real-time health impact attribution work.

Interviews lasted between 30 to 60 minutes. We allowed enough time with participants to ensure that adequate data was collected during the interview and continued the process until we reached saturation.

The Participants

A list of experts was generated by the team in collaboration with The Wellcome Trust expertise. This expert database was populated with names, institutions, contact emails, and the name of the team member suggesting the expert. We conducted a tiered prioritisation exercise that adhered to equity, diversity, and inclusion principles, with a specific focus on achieving gender balance and ensuring a well-rounded representation of areas of expertise. We defined the prioritisation criteria in collaboration with the Wellcome Trust.

The expert list contained 72 names, of which a total of 25 participants agreed to being interviewed (Figure 4.1). The group of 25 individuals interviewed exhibited a wide range of expertise. Among them were professionals, including researchers dedicated to assessing how climate change affects health, with a strong focus on detection and attribution. Additionally, there were climate scientists who, while not directly collaborating with healthcare experts, contributed their knowledge to our understanding of climate patterns and trends. Economists and mathematical modelers also participated, deeply involved in studying how climate change impacts the occurrence and severity of extreme weather events.

Moreover, interviewees included epidemiologists who provided specialised insights by analysing disease patterns and health outcomes to uncover possible associations with climate-related variables. Notably, the group of interviewees also featured an infectious disease ecologist, a researcher specialising in the intersection of climate science and legal aspects, a veterinarian with expertise in public health, as well as a scientist with expertise in food-related health impacts, exploring the intricate linkages between climate change, agriculture, and nutrition.

Figure 4.1
Number of interview participants by country

Consenting and Ethics Approval

The semi-structured interview guide, consenting process, and protocol was approved through the Science Faculty Research Ethics Committee at the University of Cape Town. Prior to interviewing, the study purpose and expectations of involvement were explained to the participants. We obtained oral and written informed consent from all participants. Permission was obtained to video record the interviews using Zoom.

Data Analysis

Before conducting interviews, the team regularly convened meetings both internally and with Wellcome Trust staff. These meetings served the purpose of gaining insights into the contextual factors that would influence the opinions and viewpoints of potential participants.

After conducting interviews, the enumerators securely stored the transcripts and notes for data analysis. They prioritised participant anonymisation and confidentiality, adhering to ethical guidelines and regulations. A codebook (spreadsheet) was created to assign code names to interviewees for de-identification and clear reference during analysis.

To transcribe the data, enumerators used Otter (https://otter.ai/). To ensure accurate transcriptions, the enumerators cleaned the data, diligently checking for missing or incomplete data in transcripts. To facilitate data analysis, enumerators developed a thematic analysis framework aligned with project objectives. They further employed manual coding methods to categorise text segments based on specific themes, concepts, and topics of interest.

The State of the Field

Health Impact Attribution at 10 Years

"People are suddenly realising how important detection and attribution work is. I think there's an enormous backlog of evidence and research that we need to fill in as quickly as possible."

"There's always a huge interest in this kind of research. We've never had anyone saying, 'Oh, no, thank you.' It was always, 'Oh, yes, please, and can you do more?'"

Overall, interviewees agree that detection and attribution has an important role to play in the climate-health research space. A diverse group of experts across health sciences, natural and social sciences are involved in health impacts attribution work. Respondents identified a continuing focus on heat-related mortality. Additionally, researchers mentioned forthcoming impact attribution work on infectious diseases, especially vector-borne diseases. Health outcomes attributed to worsened air quality from wildfires were also mentioned. Some respondents mentioned much less-explored health outcomes of climate change, such as multiple sclerosis, suicide rates, and skin-related conditions such as melanoma. Participants noted that less work has been conducted on other direct climatic effects (e.g., cold-related mortality); infectious diseases, including vector-borne and water-borne diseases; respiratory and cardiovascular diseases; malnutrition; or mental health.

Why Health Impact Attribution Matters

Interviewees generally emphasised the significance and urgency of health impact attribution, with three general themes:

Climate change literacy for health impacts. Interviewees stressed the potential for detection and attribution studies to create greater awareness of health impacts among the public and decision-makers, as well as for generating a sense of urgency for action on climate change mitigation and adaptation. Health impact attribution studies could help foster evidence-based conversations about climate change and health that focus on strategies for risk reduction and the urgency of mitigation and adaptation action.

Resource prioritisation. Health impact attribution studies can help identify communities and specific risk groups already being more severely impacted by climate change, and direct funding and other forms of support accordingly, especially for adaptation. At present, limited understanding of the differential impacts of climate change on health conditions makes it very challenging to allocate the limited available resources in an efficient manner. Related to this, detection and attribution studies might also be informative in the allocation of funds for loss and damage across different countries. Attribution studies can also help inform adaptation policy by identifying limits to current levels of adaptation and guide health infrastructure investment. Lastly, attribution evidence can inform future research priorities and funding agendas.

Liability. Many interviewees highlighted the potential importance of health impact attribution research for litigation, by helping to establish the liability of specific emitters for impacts.

Gaps in Research Support, Effort, and Participation

Interviewees identified many important gaps

Participation. Several respondents highlighted the bias in attribution research, with most research conducted by researchers in high-income countries (HICs) and very limited resource investment in low- and middle-income countries (LMICs). A lack of human resources in terms of low numbers of researchers doing health impact attribution work was identified as an important constraint. Respondents identified a clear need for more funding for attribution research work by researchers based in LMICs, particularly in Africa.

> "I would see it as how unbalanced the academic world is in terms of developed countries versus LMICs…and who is most affected by climate change, it's not the places where you have the most scientists."

Research Topics. Participants highlighted that health impact attribution has been disproportionately focussed on heat-related deaths. More research is needed to account for heat-humidity interactions, as well as health impacts beyond heat-related mortality and morbidity, including infectious diseases and mental health impacts. The field also needs to expand beyond attribution of health impacts from heat waves to other kinds of extreme climate and weather events with high potential for attribution of health impacts, such as floods and wildfires. Finally, there is also a crucial need to focus on health impacts attribution research for vulnerable groups such as children, the elderly, pregnant women, and indigenous populations, and on health outcomes relevant to LMICs.

> "I think if there was dedicated funding for people in…the global South, specifically in Africa… that's the place that I see that has the biggest gaps in data. You have the fastest growing population and you have the fastest growing urbanisation projected in the next 50 years…. So I think you'd get a lot more bang for your buck by focusing on research groups that are living in and dedicated to doing projects in Africa."

Funding. There has been very limited funding for health impact attribution research, especially for researchers in LMICs. Respondents also reported difficulties in accessing funding in HICs. One important reason given for this is that research funding tends to operate in silos, with different disciplines having different mainstay funders, and health funding proposal review panels operating independently from climate change funding review panels. There was also a perception that health impact attribution research can be politically sensitive in HICs, and might not be funded for this reason. Experts agreed that the lack of funding has limited research and has also prevented establishment of research networks on health impact attribution.

The Challenges

Data Availability, Access, and Sharing

Health data. Lack of geo-located, publicly available, and accessible health outcome data is a major barrier to health impacts attribution research. Difficulty accessing health impacts data and lack of data were highlighted as barriers especially for LMICs in Africa and Asia. The absence of climate-related health impact monitoring systems was highlighted as a barrier. This means the long-term datasets often needed for health impacts attribution are not available. For specific health impacts, like heat-related mortality, daily death registration data were highlighted as important for being able to link a health impact to a particular temperature event, but these are often unavailable in LMICs contexts without electronic health records. The lack of a dedicated platform for experts from different fields to exchange data, methods, and collaborate on health impact attribution was also highlighted as a barrier to research.

Climate data. Availability and coverage, both spatial and over time, of climate data and data access were highlighted as major barriers. The sparse spatial coverage of ground-based weather stations and the lack of regularly reporting weather stations in many LMICs may introduce biases in observed climate data products, and also limits availability of the high temporal and spatial resolution observational data needed for statistical analyses.

Although global gridded climate model data are available online, access to these climate model data is constrained by lack of computational resources in many contexts. A further challenge is generating bias-corrected climate model data, which requires expertise often not readily available to health researchers. Respondents also highlighted the difficulties of integrating climate data and health impacts data that are captured at different spatial and temporal scales.

> **"It's clear that climate health issues, including attribution, are fundamentally hamstrung by data availability."**

> **"If you want good detection and attribution, you generally need to have good time series of observations. And if you want to have good time series of observations, generally developed countries have better, longer, more homogenous time series of observations than LMICs."**

> "I think a lot of climate scientists don't realise how complicated it is on the health side, how many possible causal factors are going on."

Converging on a shared vocabulary. Differences in terminology between climate science and epidemiology may be creating a key point of confusion that holds both fields back. Respondents working in health-related fields highlighted the long history of causal inference research in health, including as it relates to climate change. To some researchers in public health, this much broader evidence base (discussed in this report as "impact assessment") revolves around the attribution of disease burden to explanatory variables related to climate change, and the term "attribution" may be used interchangeably to discuss both categories of work, to the detriment of shared understanding. This distinction is more than semantic: some categories of climate policy work may require the specific evidentiary standards used in health impact attribution; diluting what counts as "detection and attribution" will only reduce the impact of this work. At the same time, this tension highlights the need to take advantage of the (much broader, and more complete) body of existing work in impact assessment, which still unequivocally supports climate change as a public health crisis, and points to numerous solutions; most life-saving adaptation measures can be implemented without specific support from attribution studies.

Methodology shapes impact. Different methodological approaches to attribution can have different policy messages and implications for emphasising either the importance of reducing greenhouse gas emissions or the importance of adaptation actions. A probabilistic approach saying an extreme weather or climate event was 'X' many times more likely because of anthropogenic greenhouse gas emissions places emphasis on much-needed mitigation action, and can provide evidence for liability for loss and damage from historical emissions. However, a probabilistic approach may not be as useful as other approaches such as the storyline approach for identifying the need and potential for adaptation actions at national or subnational levels.

> "I often hear climate scientists say there hasn't been much attribution done in health. And what they mean is that it hasn't been called attribution when you do a word search because it's called, you know, risk factors. There's different terminology being used."

“The probabilistic approach… it doesn’t give you agency… The storyline approach has the benefit of identifying where the agency is, and it might be at the household level, …village level, …community level, …government level… that might have been able to do something to reduce some of the harm.”

Collaboration across climate and health. Health impact attribution is a field where research experiences are not being shared widely, and research groups in climate and epidemiology operate in silos with relatively little cross-disciplinary communication or collaboration. The highly interdisciplinary projects needed for health impact attribution research are often significantly more time and resource intensive to establish. A lack of funding incentives to set up platforms for interdisciplinary communication and for establishing networks between climate and health disciplines for impact attribution is an important constraint.

“These sorts of interdisciplinary projects, which take up a lot more time, but are likely much more interesting, get shelved just because we don’t have the resources or energy to put into them, which is a real shame.”

The Role of Data Science

Respondents were able to identify a number of barriers and opportunities related to digital tools for data collection, access, processing, storage, and analysis.

Digital tools. Overall, interviews suggested that investment in digital tools could help improve data collection, and that investment in computational resources and training is critical for increasing research participation, especially for researchers in LMICs. Respondents did not identify a lack of software or digital tools as a general foundational problem for data analysis.

Data collection, access, and processing. An important challenge is limited availability and access of long-term, high quality health outcome data, especially in LMICs. Increasing support for electronic record keeping of health outcomes could enable collection of higher temporal resolution datasets, such as daily death registration, that can be more precisely matched with weather and climate events.

Another challenge is access to appropriate climate data. Reducing the need for each attribution research team to generate their own bias-corrected climate model dataset could make it easier for teams of health scientists to pursue questions of interest. One solution could be creating bias-corrected climate model datasets that are easily accessible to a wide range of researchers, and that can be used for many health impact attribution modeling purposes across many regions. However, without supporting large-scale investment in weather stations and their upkeep, limitations on coverage of weather station data in many LMIC regions is expected to remain a challenge for deriving high quality climate data for impacts attribution.

Data analysis and training. Most public health researchers are not accustomed to handling large, high-dimensional climate datasets. Respondents highlighted the need for training and capacity building for health scientists in how to interact with and manipulate climate data to match the spatial and temporal scales of health data, including training on software for climate data manipulation. The lack of training and capacity building for researchers to deploy health impact attribution methods was cited as a challenge.

Some respondents finally highlighted the need for diversifying statistical approaches beyond panel regressions for impact attribution, and for development of new statistical approaches and higher resolution climate models to better capture climate phenomena at spatial and temporal scales more closely matched to health outcomes.

The Future of the Field

> "It's so important to invest in this area, so that we can monitor the effects of climate change on health more effectively and more accurately than we are at present."

Across respondents, we identified three major priorities: 1) building better systems for data collection, access, and processing; 2) increasing support for interdisciplinary work; and 3) increasing training and research funding for new experts, especially funding for research groups in LMICs to lead research projects.

Some more granular recommendations synthesised from the interviews include:

1. **Closing gaps in health data:**
   a. Invest in new long-term data collection on climate-sensitive health outcomes at fine spatial and temporal resolution (e.g., daily) – especially in LMICs.
   b. Improve access to existing health data, including by supporting data digitisation and data synthesis, especially for key outcomes like all-cause mortality.
2. **Fostering scientific collaborations:**
   a. Establish funding opportunities that support existing platforms for collaboration, data sharing, and training activities across climate, health, and social sciences.
   b. Establish funding opportunities that help researchers form new climate-health research teams that can break down cross-disciplinary barriers.
3. **Centering health in attribution science:**
   a. Fund research on more diverse health impacts of climate change, and increase the involvement of health professionals, whose expertise is essential for unpacking the complex pathways underlying climate-sensitive health conditions.
   b. Enhance health impacts attribution research through co-creation with decision-makers to increase relevance of research for climate action.
4. **Enhancing capacity at the frontlines:**
   a. Increase funding for research groups in LMICs to lead research projects.
   b. Enhance access to training and infrastructure for climate- and health-related data science, data analytics, and attribution methods, especially in LMICs.
5. **Building climate-health monitoring systems:**
   a. Invest in new weather stations in regions with sparse weather station networks and high potential for health impacts from climate change. This includes co-location of nodes in climate impacts and weather monitoring networks.
   b. Develop real-time platforms for monitoring the health impacts of climate change—including health impact attribution studies—that coordinate across national governments, meteorological services, health systems, and international organisations (e.g., the IPCC, UNFCCC, WMO, and WHO).

Chapter 5

Chapter 5: Opportunities for Future Work

Our Priorities

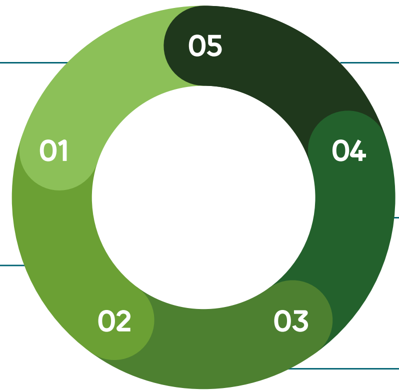
Given the current state of the climate crisis, we believe that today, every facet of health impact attribution—the size of the community of practice, the limited toolkit of methods, and the small handful of evidentiary statements—is lacking. Meaningful change will require considerable investments in the field as a priority area for climate and health research and practice. There are substantial opportunities for funders to support innovative and urgent research in this space. In this chapter, we group our recommendations based on the research cycle (Figure 5.1):

1. The development of a well-supported community of practice
2. The prioritisation of impactful and policy-oriented scientific questions
3. The generation, sharing, and processing of new and established health and climate datasets
4. The continued development of innovative methodologies and better tools to implement them
5. The translation of findings through peer-reviewed publication and other faster channels.

Figure 5.1
Improving the research life cycle in health impact attribution

Engaging new researchers
The only path to more health impact attribution research is to engage more scientists in the specialised tools and methods required for attribution studies.

Designing questions
Understudied geographic regions and health burdens of climate change need to be addressed – and the backlog of un-attributed impacts is growing.



Publication and dissemination
Rapid assessments, living studies, and standardised reporting call all increase the visibility of the climate crisis - and better inform scientific synthesis and policy.

Analysis and simulation
Standardised analysis with cleaner code - running on high-performance computing clusters, and shared on Github - will make research more reproducible, and lower the barrier to entry in future work.

Getting the data
Researchers need easier ways to access and manipulate observational climate data and climate models, and health data capturing new kinds of impacts.

The Community of Practice

Bridging Disciplinary Gaps

One major finding of the expert elicitation was that a significant amount of the work happening in the health impact attribution space is only organised through small, informal collaborative networks, rather than formal collaborative networks or as part of broader climate programmes. Funding more established and visible open science programmes could lower the barrier to entry for interdisciplinary work, especially for researchers looking for specific expertise or data science skills (e.g., bias correction). These kinds of coordinated efforts could be a co-leadership opportunity with experts from the health sciences, who can best advocate for work on under-studied impacts and regions and can actively pursue expertise from other under-represented fields relevant to climate change impacts on health, such as economics, agriculture, or behavioural sciences. Similarly, these programmes can help support cross-disciplinary research on the legal and policy implications of health impact attribution research, including relevance to key issues like litigation or loss and damage financing mechanisms.

Building Expertise at the Frontlines

One of the most urgent problems is the high level of specialised knowledge required for researchers – even those with a strong grounding in climate epidemiology – to contribute to the field of health impact attribution. Interviews revealed that the active community of practice in health impact attribution is incredibly small, and almost entirely concentrated in the Global North; the literature review further showed that while a number of LMIC coauthors are included on studies as collaborators on the health aspects, they seldom sit in the role of lead or senior author. These dynamics are reflective of broader injustice in both the global health and climate change literature. Moreover, all health risks are context specific, and region-specific expertise from the Global South – especially from public health researchers and clinicians – is a prerequisite for robust study design and interpretation.

One path forward, suggested nearly unanimously by interview respondents, is to train and fund new researchers, including those based in LMICs and working at the frontlines of climate change impacts, and particularly those who are familiar with health impacts of climate change beyond simply heat (e.g., infectious disease epidemiologists or psychologists); as well as a substantial increase in funding for research groups in LMICs (especially in Africa) to lead attribution research projects. Building a community for climate-health researchers that unlocks key methodological steps—especially for working with climate data (e.g., bias correction, statistical downscaling)—would give health researchers more agency in shaping the field, and reduce the dependence of a small number of Global South experts on a small handful of Global North climatologist collaborators who can execute these methods. Funding on-site or remote computing resources would go even further to support their autonomy, and is ultimately inseparable from building new climatology experts.

Other successful funding schemes may have important lessons for how to structure this work. For example, the Degrees Modeling Fund (degrees.ngo/dmf) has supported 150 researchers from 21 low- and middle-income countries to conduct basic research on solar geoengineering. Some of the programme's defining features – limiting the use of funds to Global South institutions; region-specific efforts to fill participation gaps within the Global South (rather than treating it as one entity); hosting training workshops around the world that pass on not only modeling expertise but also pre-packaged climate data for impact assessment work; leadership of research by Global South researchers – could be adapted to the climate-health area.

The Scientific Questions

One of the highest-impact ways we identified to move the field forward is to incentivise research that pursues new questions about health risks, climate phenomena, or their linkages. The most impactful efforts might be those that address never-quantified health outcomes, including major escalating infectious diseases (e.g., cholera; dengue fever), chronic burdens that reduce life expectancy (e.g., diabetes; chronic kidney disease; climate change-related cardiorespiratory impacts of air pollution), and mental health impacts. Defining these questions and selecting appropriate health outcome data will require additional funding for relevant health experts in those medical specialties, and an increase in the overall involvement of health disciplines.

Future work could aim to borrow more from environmental health and generate estimates that address disproportionate impacts on the most vulnerable populations, including children, the elderly, racial minority and indigenous communities, migrants and displaced persons, workers with significant environmental exposure, and unhoused persons. Similarly, future work could better incorporate the impact of adaptation measures, going beyond non-specific changes in the risk relationship to identify which interventions (e.g., air conditioning; green space; vaccines; universal health coverage) produce the greatest or most cost-effective reductions in mortality.

The Data

Both our literature review and expert elicitation identified data as the most significant bottleneck for future work that asks new questions about climate change impacts on health, and one of the most significant blockers in terms of the technical barrier to entry for new researchers. Solving these problems means surfacing new health data, and making climate data more tractable.

Digital Solutions for Health Data

We identified access to health data as one of the biggest factors limiting attribution work. Major challenges include: moving past all-cause mortality data to epidemiological datasets with specific causes of morbidity and mortality; accessing data disaggregated by factors such as age, gender, race, housing type, and income, to permit research on differential vulnerability and impacts; balancing work with potentially identifiable clinical data, especially curated by governments, with the need for reproducibility and transparency; compiling datasets across countries; and accessing non-digitised health data.

These problems are an area where digital technologies could substantially enhance future work:

- Some of the most important data will likely be curated by long-term academic programmes: while open data shared alongside publications or in data repositories (e.g., DataDryad, Figshare) are useful, those data may not be easy to find, and are accompanied by minimal research support. Even if data are shared, key variables such as geolocation and date of health outcome are often removed or coarsened, rendering these data unusable for impact research, where temporal and geospatial linkage to climate-related predictors is necessary. Public online interfaces like those curated by the Malaria Atlas Project (malariaatlas.org) or the IHME GHDx data portal (ghdx.healthdata.org) offer more to researchers, helping them search through large compendiums of data to find what they need more easily, and visualise dataset coverage and structure before beginning their work.
- Many of the academic datasets of sufficient regional scale for impactful work take years or even decades to synthesise (e.g., (Snow et al. 2017)). Tools for semi-automated data mining from peer-reviewed literature through natural language processing could accelerate future efforts to develop transnational, synthetic datasets, particularly focussed on infectious disease prevalence, incidence, or outbreak occurrence. However, the use of these tools may be hindered by journal paywalls – an ongoing barrier to open science.
- Disaggregated epidemiological and clinical data are mostly gathered and curated by either the healthcare sector (e.g., clinics, hospitals, and firms maintaining electronic health records) or by surveillance systems (i.e., health ministries). Many of these data are protected for privacy or security reasons, making them laborious for researchers to access, and any available software interfaces are often either deprecated, outdated, or in a constant state of flux. Engaging stakeholders in data-driven partnerships could help surface new sources of high-resolution data, and prioritise efforts to develop new software interfaces to those data that allow researchers to access them easily while managing privacy and security (e.g., OpenSAFELY, which provides access to electronic records from the UK National Health Service (Andrews et al. 2022)).
- Where clinical data cannot be easily or safely surfaced, federated learning (a framework for machine learning trained on datasets stored in several separate locations) is becoming a widespread practice in different kinds of machine learning work with digital health data (Brisimi et al. 2018; Rieke et al. 2020), and could be used to estimate health-climate response functions in a methodologically robust way that accesses transnational or private sector data sources.
- An even more transformative option would be increasing engagement—from public health broadly, and specifically the climate-health community of practice—with open-source programmes like the global.health initiative, the first open online repository of deidentified line-level epidemiological data (Benjamin et al. 2022). So far, these platforms have mostly been deployed in outbreak response settings, and have yet to be used in this area.

All of these solutions should be proposed, considered, and implemented with data justice as a first principle. Filling health data gaps in South America, Africa, and Asia could lead to work that provides a clearer view of climate injustice, but parallel challenges around genomic sequence data sharing—most notably in the Covid-19 pandemic, but also a decade earlier in the 2009 influenza pandemic—highlight the core tension in global data governance: in a world where the right to science is not equally realised, it is not enough for scientific progress anywhere to be a public good everywhere (Phelan 2020). Global North researchers will continue to benefit the most from Global South health data unless active steps are taken to ensure that data access is approached without an entitled or extractive dynamic; that both health and climate experts in LMIC settings are equal partners with leadership roles; and that the benefits of the research are shared equitably.

Digital Solutions for Climate Data

Climate models are generally coordinated through major initiatives (usually called **model intercomparison projects**, or MIPs), creating a key entry point for data science-oriented solutions. Several existing or new MIPs are pursuing work relevant to health impact attribution:

- At least two existing projects are designed specifically to support detection and attribution studies. The Detection and Attribution Model Intercomparison Project (DAMIP; damip.lbl.gov) (Gillett et al. 2016) supported 4 of our 13 studies; the "Climate of the 20th Century + Detection & Attribution" (C20C+; portal.nersc.gov/c20c/data.html) (Stone et al. 2019) project supported a fifth study.
- The forthcoming Large Ensemble Single Forcing Model Intercomparison Project (LESFMIP) (Smith et al. 2022) is a new initiative focussed on the attribution of longer-term unusual weather (e.g., major droughts or other phenomena that span several years). LESFMIP will run a similar setup to C20C+, although it anticipates smaller sample sizes, with a minimum recommendation of 10 ensemble members.
- The Inter-sectoral Impact Model Intercomparison Project (ISIMIP) (Warszawski et al. 2014) provides a systematic framework for processing climate data from various initiatives, and formatting it to be useful to a range of impact models, including those related to human health (Leedale et al. 2016; Gasparrini et al. 2017; Guo et al. 2018). To achieve this, ISIMIP employs a shared bias correction method (Hempel et al. 2013) that is applied to multiple impact-related variables, across various scales. Although their primary focus is not attribution at present, ISIMIP is gradually venturing into this area: for example, a detrending method called ATTRICI has been developed and used to generate counterfactual scenarios for ISIMIP3a (Mengel et al. 2021; Park et al. 2023).

Across these projects, relevance to health impact attribution can be maximised by focusing on health-relevant experiments and outcome variables; sharing models that are already bias corrected to commonly-used observational weather and climate datasets; and increasing the visibility of these efforts with public health researchers, hopefully sparking new collaborations.

On the researcher side, lowering the barrier to entry for the climate-related data science steps in the attribution workflow could be one of the most important steps towards expanding the field. One option could be packaging some of the foundational techniques to work with climate data (in particular, bias correction and statistical downscaling) into well-documented and accessible software packages in languages like R and Python (most commonly used by the impacts community), with clear protocols and vignettes to train new users; in some cases, these resources may already exist, but lack visibility in health research spaces. Using software to reduce reliance on external collaborators for these techniques could help many health researchers – provided that tools are designed to ensure correct implementation even by health experts with low to medium amounts of climate science expertise.

A lower-risk option is to begin consolidating resources such as paired and pre-processed observational climate data and climate model outputs, accompanied by suggestions for analytic best practices. A close parallel can be found in the legacy of the WorldClim dataset (Hijmans et al. 2005; Fick and Hijmans 2017) which was launched in 2005 and almost immediately became the fundamental climate data source for modern ecology. Its success lies in two features:

1. Pre-processing: The first version provided "present-day" climate layers (1960-1990) globally based on interpolated weather station data, bundled with future climate layers (2041-60 and 2061-80) generated from downscaled and bias-corrected climate models, allowing researchers to work with both out-of-the-box (notwithstanding methodological and data issues of poor representation of certain regional and local climate phenomena (Bedia, Herrera, and Gutiérrez 2013).
2. Interpretability: In addition to average temperature and precipitation, WorldClim introduced a core set of over a dozen biologically-meaningful variables constructed based on their seasonal dynamics and interactions.

Without WorldClim, ecology would have been substantially slower to adopt the representative concentration pathway framework for climate scenarios, and the explosion of species distribution modeling research – including substantial work of both high and low scientific quality – might never have happened. Climate change and biodiversity research owe a significant debt to WorldClim, but its history also highlights the tradeoff between ease of use and potential user-end thoughtfulness about where data come from, what they mean, and how to use them.

As a final point of consideration, working with big data remains a prohibitive step for many researchers, not only due to the need for specialised techniques, but also due to more practical challenges like internet access and bandwidth, and file storage. Many researchers – especially in LMICs – would benefit from computing resources that are cheap or ideally free, well-maintained, have abundant storage, include resources for specific workflows, and potentially lower the barrier to entry for cluster computing (e.g., through the use of RStudio servers). One relevant example is the United Kingdom's Joint Analysis System Meeting Infrastructure Needs (JASMIN; jasmin.ac.uk) project, which offers access to tens of petabytes of climate model and observational datasets as a "community cloud" for environmental research, and provides common extraction and analytical tools, including specialised tools for detection and attribution. International frameworks, albeit with less data, such as Europe's Copernicus Climate Data Store (CDS; copernicus.eu) are also available and readily accessible. CDS integrates different climate datasets of the past, present and future, along with visualisation toolboxes, analysis tools, bespoke code, and a dedicated API. Developing new resources like these for capacity-limited regions, and explicitly incorporating platforms for easy remote work over a web browser, could transform not only health impact attribution but climate science more broadly.

The Methodological Frameworks

Exploring New Methodologies

Health impact attribution has progressed much slower than the broader field of detection and attribution, and many of the methodological advances in that field have yet to be applied to health problems. While the studies we examined had a high degree of variability in their design, this reflected a mix of *ad hoc* approaches rather than a set of established methods paired with the problems for which they are well suited. Future work should explore new methodologies from both climate science and epidemiology, with the aim of finding new combinations that can capture under-represented impacts.

Newer methods from climate science, such as storyline-based approaches (Mester et al. 2023; Shepherd et al. 2018), could be utilised more, especially when there are large uncertainties in the observed trend. To date, no published studies have explicitly tried to layer a health outcome on top of a storyline event attribution. This approach could be used to untangle complicated health risks like El Niño related phenomena, or to measure impacts in new kinds of health outcome variables, such as the total population experiencing a flood, storm, or heat wave based on its extent, or the different geographic distributions of risk.

Additional work could explore new attribution-adjacent approaches in climate science, such as those that use operational weather forecasting (e.g., Leach et al, 2022, PNAS) or reanalysis models (e.g., Hawkins et al, 2023, ESD), as opposed to climate models. Forecast and reanalysis methods have very high spatial resolution, often relevant for health impacts; are more likely to capture the extremeness of an event than climate models; and often exhibit far smaller biases due to more strict model validation measures. Exploring these approaches will depend on collaborations between health experts and weather-forecasting centres with well-established infrastructure and validated models.

Meanwhile, more complex approaches from epidemiology could help disentangle the effects of other long-term changes like population growth or air pollution (Chapman et al. 2022; Silva et al. 2013). Another notable challenge could be introducing compartmental epidemiological models into attribution work, in order to better understand climate change impacts on infectious disease dynamics. These studies may be computationally prohibitive, given the large number of parameters and the need for a high number of stochastic simulations to capture uncertainty; however, the growing set of open software tools in epidemiology (e.g., the 'epiverse' family of R packages; github.com/epiverse-trace) could make this work significantly easier.

Best Practices from Open Science

We identified open science – including reproducibility, reporting, and engagement with scientific software communities – as a weak point among the studies identified in our literature review. Future work should aim for a higher standard in terms of best practices across each of these areas. Where possible given ethics constraints, studies should share all code in a Github repository or other version-controlled platform, and should share at least enough derived products from their datasets to make their work fully reproducible. Code should be organised and annotated based on minimum standards for reproducibility, interoperability, and resilience to changes in software dependencies. Studies should also document key methodological decisions in study text; to ensure that researchers meet that standard, it may be important for the community to develop specific protocols for minimum methodological detail, analogous to the EPIFORGE protocol for epidemiological forecasting studies (Pollett et al. 2021)

In the longer term, one of the most significant challenges we identified is lowering the barrier to entry (in terms of technical expertise, time, and effort) for the data science component of health impact attribution studies. One possible avenue is software development: while it would be challenging to develop an R or Python package that covers a "universal" workflow, developing targeted packages or gists for specific steps (e.g., bias correction) could make attribution more accessible to researchers with less climate science expertise. Another possible avenue is the development of study protocols: each of the 13 studies we examined has a relatively unique design, and beyond this report, there is (as yet) no comprehensive guide to what a health impact attribution study can contain. Developing standardised protocols could shorten the time spent designing any individual study, and make it easier to conduct work immediately after a particular category of extreme event—especially heat waves, for which the health outcomes are relatively well understood, and distributed-lag non-linear models are well established as a standardised approach (with accompanying software like the 'dlnm' R package). These resources might also help non-experts to better understand how these studies are conducted, and to evaluate the methodological rigour of new studies as the field continues to grow.

The Publication and Translation Process

Standards for Study Reporting

One priority we identified for higher-impact work was the sharing of more standardised and intercomparable findings. Peer-reviewed studies—especially in high-impact journals with a condensed narrative format—are sometimes dis-incentivised from reporting their results in detailed, disaggregated tables, but studies that do (e.g., (Vicedo-Cabrera et al. 2021), who disaggregate mortality estimates by country) are likely to be more impactful for policymakers or public communication. Developing a standard set of reporting guidelines could improve efforts to not only directly compare studies, but to facilitate the synthesis of different findings in formats like the Lancet Countdown or IPCC reports.

Better and Faster Ways to Share Findings

We identified several intersecting aims for how future work can improve its translational impact. Across these areas, the common theme was a need to transition the field from a collection of disparate one-off studies (which can take several years even just to pass through peer review) to more real-time findings shared directly over the internet.

In terms of public engagement, one of the most impactful developments in detection and attribution has been the rise of platforms for rapid assessment and dissemination, most notably the World Weather Attribution (WWA; worldweatherattribution.org) program, established in 2015. The development of standardised methods (S. Philip et al. 2020) and in-house capacity has allowed WWA to regularly publish analyses within weeks of an extreme event. By building that capacity, WWA has quickly become one of the highest-visibility sources of information on climate change, especially for journalists covering climate disasters as they unfold.

A shift towards rapid attribution could be an important next step for climate-health work, particularly given extensive research that shows the value of public health-based framings to motivate climate action (Dasandi et al. 2022). At present, we are aware of no health-specific impact attribution studies that have been conducted through rapid assessment programmes. Existing programmes like WWA could develop impactful new partnerships with epidemiologists, and develop guidelines for how to address health impacts in rapid assessments (particularly given the growing desire to shift away from fractional methods). However, researchers will need to be cautious – as will journalists, while interpreting their findings – given the challenges of rushed work and the potential for error while operating outside the normal peer review process.

Alternatively, with some guidance, national governments—especially in the settings where the health burden of climate change is already severe—could consider establishing new programmes based in partnerships between health and environment ministries, and meteorological services. Over the last decade, this approach has been moderately successful in developing and implementing digital early warning systems for climate-sensitive infectious diseases (Neta et al. 2022); moving towards a similar system for impact attribution could empower countries and specific vulnerable populations to better advocate for themselves.

A final area of potential progress we identified is the development of “living” attribution studies, which can be updated year-to-year as new health data are generated. In order to reuse existing protocols, researchers will need well-annotated code for analysis; platforms to maintain, rerun, and version control their work; standardised observational climate datasets that can be used without continuity gaps over several years; and incentives to continue updating findings, rather than continually pursue new (and potentially higher-profile) topics.

Chapter 6

Chapter 6: Glossary

Bias correction: A set of procedures for processing climate models, based on observational data, that reduce error and increase the interoperability of the observational and simulated data.

Climate-attributable: An impact or a component of an impact driven at least partially in its frequency, intensity, or duration by variability in weather or climate-related phenomena. A climate-attributable impact may or may not be altered by human-caused climate change.

Counterfactual scenario: In detection and attribution studies, an estimate of or quantitative narrative about observed (historical or present) climate that deliberately omits human impacts on the climate system, but ideally preserves natural variability.

Detection and attribution: An area of climate science focussed on distinguishing sources of variability in the climate system, including anthropogenic external forcings (human-caused climate change), natural external forcings (e.g., solar radiation and volcanic eruptions), and natural internal variability (noise).

End-to-end: A wide-reaching approach to impact attribution that traces impacts all the way back to human influence on the climate system.

Event attribution: An attribution framework focussed on understanding the role of climate change in the likelihood, severity, or other characteristics of specific weather events or climate-related phenomena, such as specific hurricanes or heat waves.

Extreme events: Specific instances of particularly unusual or impactful weather or climate-related phenomena, including both short-term (e.g., floods, wildfires) and medium-term (e.g., droughts) events. Used interchangeably with extreme weather events throughout.

Fraction of attributable risk: A measure of a particular driver's contribution to the risk of a particular outcome, calculated as $(P_{\text{with driver}} - P_{\text{without driver}}) / (P_{\text{with driver}})$; used to describe causal effects in various fields, including both epidemiology and climate science.

Forcings: Drivers of the earth's climate that change the energy balance. These can be natural, such as solar output, or changes in atmospheric aerosols from volcanoes. Or anthropogenic, such as changes in CO_2 or methane.

Health impact attribution: The field of scientific research concerned with the human health impacts of human-caused climate change.

Human-caused climate change: The component of climate change caused by human activity – most notably, but not exclusively, global warming due to greenhouse gas emissions – and is used in this report interchangeably with **anthropogenic climate change.**

Impact assessment: The broad field of research on the social, ecological, and economic impacts of human-caused climate change, past, present, and future. Only a small proportion of these studies use formal methods from the detection and attribution space, but they often draw on a rich set of methodological traditions from other fields.

Impact attribution: An area of detection and attribution research focussed on the effects of human-caused climate change on biosocial, economic, or environmental outcomes, and on separating these impacts from those that are driven by natural climate variability or other sources (e.g., social or economic change, measurement error, confounders, etc.).

Model intercomparison projects: Collaborative scientific programmes that organise climate model simulations around a shared set of scientific questions and priorities, and almost always, share their outputs with the broader community.

Natural variability: Aspects of the earth's climate that are driven by internal variability (noise) and natural external forcings (e.g., solar radiation and volcanic eruptions); i.e., all "climate change" and finer-scale variability that is not human-caused.

Probabilistic event attribution: A framework for the detection and attribution of extreme events focussed on the contribution of human-caused climate change to the likelihood of their occurrence, relative to a counterfactual climate without anthropogenic influence.

Storyline event attribution: A framework for the detection and attribution of extreme events focussed on the contribution of human-caused climate change to the characteristics of the event, including properties such as its severity, duration, or spatial intensity. The storyline-based approach diverges from probabilistic event attribution by taking the existence of the event of interest as a starting point for the analysis, and does not consider its probability of occurrence.

Trend attribution: Detection and attribution of long-term trends in climate change (in contrast with event attribution, which focuses on the short- to medium-term).

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Annexes

Annex 1. Search terms

We used the following search terms for our systematic literature search on PubMed: (“climate change*” OR “climatic change” OR “changing climate” OR “global warming” OR “drought” OR “flood*” OR “storm*” OR “cyclone” OR “extreme weather” OR “monsoon” OR “sea level rise” OR “sea-level rise” OR “heat stress” OR “global heating”) AND (health OR mortality OR morbidity OR “infectious disease” OR “non-communicable disease” OR suicide OR stunting OR miscarriage OR diarrhea OR diarrhoea OR injuries OR cancer OR diabetes OR cardiovascular disease OR stroke OR malnutrition OR malnourish OR anxiety OR depression) AND (attribut* OR counterfactual OR “excess mortality” OR “excess cases” OR DAMIP).

Annex 2. Interview guide

Consent script

Thank you for meeting with us today. My name is _______ and I am part of the team of researchers studying the current state of the art of detection and attribution of climate change impacts on human health, and identifying needs and barriers to the utility of detection and attribution methods, based on researchers’ perspectives of working in this field. This project is supported by the Wellcome Trust, whose mission is to support discovery research into health and wellbeing.

Wellcome has contracted the University of Cape Town to conduct this study with experts and key stakeholders – like you – around the world.

The goal of this interview is to explore your experiences and identify needs and barriers to utility for detection and attribution of human health, and to inform how challenges might be addressed by support from Wellcome Trust.

Please feel free to ask questions throughout the interview.

I am interested in your opinions and any experiences you would like to share with me. This interview is confidential and I will not share names or other identifying information with anyone. You can choose to respond or not respond to any question, and you can choose to end the interview at any time.

Do I have your permission to audio record this interview?

Interview questions

1. What detection and attribution methods do you and/or your research group currently use in human health research? (If they say they don't use any, follow up with 1B)
   - What climate and/or health outcomes do you focus on?
   - What methods do you use for each of the health outcomes? Specifically, are there statistical frameworks or software packages you use?
   - Do you use similar methods for multiple health outcomes?
   - Are there challenges to obtaining key datasets or model inputs?
   - Are there challenges to generating model outcomes?
   - Can you describe the tools and datasets you use, including the process from analysis to reporting? (from data acquisition to results dissemination, including the software(s) used).

1B. What detection and attribution methods or outputs could you and/or your research group use for each of the health outcomes you work on?
   - What climate and/or health outcomes do you focus on?
   - Who makes decisions about what questions to pursue, in your group?
   - What further outcomes or methods would you hope to pursue?

2. What are the key barriers preventing this work from being done efficiently (i.e. physical and human resources, institutional/political barriers, training and implementation)
   - How could these barriers be most usefully addressed by science/software tools?
   - How could these barriers be most usefully addressed by training and capacity building?
   - What opportunities in this space do you think that further tool and software development would impact?
   - Are there any health outcomes that you don't think could be put into a detection and attribution framework?
3. How do you see the role of detection and attribution in the climate-health space, particularly as it relates to policy impacts, evidence bases, or agenda setting?

Conclusion

Would you mind sharing the names of others who you think would be useful to interview on this subject? (Get contact information)

Would you be interested in receiving information from the results of this project by email?

Do you have any questions for me/us? Is there anything else you'd like to share?

You've been so helpful; I really appreciate the time you've taken to talk with me today. Do you mind if we contact you in the future with any follow-up questions that may emerge?

Thank you very much.

Wellcome supports science to solve the urgent health challenges facing everyone. We support discovery research into life, health and wellbeing, and we're taking on three worldwide health challenges: mental health, infectious disease, and climate and health.

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