Assess the Rains Down in Africa (and everywhere else): Improving understanding of the extreme weather impacts of anthropogenic climate change by utilising extreme event attribution

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Abstract

Extreme weather risks arise due to the intersection of a meteorological hazard with the exposure of people and assets, and their vulnerability, to this hazard. Anthropogenic climate change (ACC) is driving changes in the likelihood and intensity of many such hazards, at different rates in different regions, and with feedbacks to exposure and vulnerability. With warming of 1.2 °C, the impacts of ACC are growing cumulatively, but the array of drivers in any given event means that its influence often remains enigmatic.

Extreme event attribution (EEA) encompasses a range of approaches to detect the influence of ACC on a given event. Since its conception, the field has matured and expanded, with hundreds of events studied. I first conduct a broad review of EEA to study climate change impacts. This shows the stark juxtaposition between the impacts of climate change with efforts to mitigate and adapt to it. It also highlights the gaps in present knowledge of both attribution and impacts. There are three recommendations for improving this: documenting extremes and their impacts systematically, improving the spatial and hazard-wise coverage of attribution studies, and integrating attribution with risk analysis.

The subsequent thesis chapters each explore one approach to each of these. First, I construct an inventory framework for documenting extremes and impacts. This has implications for risk and adaptation planning and loss and damage assessment. Second, I show how attribution studies in some regions are unnecessary based on the plethora of existing evidence. This implies that the limited resources for attribution could be concentrated more efficiently. Third, I combine attribution analysis with direct risk assessment for a recent destructive event, showing how both approaches are complementary. The thesis concludes with broader recommendations that emerge from the research, including a path towards a global part-operational-part-scientific service for understanding ACC risks and impacts.

Chapter 1 – Introduction

1.1 Background

1.1.1 Actions and consequences: A changing climate

Ubiquitous human activities are resulting in the large-scale emission of various gases and particulates, including both greenhouse gases and aerosols, into the atmosphere. This is shifting global and local atmospheric compositions and leading to a cascade of climatic changes. Greenhouse gases include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and water vapour (H_2O), and tend to 'trap' radiation from earth's surface through absorption and re-emission, increasing the 'effective height of emission' back into space. This results in a net warming of the atmosphere.

Each of these gases behaves slightly differently and leads to different levels and patterns of warming. Carbon dioxide is a 'well-mixed' gas, meaning that it is effectively distributed equally around the globe, and is very stable, leading it to remain in the atmosphere for thousands of years. Methane causes a significantly larger amount of warming than CO_2 when calculated over a short period. For instance, over 20 years a tonne of methane causes roughly 84 times the warming of a tonne of CO_2 (Balcombe et al. 2018). However, methane is rapidly oxidised in the atmosphere and breaks down into carbon dioxide and water vapour, giving it a half-life of roughly 9 years, so the relative effect rapidly decreases with time (Muller and Muller 2017; Stavert et al. 2022).

Aerosols include a range of sulfates and particles in the atmosphere, including sulphur dioxide and particulate matter such as black carbon (or soot) (Charlson et al., 1992). Scattering aerosols such as sulphur dioxide tend to reflect incoming solar radiation, thereby increasing planetary albedo and resulting in a net cooling effect. Absorbing aerosols tend to warm the atmosphere. Both types of aerosols also interact with clouds, causing mixed effects through both albedo and heat-trapping influences. Compared to carbon dioxide, aerosols are generally poorly mixed, affecting climate more strongly on local spatial scales, and have a much wider range of influences (Li et al., 2022).

Due to human activities including burning fossil fuels and deforestation, the rapid release of each of these gases and particulates on scales far exceeding other forcings over an extended period are having a significant and growing impact on the state of the climate. At the time of writing, the concentration of CO_2 in the atmosphere has risen from 280 parts per million (ppm) in pre-industrial times by around 50% to ~420 ppm (Keeling et al. 2001), the highest level in approximately 3 million years (Rae et al. 2021), leading to rapid changes in the earth's climate.

The way that specific impacts of climate change manifest is due to the magnitude and pattern of warming, which in turn is driven by the distribution and relative abundance of these heat-affecting gases in the atmosphere and the response of internal factors. The overall levels of warming around the world are often simplified into a single quantity, the global mean surface temperature (GMST) rise since pre-industrial times. This metric is useful to scientists for quantifying the net change experienced since anthropogenic influences became a major factor driving climatic changes, and to facilitate communication to the public and policymakers alike. It also has the side effect of being more convenient from a political and corporate perspective, as it says nothing of the origin and distribution of emissions of all kinds. At the time of writing, the atmosphere has warmed by ~1.2 °C since pre-industrial times (Matthews and Wynes 2022).

This single number is merely the tip of the recently-calved iceberg in describing the climatic changes that are underway. The climate system is deeply complex, consisting of five key coupled subsystems; the atmosphere, hydrosphere, land surface (or more broadly, the lithosphere), biosphere and cryosphere (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021). Accordingly, the substantial human-caused perturbation to this system is manifesting in myriad ways (Pörtner et al., 2022).

Arctic sea ice is melting, resulting in a decrease in albedo in the high north and thus a warming feedback (Thackeray and Hall 2019). Permafrost is thawing across much of Siberia, Greenland, northern North America, Himalayas and the Tibetan Plateau, releasing methane trapped as bubbles for thousands of years (Schuur et al. 2022). Ice sheets in Greenland and Antarctica are melting, and

the West Antarctic Ice Sheet in particular is becoming less stable as the ice shelves that buttress it are undermined by warming waters (Pritchard et al. 2012). Reductions in all parts of the cryosphere due to melting, alongside thermal expansion of the oceans, are contributing to rising sea levels (Dangendorf et al. 2019). The oceans are also acidifying as they absorb carbon dioxide, creating an increasingly hostile environment for organisms dependent upon calcification, and thus the wider ecosystem (Hall-Spencer and Harvey 2019). Biodiversity is affected simultaneously by these rapid changes across all systems (Díaz et al. 2020). Inextricably linked with all of these other changes is altered weather patterns, due to direct changes in the atmosphere and the indirect influences of its coupled systems. In particular, one of the first signals to have emerged due to human influence, and one of the most pressing for societies, communities and natural habitats alike, is in changing frequencies and intensities of extreme weather events (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021).

As the concentration of CO_2 increases, it directly affects the state of the atmosphere at a given time in a given location, experienced as the weather. The temporary state of any chaotic system such as the climate is overwhelmingly determined by randomness. It is therefore challenging, or impossible, to causally link a given state to any specific perturbation; it is not that a change in CO_2 levels 'causes' any specific weather event. However, when any given state occurs, its nature is fundamentally affected by the underlying physics of the system; the presence of excess CO_2 means that the weather event is different than it otherwise would have been in a counterfactual climate of no anthropogenic forcing. Equivalently, climate change alters the likelihood of such an event. It does this through influencing a variety of properties of the system itself.

Primarily, it increases the availability of heat in the climate system, including both atmosphere and oceans. The excess heat plays both direct and indirect roles in weather events, through thermodynamic and dynamic responses, respectively. While these two types of response are intrinsically coupled, distinguishing between them is useful for understanding specific driving

mechanisms in a given event. Thermodynamically, the air itself is warmer, shifting the baseline temperature of all events. Additionally, warmer air tends to hold more moisture at a rate of approximately 6-7% per K, known as the Clausius-Clapeyron relation. Confidence is generally high in observations and models of these effects and theories are well established (Shepherd et al. 2018).

Dynamical changes, such as changes in atmospheric circulation on all scales, arise for more complex reasons and have no unified theory, nor clear signals in models or observations (Shepherd et al. 2018). For instance, one major dynamical shift may be underway because excess heat builds up at a greater rate in the high latitudes than lower latitudes. Importantly, this could affect circulation patterns by decreasing the latitudinal temperature gradient, which crucially weakens the mid-latitude jet stream. In the northern hemisphere, this jet stream drives weather systems from west to east. If it weakens, this can result in large-scale meanders, known as planetary waves or Rossby waves (Kornhuber et al. 2019). In turn, these cause extreme weather systems to stall over specific regions, bringing more severe conditions to the surface, and often in multiple regions simultaneously. While evidence of this is emerging (Rogers et al. 2022), this case exemplifies the deep uncertainties permeating potential changes in dynamics (Shepherd 2019, 2021a). Overall, shifts in both the thermodynamic and dynamic conditions due to climate change result in altered patterns, frequencies and intensities of given extreme weather events in given locations.

The weather affects societies in all sorts of ways and extreme weather events are some of the most devastating single events in history. In accordance with the threat they pose, extreme events also form experiences from which society can learn and become somewhat more resilient. Over time, in a static climate, extreme events occurring through natural variability highlight the boundaries of plausibility – that which is likely to ever be experienced. Risks can then be assessed and appropriately mitigated through resilience measures. For these reasons, we are reasonably well adapted to the relatively climatically stable conditions within which the modern structures and institutions concerned with risk

were first built, though this also varies due to other factors including absolute and relative prosperity of a region, inequalities, and socio-cultural values, among others.

1.1.2 The changing nature of extreme hazards and risks

In an increasingly non-static climate, it is becoming less and less the case that we are reasonably well adapted to it. Changes in a vast array of extremes indices are now well observed across the world (Dunn et al. 2020), with a far greater rate of new records in heat compared to cold (Coumou and Rahmstorf 2012). Since 2012, any single day of weather globally has contained a statistically significant signal from anthropogenic climate change (Sippel et al. 2020). In 2015, at global warming of 0.85 ^{o}C, Fischer and Knutti (Fischer and Knutti 2015a) found that there were approximately 22% more daily heavy precipitation events and 300% more daily extreme heat events due to human influence on the climate, rising to 65% and around 1900%, respectively, at 2 ^{o}C – and that these changes are even more significant for longer duration events, such as 5-, 15- and 31-day extremes. At the time of writing, in 2023, we are at approximately 1.2 ^{o}C, which is almost a third of the way from 0.85 to 2 ^{o}C, with a non-linear relationship between warming and the probability of extremes (Fischer and Knutti 2015a).

This represents a rapid increase in the likelihood of hazards, which is just one component of changing risk. Here, I use the terminology of risk in line with the IPCC. As such, risk means “the potential for adverse consequences for human or ecological systems, resulting from dynamic interactions between climate-related hazards with the exposure and vulnerability of the affected system.” In this context, vulnerability is “the propensity or predisposition to be adversely affected and encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt”, and exposure is “the presence of people; livelihoods; species or ecosystems; environmental functions, services and resources; infrastructure; or economic, social or cultural assets in places and settings that could be adversely affected” (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021).

As a result, on the ground, natural variability combined with climatic trends manifests as extreme events, which become disasters when combined with exposure and vulnerability of people and assets. The last two decades have seen some of the most destructive weather events in living memory (Clarke et al. 2022): for instance, Hurricanes Katrina and Harvey each caused destruction exceeding $100 billion to the eastern US; in 2008, Cyclone Nargis killed an estimated 138000 people in Myanmar, one of the deadliest disasters ever; unprecedented heatwaves in Europe in 2003 and western Russia in 2010 resulted in approximately 125000 deaths; wildfires in Australia in 2019/20 created one of the worst ecological disasters in history; and smoke from fires in Indonesia in 2015 resulted in an estimated 100000 deaths (Clarke et al. 2022).

Clearly, changes in extreme weather can adversely affect property, human health, and entire economies, with implications across the whole of society. History shows how fine this balance can be; relatively rapid changes in weather patterns among other climatic factors may have been part of what caused great civilisations of the past to wane (Haug et al. 2003; Tsonis et al. 2010; Charalampopoulos and Droulia 2020). Assuming all other factors relating to risk are equal, evolutions in the distribution of extreme weather hazards lead to additional risk, or pressure on human systems, in two interrelated ways:

First, formerly ‘expected’ extreme events become more common and intense. This represents a systematic change in risks or, equivalently, that achieving just a fixed level of societal resilience requires constant iteration of risk management measures. Second, the boundaries of plausibility shift; viewing extremes as a statistical distribution, events formerly with an infinitesimal probability, i.e. ‘beyond’ the tail, gain a non-negligible chance of occurrence each year as the tail moves over them. Over time, this results in the occurrence of ‘unexpected’ events (those without historical precedent) of ever-greater magnitude. By their nature, the most extreme events tend to cause the greatest impacts, often with a non-linear relationship between magnitude and impacts (Franzke and Czupryna 2020; Franzke 2021).

It is also especially challenging to study and predict these events, which may also fall into the class of 'Dragon King' or 'Black Swan' events. The former consists of events that do not belong to the same statistical population as the majority of extremes of a similar type (i.e. traditional extreme value distributions) often resulting from non-linear interactions between phenomena. The unprecedented northwest Pacific heatwave of 2021, in which temperature records in parts of Canada were broken by over 5 ^{o}C, can be considered a dragon king event; a wide range of phenomena conspired to create such an extreme magnitude, many of which are likely affected by climate change (White et al. 2023). Black Swan eventsrepresent unknown unknowns; those for which the bar for understanding is unknown, but which can be rationalised in hindsight after they occur (Woo 2019). An example of such an event could be the destructive flooding wrought in New Orleans by Hurricane Katrina, since the area was thought well protected by levees. Each of these event types is implicitly more likely in a changing climate because they are related to our experience of the system itself. More broadly, the concept of Black Swan events (and the tale the name is based upon) provides a cautionary lesson on the limits of human knowledge and our proclivity to limit our learning to past experience, rather than proactively planning for unlikely but plausible scenarios.

All of this motivates a greater understanding of the changing probabilities of meteorological hazards due to anthropogenic climate change. However, to have direct practical applicability to understanding and managing risks, changes in hazards must be placed within the wider risk context. This is because risks comprise not just hazard probabilities but the level of exposure of people and assets, and the vulnerability of those exposed; these other factors are constantly in flux across human systems, and thus contributing to changing risks alongside changes in hazards.

Additionally, context is crucial because the risks from different weather hazards are also not isolated. They may compound one another and result in impact greater than the sum of their parts, had they occurred independently. Such 'compound events' can occur in a variety of ways: multiple extremes occurring in the same place at the same time, such as high rainfall and high winds (potentially also

leading to storm surge and thus compound flooding in coastal regions (Bevacqua et al. 2019)); events striking the same place consecutively, as occurred in Puerto Rico when Hurricane Maria made landfall only two weeks after Hurricane Irma caused extensive damage (Clarke et al. 2021a); events striking at the same time in different places, such as occurred in 2018 when heatwaves struck several agricultural breadbaskets in the northern hemisphere (Kornhuber et al. 2019), with implications for food prices globally. In this way, linear increases in one or more hazards can result in a non-linear increase in impacts (Zscheischler et al. 2018; Zscheischler and Lehner 2022).

Furthermore, the human world is not a static environment but a series of interlinked systems every bit as chaotic in nature as the climate system. Extreme weather events can form violent perturbations to these systems, with consequences that are modulated by three key properties.

First, these systems connect the world across space and spatial scales, and time and temporal scales, from international geopolitics and globalised trade networks down to local dynamics and services. This affects where, how and when the impacts of a given event are experienced. For instance, globalised trade networks are built to minimise costs in relatively normal conditions, rather than maximising resilience to shocks. As a result, they often propagate the impacts of shocks across the world. As unprepared regions suffer shortages in supplies or price rises, this in turn can amplify other ongoing challenges such as poverty rates, malnutrition and political instability. These are known as ‘cascading risks’ (Lawrence et al. 2020).

Second, like any complex system, human systems contain tipping points; the breakdown of governance, economic and power systems can all result in major humanitarian consequences. These are known as ‘systemic risks’ (Kedward et al. 2022; Kemp et al. 2022). Through the direct impacts of extreme events or cascading impacts from one or more events simultaneously, such tipping point thresholds may be exceeded. Changes in extreme weather events may therefore increase the chance of triggering risk cascades or tipping point events.

Third, extreme events frequently occur in human systems that are almost entirely separate from climate change, such as technological disasters, war, and pandemics. For instance, the invasion of Ukraine in 2022 created a global shortage of wheat as the crop sat unharvested and ships carrying existing supplies were held up in besieged ports (Nóia Júnior et al. 2022). Additionally, the indirect impacts of this 'event' were exacerbated by the continued substantial reliance on hydrocarbons across most nations, particularly the nations of the EU directly affected by subsequent measures (Johannesson and Clowes 2022; Mišík 2022) - geopolitical sanctions caused fuel prices, and hydrocarbon companies' profits, to rocket (Yagi and Managi 2023). Nonetheless, even focusing entirely on the direct impacts, such strife also makes the global economy far more susceptible to other shocks. As the invasion began, major dry heatwaves struck India and Pakistan and lasted throughout March, April and much of May, destroying a significant fraction of the wheat crop that had been planned to account for the shortfall from Ukraine (Zachariah et al. 2022a). As a result, the price of wheat remained high throughout March and April, spiking again in May. Heavy monsoonal flooding in Pakistan later in the summer wiped out other crops, further compounding the economic and other cascading impacts in that nation (Otto et al. 2023). In this way, changes in extreme weather events can have non-linear impacts as they compound other disasters.

In essence, the changing climate is rapidly altering patterns of risk globally through its influence on extreme weather events, which may be devastating in their own right, and may compound one another and other challenges. This manifests constantly as increasingly severe impacts in most parts of the world and for most types of hazard. Year on year, the tally of climate change-related impacts grows cumulatively as a function of both increasing greenhouse gas emissions and time spent above the pre-industrial baseline. It is therefore simultaneously important and incredibly challenging to build up an accurate picture of these changes in risk, due to the high complexity involved, and thus to both adequately and efficiently prepare for them, and to document the impacts that have already occurred (and been averted).

1.1.3 Extreme event attribution

The climate has not only recently begun to change due to human influence. Decades of failure to reduce global emissions mean that thousands of impactful extreme weather events have occurred in a climate of elevated greenhouse gas levels. Consider again a society within a static climate, that is still barraged by a naturally-variable weather and thus learns and adapts to reasonable levels of risk within that climate. Our case is similar; we are still frequently struck by events from which we can learn. The only difference is that each event occurs to the backdrop of a slightly different level of anthropogenic forcing.

Extreme event attribution is a methodology developed to identify the presence and degree of a human-forcing fingerprint on a specific extreme weather event; to answer the question of whether and by how much climate change affected the likelihood and/or intensity of a specific event (or some component of the event). The field was established in a conceptual paper in 2003 (Allen 2003) and shortly afterwards in the first complete study, which assessed human influence on the extreme summer of 2003 in western Europe (Stott et al. 2004a).

The 'traditional' probabilistic framing of extreme event attribution uses the following basic method: climate models simulate thousands of years of synthetic weather, in worlds both with and without the influence of anthropogenic forcing (at the time of event occurrence). The event itself is defined as a magnitude of some meteorological variable averaged over some spatiotemporal domain. Within the two datasets, an event is considered to have occurred if it meets or exceeds this threshold. Then, the 'fractional attributable risk' (FAR) is given by comparing the two sets of events, through

$$FAR = 1 - \frac{p_0}{p_1}, \tag{1.1}$$

where p_0 and p_1 are the probability of event exceedance in the counterfactual and factual scenarios, respectively. Increasingly, due to the increasing recognition that hazard probability is not a reliable proxy for risk, the attributable influence is described using the probability ratio, given simply by

$$PR = \frac{p_1}{p_0}. \quad (1.2)$$

A significant moment for the field of extreme attribution occurred after 2010, when western Russia was struck by an unprecedented and devastating heatwave. Two attribution studies of this event produced apparently contradictory results; that the heatwave was largely natural in origin (Dole et al. 2011) and that it most likely would not have occurred without global warming (Rahmstorf and Coumou 2011). A subsequent landmark paper illustrated that these results were entirely consistent with one another, with results depending on the specific question being asked (Otto et al. 2012). It did this by showing that a given extreme event magnitude can be mostly caused by internal variability, and that a change in occurrence probability due to an anthropogenic change in this magnitude can be simultaneously mostly externally forced (Otto et al. 2012). In doing so, it underscored the importance of framing in attribution studies, which is now a core component of the attribution paradigm (Stone et al. 2021b); any attribution result depends heavily upon the ways in which the event is defined, the forcing factors considered, the methods, data and models used, and any conditioning such as specific synoptic conditions or climatic states.

Past developments in EEA

The past decade has seen a plethora of other developments in this field. These include:

Widespread uptake and methodological diversity

Regular attribution studies are now undertaken by numerous groups in academia and met services across the world. Since 2011, an annual special edition of the Bulletin of the American Meteorological Society has published a growing collection of attribution studies on events of the previous year, which is partly responsible for this growth. The increased uptake of EEA has also been accompanied by the development of a smorgasbord of different methods and approaches to answer subtly different attribution questions. A range of the most common modern methods are described in the following section.

Different event types

Some events are far more complex than others and occur over different spatial scales. For instance, while heatwaves (albeit with localised land surface interactions that modulate the peak magnitudes) often occur across the scale of a region, tropical cyclones depend on physical processes represented well only by models of ~25 km resolution (Murakami et al. 2015) . The potential for attributing a given event therefore always depends on the ability of climate models to simulate the extremes in question (Stott et al. 2016). This in turn depends on the physical phenomena resolved by the models, and the sub-grid schemes used to account for this finite resolution, as well as models' ability to simulate the antecedent conditions that lead to such events forming at the expected rate. For a probabilistic attribution study, large model ensembles are also crucial to represent the statistics of definitionally rare extremes. This creates a permanent trade-off between model resolution and complexity on one hand, and statistical sampling uncertainty on the other.

In attribution studies, the model evaluation step is crucial to determine the robustness of the results. This often takes the form of verifying that the model can reproduce the observed statistics of events similar to that being attributed. While this tests correlation rather than causation, and thus does not necessarily indicate that a model is doing the right thing for the right reasons, it is a bar that eliminates models that certainly should not be included and thus the largest source of errors. Some studies employ more sophisticated and robust tests by also ensuring that models are able to simulate the specific event dynamics (Bercos-Hickey et al. 2022).

Despite the challenges, developments in modelling resolution and physics, and ensemble sizes, mean that many types of extreme have now been attributed in at least one part of the world. For instance, Pall et al. (Pall et al. 2011a) showed that both extreme rainfall and the subsequent extreme runoff in autumn 2000 in the UK were partly attributable to human influence. Extremely cold winters such as 2010/11 in the UK were found to have decreased in probability due to anthropogenic climate change, but still lie within the realm of plausibility (Peterson et al. 2012). Using state-of-the-art convection-

permitting models, Patricola & Wehner (Patricola and Wehner 2018a) showed that extreme rainfall from Hurricanes Katrina, Irma and Maria were amplified by 4, 6 and 9% respectively, due to climate change; these increases were also projected to increase with future warming, alongside a detectable signal in wind speeds later in the century. Early attribution studies of drought include Funk (Peterson et al. 2012), who explored the role of warmer ocean temperatures in the frequency of average evaporation and rainfall in East Africa, and Shiogama et al. (Shiogama et al. 2013), who found that human influence played a role in the precipitation deficits in the southern Amazon in 2010. Yoon et al. (Yoon et al. 2015) attribute an increase in wildfire risk leading up to 2014 in California to human influence, using both drought indices alone, and climate variables coupled to vegetation models. Finally, no attributable signal was detected for extreme windstorms in Europe in early 2018 (Vautard et al. 2019b).

Attribution of impacts

Within the traditional probabilistic attribution framework, as defined above, the FAR statistic is often used to provides a first order approximation of the fraction of the impacts of the event that are attributable to climate change (Frame et al. 2020a, c; Clarke et al. 2021a). For instance, if an event was made twice as likely to occur, the FAR value is 0.5, thus approximately half of the impacts are considered attributable to climate change. As discussed by Allen (Allen 2003) and developed by Perkins-Kirkpatrick et al. (Perkins-Kirkpatrick et al. 2022), this represents a theoretical attribution of risk over some extensive time horizon in a world of fixed anthropogenic forcing, rather than a causal attribution of past impacts; following the previous example, if an event is twice as likely to occur, then over a long period of time in the same climate, the accumulated impacts from similar events will also double compared to a fixed climate without the forcing being testedOther issues with this approximation arise due to the threshold-based nature of the FAR statistic; it is valid for events of at least the magnitude of the event that actually occurred, rather than events at the magnitude in question (Harrington 2017). For instance, if a given heatwave (as an example, 40 degrees for 1 day in

a region of the southeastern UK) has a FAR value of 0.5, then within the probabilistic framing the likelihood of heat events of *at least* 40 degrees has doubled. Due to the increasing and non-linear relationship between magnitude and impacts, the impacts of the observed events are the minimum expected from an event as defined within this framing. As such, the above statement must be modified: over a long period of time in the same climate, the accumulated impacts from similar events will *more than* double compared to a fixed climate without the forcing being tested.

Above all else, this is a simple approximation because the influence of climate change on some extreme meteorological variable represents just one part of the causal chain that ultimately leads to impacts on the ground. A vast array of other factors play a part in the severity of an event as experienced by people, property and ecosystems. This means that some attributable change in the magnitude of the meteorological event, such as daily maximum temperature or hourly rainfall, almost never translates linearly into an attributable change in impacts, such as hospital admissions for heat stroke or the number of flooded properties. While trivial to state and long understood (Stone and Allen 2005), this still poses a significant challenge for modelling, and more broadly for our ability to causally attribute the tangible losses experienced to climate change.

Various exploratory studies have developed modelling frameworks for specific events, which attempt to account for these causal factors and thus attribute the change in impacts directly. For instance, Schaller et al. (Schaller et al. 2016) used a cascade of models, generating rainfall and temperature fields and using these as input into a hydrological model, to attribute the number of properties flooded in the wet winter of 2013/14 within the Thames catchment to anthropogenic influence. Due to compounding uncertainties, this method showed that anthropogenic climate change was responsible for flooding 4000 additional properties in the region, with an uncertainty ranging between 8000 more and 1000 fewer. This study also investigated the relative roles of both dynamic and thermodynamic drivers of the extreme precipitation.

Looking at the widespread 2000 floods in the UK, Pall et al (Pall et al. 2011a) used a large-ensemble climate model to simulate extreme autumn precipitation in England and Wales. This is used to drive a rainfall-runoff model and thereby attribute the change in flood probability. Kay et al (Kay et al. 2011) then extended this analysis, using the same weather data to drive models for changes in 'risk' in specific river catchment areas. Mitchell et al. (Mitchell et al. 2016a) assessed the attributable mortality of the 2003 European heatwave by feeding the results of a probabilistic attribution of this extreme heat into a health impact assessment model. Similarly, for the 2006 summer heatwave in the UK, Perkins-Kirkpatrick et al. (Perkins-Kirkpatrick et al. 2022) explicitly illustrated the difference between a FAR-based and magnitude-based attribution of mortality using a simple health impacts model. And for tropical cyclones, multiple studies investigate different anthropogenic influences; for the storm surge of Hurricane Sandy and Cyclone Amphan, attributable increases in sea level rise were used to drive flood damage models (Strauss et al. 2021a; Mitchell et al. 2022), and for Hurricane Harvey, existing attribution estimates of the extreme precipitation totals were used to drive an inundation model (Wehner and Sampson 2021).

Rapid attribution and good practice

World Weather Attribution is an international consortium of experts working to provide attribution results in the wake of an extreme event (usually within days to weeks). Due to the rapid timeline required to satisfy public and media interest, studies are produced based on peer reviewed methodology (Philip et al. 2020; van Oldenborgh et al. 2021), then later submitted to the peer review process for the specific results and conclusions to be scrutinised.

The need for a peer reviewed methodology to support rapid studies has resulted in the iteration and development of standardised protocol. In particular, this protocol was developed based on the experience of the group in producing attribution studies for a range of stakeholders including the public, risk managers and the scientific community (Otto et al. 2022a). It includes a series of steps, beginning with a trigger based on the impacts of the event, determining the event definition based on

these impacts, analysing observational trends, evaluating and analysing climate models, synthesising these results, considering vulnerability and exposure factors, and finally communicating the overall results (van Oldenborgh et al. 2021).

Key developments throughout several years of experience include tailoring the event definition to closely relate to the impacts of the event, using multiple models with large ensembles and/or long running experiments, accounting for forcings from global to local, and studying the results across multiple event definitions to test the sensitivity of the results to this choice (van Oldenborgh et al. 2021). While the good practices used by WWA are not universally adopted, nor are they necessarily applicable for different forms of attribution (as detailed in the following section), they form guidelines towards ensuring individual studies are as useful as possible.

The attribution method has been further refined through semi-regular reviews of the literature. These include broad reviews of good practice (Otto et al. 2016, 2017; Stott et al. 2016) reflective commentary on ensuring the usefulness of future studies (Stone et al. 2021b; Raju et al. 2022), as well as reviews tailored towards specific purposes, such as how attribution may inform loss and damage (James et al. 2019) and liability (Stuart-Smith et al. 2021), the improvements needed to move towards operationalisation (Otto et al. 2022a; Stott and Christidis 2023), or formally establishing standards of evidence across studies (Otto et al. 2020c).

Future developments in EEA

In spite of all of these active developments, the field is still relatively young. The majority of events that occur are not studied, either because of a lack of observational data, modelling capabilities or because of limited time and other resources. Additionally, many events are studied in a simplistic manner, based on single meteorological variables and/or not tailored to the resultant impacts. Now, another phase of methodological and practical developments is required to address some of the most pressing challenges:

Operationalisation

For many event types in specific regions, the fingerprint (or lack thereof) of human climate change is consistent across trends in extremes and individual studies. In addition, with the development of a protocol such as that employed by WWA, providing an attribution study for many such events is little different to providing a weather forecast. The research community has recognised the potential benefits for the operationalisation of attribution, such as through a consortium of national met services, for years (Stott et al. 2016). Such a system would provide a reliable, consistent and valuable public service, and save research resources for more pressing advances in both risk understanding and global equity, like those described below. A recent pilot project by a pan-European collaboration of attribution experts and met services reported that the attribution protocol employed by WWA is robust to different models and datasets (Otto et al. 2022a).

Ongoing challenges and considerations include the following: ensuring that appropriate methods are selected to avoid overstating or understating the role of climate change; improving understanding of user requirements and effective communication of results; improving capacity, both for studies tailored to user needs, and for the types of events that can be studied (Otto et al. 2022a; Stott and Christidis 2023).

Other events and regions

There is still a vast heterogeneity in the distribution of attribution studies across regions of the world and different event types. This is for a host of reasons. First, as a result of the modelling challenges described above, many of the phenomena involved in extremes such as localised flooding and heat, drought, windstorms, and fire conditions are still unresolved, poorly represented, or not represented at all within most models (Van Oldenborgh et al. 2022; Stott and Christidis 2023).

Second, some regions have far more consistent and long-standing meteorological records than others. Where there are limited observational data it is impossible to test models for all types of extreme

events, resulting in irreducible deep uncertainty and thus complete lack of robustness in any results. Coupled to this challenge, climate models are generally most extensively tested where they are developed, and both climate models and attribution experts are more heavily concentrated in the global north, meaning that attribution studies in the global south suffer from a lack of local expertise on multiple fronts (Otto et al. 2020a).

Third, event attribution studies are typically undertaken based on the occurrence of extreme impacts, especially in the case of the quasi-operationalised World Weather Attribution, and the proposed system for national met services. Currently, the reporting of impacts is deeply disparate across the world due to systems of information gathering; in the global north it is largely driven by public services, in the global south by NGOs, which themselves only respond on an ad-hoc basis. This is exemplified by extreme heat, as summarised by Clarke et al. (Clarke et al. 2022): "EMDAT lists 147 instances of impactful heat events from individual countries for the period 2000-2020, only an improbably low 58 of which are from all of Asia, Africa, South and Central America and the Caribbean combined (EMDAT 2019). Of the 157,000 total deaths recorded in the database, only 10,000 – or 6.3% – were recorded in these regions, which together constitute almost 85% of the world's population, over 60% of the land mass, and many of the hottest and most humid climates." There is thus no basis for an attribution study in many of the potentially most destructive events that are occurring.

Further research is required across many fronts. Crucially, this research should generally focus on those regions and hazards for which the fewest attribution studies already exist and therefore where the need is, almost by definition, the greatest. The hazards listed above are pressing across much of the world, and chapter 4 in this thesis further highlights the overlap between many understudied hazards and regions, specifically extreme precipitation in most of Africa and South and Central America; tropical storms for most basins in the Indian and Pacific oceans; storm surges, drought and wildfires worldwide, especially South America, and much of Asia and Africa.

Most of the regions in which we have the least knowledge of extreme event attribution are those with the lowest historical emissions of greenhouse gases. Going further, the inequity arising from the climate change impacts of extreme weather (and most other climate impacts) is systemic and multi-layered, with inequalities in how we observe and understand changes in hazards and impacts, the magnitude of hazards and impacts that have already occurred and are likely to occur in the future, and the vulnerability of the human systems that are exposed to them. All of these factors contribute directly or indirectly to risk itself, highlighting not only the fundamental inequities across the world, but also the non-linearity of this as multiple factors compound one another. Attribution is one way in which we could and should begin to make a tangible difference in this realm. In doing so, we can inform the mechanisms that are finally emerging on the global stage to address these issues, such as informing the Loss and Damage Fund begun at COP27 (Mahase 2022).

The most immediate developments required to improve on this all constitute a more comprehensive attribution framework. For instance, a deeper understanding of the range of questions that can be answered through attribution, across the spectrum of conditioning levels, given different levels of data. In any given case, the method applied should be decided through both the needs of the user and the limits of the data, and will by necessity include greater room for qualitative statements about other drivers of risk, such as exposure and vulnerability (Otto et al. 2020a); this is a pragmatic approach towards saying something useful in the presence of large uncertainty, rather than giving up. Furthermore, improved techniques are required for evaluating models when there is a dearth of data, as further discussed for compound events below. Finally, new cutting-edge techniques, such as the use of operational weather models for attribution (Leach et al. 2021), should be extended to the most pressing event types and regions.

Compound events

As described in the previous section, compound events may consist of compounding meteorological phenomena in space, time, or both, often resulting in disproportionate impacts. By their very nature,

specific compound events are rarer than single extremes, meaning that even in regions with extensive observational records, comparable examples are challenging to come by. This poses significant challenges for both model evaluation and developing large enough sample sizes for statistical analysis. Zscheischler and Lehner (Zscheischler and Lehner 2022) provide insights into the core challenges and developments required to robustly attribute changing compound risks, which will be further explored in an upcoming study focusing on the multi-faceted extremes experienced by Pakistan in 2022.

Events with compounding factors that are both climatic and non-climatic in origin represent an even greater departure from traditional modelling and observation-based attribution. Systems of such deep uncertainty will likely always lie within the remit of a storyline or scenario-driven approach to assessing risk drivers, but this is fully commensurate with an attribution perspective, and may benefit from probabilistic analysis of specific drivers (Shepherd 2016).

A pragmatic approach

Only a fraction of all events that have occurred since this field was established have been assessed for their connection to anthropogenic climate change. However, for the purpose of assessing the impacts that have already occurred and the ever-changing landscape of risk, we do not have the luxury of waiting for future developments in this field. Additionally, despite this incompleteness, there are still hundreds of attribution studies covering even more extreme events. This represents a substantial and underutilised body of evidence. This thesis primarily aims to build upon this vast evidence base, utilising these experiences of a changing climate to learn about climate risks going forwards.

1.2 Methods and aims

1.2.1 Underlying methods in extreme event attribution

The varied methods of the field of extreme event attribution underlie this thesis, and can be divided into two broad classes: probabilistic event attribution and storylines. The distinction between these is actually arbitrary; they generally describe two ends of the spectrum along which all event attribution studies lie, from very little conditioning (probabilistic) to high conditioning (storyline). In this section, I first give a brief overview of the different types of methods, then give a more detailed breakdown of the main data sources, individual methods and examples of past studies within each type.

The probabilistic (often frequentist, but could be Bayesian) approach typically features rates of occurrence of some meteorological extreme in a modern factual scenario and a counterfactual scenario, with the forcing factor of interest – often anthropogenic forcing of the climate system in the industrial era – removed. It is therefore an investigation of the overall change due to the combined effects of climate change, and as such is a function of many potentially reinforcing or cancelling influences. This approach tests the overall likelihood of events in the present day and future scenarios, thus providing highly actionable information in the presence of clear signals, and provides the closest answer for questions posed by the public (Ettinger et al., 2021; Shepherd, 2016; Stott et al., 2015) in the wake of extreme events; whether and to what degree climate change influenced the extreme. In addition, the lack of conditioning means that there are relatively few value-based decisions involved in constructing a study and therefore that, while a degree of expert judgement is still necessary, it could be considered to be, in some sense, fairly 'objective'.

However, as explored by Lloyd & Shepherd (Lloyd and Shepherd 2020), this approach is implicitly tailored to minimise type I errors, or false alarms – it aims for reliability, preventing the incorrect attribution of signals which cannot be distinguished from natural variability. In particular, the use of multi-model multi-method attribution optimises robustness of any detected signals by synthesising

many results. As well as combining the many influences of climate change into one statement, this approach therefore also combines the uncertainties on each of these. Crucially, these uncertainties are fundamentally different in nature; thermodynamic influences of climate change are dominated by well-constrained uncertainties due to natural variability, while changes in dynamical, circulation-based phenomena are fundamentally poorly understood.

In general, this means that it is possible to make fairly concrete statements about the thermodynamic influences of climate change, but less so the dynamical influences. In part this is because the latter are often smaller in magnitude, though our confidence in this is severely limited by the veracity of observational records, the lack of unified theory for dynamical changes, and the lack of model agreement on even the sign of such changes. There is therefore a risk in probabilistic methods of being too conservative around at least some of the influences of climate change.

Meanwhile, a storyline is based on a physically-consistent unfolding sequence of events. It is highly conditional on the initial state of the system preceding an event and the drivers that interact throughout it. By selecting which aspects of the event are held constant, as preconditions, the influence of climate change is explored through its influence on specific drivers. The focus of storyline methods is identifying plausibility rather than probability. This enables the disentangling of uncertainties into different types; in the face of substantial deep uncertainties, it can still provide information about the other, clearer aspects that would be shrouded within a probabilistic framework. The sources of the deep uncertainty may then be subject to further research independently. This addresses type II errors – the warnings that could be missed by a frequentist approach, but at the cost of increased conditioning and thus breadth of applicability.

The potential for alternative treatments of uncertainties suggests that the use of a probabilistic approach, as in all storyline studies, also contains a degree of value-based decision making; subjectivity is inherent in event attribution as in broader climate science. This is not in of itself a problem, but must be understood and considered in study design to ensure an optimum balance

between reliability and informativeness (Shepherd 2021a; Shepherd and Lloyd 2021; Pulkkinen et al. 2022).

In summary, these two approaches to attribution are fully consistent and complimentary with one another and, as discussed above, are almost never mutually exclusive. Probabilistic studies always contain some degree of conditioning (such as only studying events occurring during certain ENSO states), while storyline approaches often use a probabilistic framing for changes in specific drivers (such as the temperature distribution of extremes occurring given an initial synoptic state and scenarios of urban development). More broadly, both methods inherently contain elements of subjectivity through the conditioning of the study and how uncertainties are dealt with and valued. The most appropriate method for a given study is highly dependent upon the question being asked and the dominant sources of uncertainty. Here, in accordance with the development of the literature that I elaborate on below, I will discuss studies as falling within these broad categories. However, I maintain that they ought to be – and increasingly are being – considered within a unified framework moving forwards.

Probabilistic Methods

The early history of extreme event attribution, grounded in a probabilistic or 'risk-based' approach, is set out in the previous section. These approaches have been further refined but remain fundamentally the same. The foundation for statistical analyses of extremes, which are by definition rare events, is in large ensembles of multiple climate models and observational and/or reanalysis.

The earliest truly large ensemble used for attribution was weather@home, a regional climate modelling system built using the volunteer distributed computing network of climateprediction.net, in which a global atmosphere-only climate model, HadAM3P, is used to provide boundary conditions to a higher resolution regional model, HadRM3P (Massey et al. 2015). This system has been extensively validated (Massey et al. 2015; Guillod et al. 2017) and provided tens of thousands of years

of synthetic weather widely used in attribution studies (Van Oldenborgh et al. 2017; Frame et al. 2020b), though has several known biases including high summer temperature variability over Europe (Leach et al. 2020). Similarly, the HadGEM3-A atmosphere-only model has been used as the basis for an attribution-ready system (Christidis et al. 2013a). Within this system, factual and counterfactual simulations are created by changing the magnitude of atmospheric forcing such as greenhouse gases, and driving the model with prescribed SSTs and sea ice extents; for the factual world these are drawn from the observed Hadley Centre Sea Ice and Sea Surface Temperatures (Rayner, N., Parker, D. E., Folland, C. K., Horton, E. B., Alexander, L. V., & Rowell 2003a), and for counterfactual the change in these due to anthropogenic forcing is estimated and subtracted (Pall et al. 2011a; Christidis et al. 2013a).

The most recent Coupled Model Intercomparison Projects (CMIP5 and CMIP6) provide a range of single and multi-model ensembles of global climate, many of which run from 1850 to present day and a range of emissions scenarios beyond (Eyring et al. 2016). In addition, a range of projects probe these models in greater detail for specific purposes, such as HighResMIP, which explores the impact of higher resolution on weather scales (Haarsma et al. 2016). In particular, the COordinated Regional Downscaling EXperiment (CORDEX) features an ensemble of downscaled regional models driven by global climate models, running from 1950-2050, and has been used in a range of attribution studies (Zachariah et al. 2022a; Otto et al. 2023). Most recently, in recognition of the formidable challenges posed by the sheer quantities of data required in many aspects of climate science (especially including study of extremes), data repositories featuring models from many of the above have been compiled to facilitate such analyses. For example, the Multi-Model Large Ensemble Archive combines both a range of models and many ensemble members from each model to simultaneously improve robustness through understanding model differences, and statistical power through big data (Deser et al. 2020).

Observational data comes from a range of sources and is more dependent upon the location of the event. Weather station data contains the more accurate information at a local scale, but records are often incomplete or inconsistent, containing time gaps, recording errors, and historical changes in recording methods (Philip et al. 2020), and they are not spatially homogeneous. Gridded datasets, developed through interpolation of nearby stations, can address the latter challenge to some degree, but the uncertainties on this remain a function of the number of available stations. In Europe, E-OBS provides a reliable and long-term record of gridded meteorological data across much of the continent from 1950 at a fairly high resolution of up to 0.1° x 0.1° (Haylock et al. 2008). The historical data to construct such a dataset is simply lacking in much of the world (Otto et al. 2020a). Nonetheless, such products do exist on the global scale. For instance, the Climate Prediction Centre's daily gridded temperature and precipitation datasets are available at 0.5° x 0.5° resolution globally (Chen et al. 2008). These only go as far back as 1979, making it challenging to identify attributable trends, but they are frequently used in studies in regions for which there are no lengthier alternatives (Pall et al. 2017; Otto et al. 2018a; Rimi et al. 2019).

Satellite data is still too recent for most trends and has significant bias compared with ground measurements (Philip et al. 2020). However, developments in post-processing algorithms means that datasets such as GPM-IMERG (Hou et al. 2014) form a useful line of evidence alongside other observational sources (Otto et al. 2023). Reanalysis products, in which observations of different kinds are assimilated into a climate modelling system, are often the most consistent and reliable pseudo-observational data possible, especially where data is sparse. For example, the ERA5 reanalysis dataset (Hersbach et al. 2020a) is widely used in attribution (Krikken et al. 2019; van Oldenborgh et al. 2020; Philip et al. 2022) and now stretches back to 1950 (Bell et al. 2021). It is widely understood that use of multiple observational and/or reanalysis datasets is crucial when studying the tail of variable distributions (Donat et al. 2014; Angélil et al. 2016).

Probabilistic analyses of the observations and model data utilise statistical fits of (typically) extreme value distributions to the variable of interest. Once an event has been defined through a spatiotemporal scale and observed magnitude, the return period of this in the current climate is ascertained through extreme value theory; an appropriate distribution, such as a Generalised Extreme Value (GEV) Distribution for block maxima or Generalised Pareto Distribution (GPD) for values above a threshold, is fit to recent observational data, thus enabling a probabilistic estimate of extreme occurrence. Then, there are broadly two methods for elucidating the influence of anthropogenic forcing (the following methods correspond to those used by World Weather Attribution and are both simple and well-established within the community at large).

First, 'fixed forcing' involves comparison of the occurrence of extremes in two independent time periods. This involves running simulations at fixed levels of anthropogenic forcing, typically the level around time of event occurrence and a pre-industrial 'natural' climate, and fitting extreme value distributions to the variable of choice in each. The return period calculated from observations is used to define the magnitude of an equivalent 'event' within the model data; this reduces the need for bias correction as it corresponds to a quantile mapping method for the variable of choice. Then, the change in the magnitude of events of equivalent rarity, or change in likelihood of events of equivalent magnitude, can be calculated across the modelled scenarios. The uncertainty on this is typically estimated using a non-parametric bootstrapping procedure.

Similarly, observational data or climate models with historical levels of forcing (i.e. continuously changing, rather than some fixed level) can still be analysed in this way by selecting time periods of ~30 years, in which the forcing can be considered to be reasonably steady. In these cases, this method ultimately sacrifices statistical power by discarding data. However, it also makes fewer assumptions implicit in the second approach, 'transient forcing'.

The transient forcing method is used to analyse trends in extreme variables due to some changing forcing factor; capitalising on the full range of available data while making simplifying assumptions

about the behaviour of the non-stationary extreme distributions. In this case, the factor of interest – most commonly global mean surface temperature – is treated as a covariate. Certain properties of the extreme value distribution are assumed to vary with this; for temperature extremes the distribution is assumed to shift with warming, for precipitation it is assumed to scale. The event magnitude within models is defined in the same way as for the fixed forcing; using the return period of the observed event. Then, by selecting the forcing level of interest, the return period at that point can be calculated from the distribution at that point.

Storyline Methods

Early examples of the storyline method include the Texas drought of 2010/11, in which years with similar La Nina conditions at different levels of anthropogenic warming were considered (Peterson et al. 2013), and how the observed SST anomalies and anthropogenic forcing affected different aspects of the drivers of the drought (Hoerling et al. 2013). Another studied the European winter cold spell of 2009/10, analysing the effect of thermodynamic influences of climate change by conditioning on circulation patterns similar to those observed, showing that the temperatures were warmer than would be expected given this conditioning (Cattiaux et al. 2010).

The storyline method became formalised in a series of papers from 2015 onwards. Trenberth et al. (Trenberth et al. 2015) first introduced the concept formally by directly proposing that attribution studies should be conditioned on the circulation regime or occurrence of the event itself (assuming that these remain largely unchanged) and exploring the thermodynamic effects only, with a focus on recent cases linked to elevated SSTs. In 2015, Hazeleger et al. (Hazeleger et al. 2015) proposed that the risk of future impactful weather events could be understood through constructing highly conditional ‘tales’ or ‘storylines’ of plausible events using high resolution weather models. This approach offers a more physically consistent picture and more accurate modelling of the relevant phenomena. In addition, the results can be more easily communicated to and even actively involve

decision makers, with respect to the traditional “top-down” modelling and downscaling approach for assessing risk.

The concepts within these papers were further unified and developed by Shepherd (Shepherd 2016), beginning the process of integrating the storyline method into a consistent framework with the traditional probabilistic approach. This paper argued that distinguishing between thermodynamic and dynamic drivers of an event would help to reduce and clarify uncertainties on the attribution result, albeit by providing only a partial attribution. In particular, it argued that this method is useful when a probability-based approach of all drivers either cannot provide a detected result, or may provide an inaccurate result. This often arises due to the deep uncertainties associated with changes in complex and poorly understood dynamics. Further, it argued that while the use of multiple models to test the sensitivity of the results to this choice are crucial for robustness, a multi-model ensemble is not a meaningful distribution for the purpose of quantifying the deep uncertainty on a single result (i.e. beyond sampling uncertainty).

Shepherd et al. (Shepherd et al. 2018) then developed a typology of reasons for using storyline methods to represent uncertainty in climate change analysis. This discussion was not limited to the case of attribution, but all of the arguments apply to attribution as well as the broader applicability to developing useful regional climate information (Shepherd 2019). The categories of cases suggested include: framing risk in terms of plausible events (i.e. how risk is experienced) rather than in a relatively abstract probabilistic sense; informing decision making by tying analysis to specific vulnerability or decision, such as an adaptation policy; consider the uncertainties on different elements of the climate system separately, in a way that provides useful insight; change framing from what is the probability to what is the plausibility, thus helping to highlight potential surprises.

Studies taking a conditional perspective to assess anthropogenic influence are now commonplace, and employ a variety of methods. For instance, in a landmark paper, Patricola & Wehner (Patricola and Wehner 2018a) use hindcasts of Hurricanes Katrina, Irma and Maria (as well as 15 similar

hypothetical events in the future) with boundary conditions altered based on the thermodynamic influence of climate change, to explore the direct influence of this warming on both rainfall and wind speeds. Similar approaches were applied to Hurricanes Florence and Dorian (Reed et al. 2020, 2021) and are now a well-established system for attributing tropical cyclones (Wehner et al. 2019). An alternative approach is nudging. Within this method, the large-scale upper atmospheric conditions (i.e. vorticity and divergence) are pushed to those seen in reanalysis using global spectral nudging, allowing the lower atmosphere to evolve freely, while counterfactual scenarios are created by simultaneously altering SSTs and greenhouse gas concentrations (Van Garderen et al. 2021), as applied to the 2011/12 summer drought in SE South America, showing how the wetting and warming trends counterbalance to likely reduce impacts on agriculture in the region (van Garderen and Mindlin 2022).

Taking a highly mechanistic approach, Trenberth et al. (Trenberth et al. 2018) showed that record heat in the waters of the Gulf of Mexico amplified the exceptional rainfall from Hurricane Harvey, by providing it with additional sustenance through warmth (especially in the subsurface, which helped maintain the high SSTs) and additional rainfall through atmospheric moisture. In addition, the authors argue that while frequentist analysis generally shows an increase in rainfall of 5-15% from tropical cyclones, due to the non-linear effects involved, the majority of the impacts ("in this case hundreds of billions of dollars") may be prescribed to climate change. This is a non-exhaustive list of examples of the storyline approach in action but demonstrates the range of possibilities for controlling dynamic conditions to provide deeper insight.

'Unified' methods

All forms of attribution contain some degree of conditioning and some element of probability. However, the inherent link between the storyline and probability-based approaches is most clearly exemplified in new approaches using operational weather models. Recent studies use operational weather forecasting models that successfully predicted an extreme to perform hindcasts of the same event, with and without the influence of anthropogenic forcing. The benefits of this method are that

model evaluation is pre-established by the success of the forecast, that such models tend to be far higher in resolution than climate models, and that this represents a direct attribution of the event itself, rather than a similar hypothetical event (Leach et al. 2021). Furthermore, this combines the storyline and probability-based approaches in a way that can be tailored extremely closely for each study. The lead time used in each run of the forecast corresponds directly to the level of conditioning on the dynamical drivers of the event, with the shortest lead times showing most closely the direct radiative effect of anthropogenic forcing, and the longest including greater aspects of dynamical variability. As such, a lead time can be selected to answer specific questions about the role of climate change, or the results from a range of lead times can be compared to explore the relative contributions of different factors.

As set out above, the two broad categories of methods are two sides of the same coin; two somewhat arbitrary categories along the spectrum of conditioning. The operational forecasting approach illustrates this most clearly. However, all forms of attribution lie along this spectrum. In particular, as future extremes occur, these methods should be considered within the suite of tools that can be employed to elucidate the present and future role(s) of climate change in such events. There is no one-size-fits-all approach to attribution. Therefore, within these options, a selection should be made based on the core questions being asked by stakeholders, considering the kinds of uncertainties that are relevant and acceptable to maximise informativeness.

1.2.2 Thesis aims

This thesis is concerned with the overarching and substantial challenge of understanding the risks and impacts of climate change on human systems through its influence on extreme weather around the world. The challenges of determining both the impacts of climate change through its influence on past events, and the risks in the present and future, are myriad. The landscape of risk is multidimensional and constantly shifting, largely becoming increasingly severe but at different rates in different places and for a variety of reasons. The questions of when and who should mitigate these changes and how

to distribute limited resources to most effectively manage these risks are both important and formidable. Accurately informing these discussions is predicated partially on understanding these risks.

However, the field of attribution has now existed and evolved consistently for just over 20 years. During this time, hundreds of studies on individual events have been undertaken, representing a substantial body of evidence on what has occurred and is therefore, by definition, plausible. So far, these studies have almost entirely been considered in isolation and largely of interest in the aftermath of an event. The foundation of this thesis is that these individual data points together constitute a useful (albeit heavily caveated and partial) illustration of the risk landscape, and the individual studies within the thesis explore methods for utilising this information, broadening it, and linking it with other related fields of risk analysis.

As a starting point, I set out a review of the current literature on attributing impacts for different hazards and the key knowledge gaps. This consists of extreme weather attribution for a range of hazards, followed by how such meteorological hazards connect to the observed impacts in different regions, and cases in which this connection has been explicitly studied. This review has been published in a peer-reviewed journal (Clarke et al. 2022) and its recommendations determine the remainder of the work presented in this thesis. This review is presented in the following chapter, but the aims of the thesis that emerge from its primary conclusions are detailed below.

1) Documenting past events in a standardised inventory system, and meta-analysis of such as system

The first aim of this thesis focuses on bringing together the fields of extreme weather attribution, which can now aid understanding of the key drivers of impacts of events that have happened, with efforts towards disaster risk reduction. This is based on an extensive review of recent extreme events, the drivers of their impacts, and the impacts themselves in two regions, the UK and Puerto Rico, for the years 2000-2019. This review is compiled into a formal inventory structure and the challenges and implications of constructing such inventories for these regions and those more widely across the world

are explored. The two regions themselves form useful proxies for regions across the world in terms of the hazards represented and the levels of both attribution study and impacts recording available.

2) Deriving new attribution statements based on existing evidence and prioritising the most important regions and hazards for new studies.

The second aim involves increasing the utility of attribution studies that we already have. First, I explore the key uses for attribution results through discussion and bringing together arguments presented in the wider literature. This forms the basis for the aim of the chapter itself; exploring how, in the event of a new extreme occurring, such use cases may be satisfied by drawing on the extensive body of studies that already exist. The rationale behind this is that by drawing more information from existing studies, we may prioritise limited resources for attribution on regions and hazards that are both underrepresented and less well understood.

3) Integrating probabilistic event attribution with risk analysis

The third and final aim of the thesis is to apply attribution to recent highly impactful extremes in Pakistan in 2022; the hot spring period followed by heavy precipitation leading to extreme flooding in late summer. First, this chapter builds upon existing study of the rainfall events (Otto et al. 2023) using high resolution observational and reanalysis datasets and CMIP6 models and using attribution to provide insight into changing risks in several ways. First, the features and drivers of the 2022 extreme events are investigated, alongside the similar disasters of 2010. Then, changes in May temperatures and the same rainfall event definitions as Otto et al. (2023) across future emissions pathways are estimated, both in isolation considering both rainfall events as a single compound event, as part of a novel compound events framework. The direct influence of warming May temperatures on extreme monsoon rainfall is also explored. This work develops new approaches in probabilistic event attribution and provides multiple lines of evidence for analysis of present and future risk.

The remainder of this thesis is set out as follows. Chapter 2 is a literature review of the attributable impacts of climate change. Chapters 3, 4 and 5 each consist of an original research paper or chapter addressing one of the core challenges identified by the literature review (published, accepted for publication and in prep, respectively). Chapter 6 concludes by summarising the findings of the thesis as a whole, the wider implications for the field of extreme event attribution and its use cases, pathways for future work to build on these findings, and my preliminary efforts towards these extended goals. In the appendices, wider contributions to the field of climate science, communication and policy as a whole are detailed, which are related to the field of extreme event attribution but do not fit directly into the thesis itself.

Chapter 2 – Extreme weather impacts of climate change: an attribution perspective

Abstract

Extreme event attribution aims to elucidate the link between global climate change, extreme weather events, and the harms experienced on the ground by people, property, and nature. It therefore allows the disentangling of different drivers of extreme weather from human-induced climate change and hence provides valuable information to adapt to climate change and to assess loss and damage. However, providing such assessments systematically is currently out of reach. This is due to limitations in attribution science, including the capacity for studying different types of events, as well as the geographical heterogeneity of both climate and impact data availability. Here, I review current knowledge of the influences of climate change on 5 different extreme weather hazards (extreme temperatures, heavy rainfall, drought, wildfire, tropical cyclones), the impacts of recent extreme weather events of each type, and thus the degree to which various impacts are attributable to climate change. For instance, heat extremes have increased in likelihood and intensity worldwide due to climate change, with tens of thousands of deaths directly attributable. This is likely a significant underestimate due to the limited availability of impact information in lower- and middle-income countries. Meanwhile, tropical cyclone rainfall and storm surge height have increased for individual events and across all basins. In the North Atlantic basin, climate change amplified the rainfall of events that, combined, caused half a trillion USD in damages. At the same time, severe droughts in many parts of the world are not attributable to climate change. To advance our understanding of present-day extreme weather impacts due to climate change, developments on several levels are required. These include improving the recording of extreme weather impacts around the world, improving the coverage of attribution studies across different events and regions, and using attribution studies to explore the contributions of both climate and non-climate drivers of impacts.

2.1. Introduction

Every year, climate change manifests through more intense extreme weather events, including heatwaves, droughts and heavy rainfall. This leads to impacts upon people, property and nature that would not have occurred in the absence of these increases in events' likelihood and intensity. Unlike some other impacts of climate change, extreme weather events are manifesting on immediate timescales and changes in extremes are poorly described by the climatological means studied in many projections. Unfortunately, there is currently no standardised way of, or effort towards, documenting climate change related harms systematically. As a result, there is no systematic basis to quantify the major contribution of human influence on extreme weather to the costs of climate change. This contributes to the challenge that measures taken to mitigate and adapt to current (of ~1.20 °C at the time of writing (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021)) and future levels of global warming are not based on what could be the best available evidence.

Extreme event attribution is the method through which the role of climate change in an individual event can be assessed and quantified (Allen 2003; Philip et al. 2020; van Oldenborgh et al. 2021). Over the past two decades, more than 350 studies have quantified the role of climate change in over 400 extreme events (Carbon Brief 2021). This growing body of evidence is complementary to other analysis, such as work documenting observed and modelled trends in extremes due to climate change, and projections of future risk. The evidence from attribution studies adds value by highlighting the role of climate as a risk driver in experienced events, which in turn is useful for building future resilience (Raju et al. 2022), and it enables the attribution of impacts, which is useful for cost-benefit analysis of mitigation and is a potential avenue for the exploration of drivers of loss and damage from climate-related extremes (James et al. 2019) . There is currently very little discussion of the role of science in determining loss and damage from anthropogenic climate change.

However, the number of events that have been studied using attribution methods is just a small fraction of all impactful extreme weather events that occurred over the same period. It is almost

impossible to document this comprehensively due to data, time and resource constraints (Harrington and Otto 2020a; van Oldenborgh et al. 2021). Furthermore, these studies overwhelmingly focus on events that occurred in the global north (Otto et al., 2020). This pattern is mirrored in the unequal recording of impacts from extreme events, although nations in the global south are experiencing the most rapid changes in risk (Byers et al., 2018) and often have high levels of underlying exposure and vulnerability to climate-related events.

The Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) provides a synthesis of attributable changes in extremes in regions across the world (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021). This forms a core part of the evidence base in this literature review. However, in order to link regional assessments of attributable risk to impacts that have occurred, it is necessary to compile attribution statements for individual events. In doing so this review builds on the IPCC assessment, linking broad changes in hazards to the ways in which these manifest and interact with exposure and vulnerability, and result in tangible impacts, with a bottom-up methodology, in which I develop insight into human influence on assessed extreme weather event categories based on literature on individual events. Further, the distinction between regional assessment and individual events is particularly important in adding evidence for more complex events, such as droughts, and at smaller spatial scales than the IPCC's regional aggregations, at which other phenomena may affect the influence of climate change.

Overall, the review brings together the best evidence we have on changes in extreme weather hazards and the impacts of past events, covering five key hazards: heatwaves, rainfall-based flooding, droughts, wildfires, and tropical cyclones. It is important to note that several of these hazards fall along different parts of the causative chain that stretches from anthropogenic climate change to impacts; each was selected as an appropriate intersection between attribution science and impact-relevance. As such, for each hazard, I assess the degree to which past impacts can be attributed to anthropogenic climate change, and the limiting factors associated with this. In doing so, I also build a

picture of where evidence is most lacking, and therefore most urgent, for both attribution science and the documenting of impacts.

Each hazard section is laid out as follows. First, I describe attributed changes in extremes on global and regional scales, then how individual event attribution fits within this. Second, I discuss why it matters, describing the causative chain that results in key impacts arising due to such hazards. Finally, I discuss the 'attributable impacts' for each hazard. The intent of this subsection is not to suggest that the impacts of an event with any degree of anthropogenic influence, no matter the scale, are all attributable to climate change. Instead, these sections contain individual attribution statements alongside the impacts of those events, in the context of their connections as described previously. This should be interpreted as a snapshot, constrained by the body of existing attribution statements and to date, of the types and magnitude of impacts that have manifested to some degree by anthropogenic climate change. I posit that this is currently the most we can know based on existing evidence. And, in the absence of science to accurately attribute impacts using an end-to-end system for every event (and understanding that a FAR-based attribution of impacts is most applicable to classes of event (Perkins-Kirkpatrick et al. 2022)) this is nonetheless more useful than neglecting to combine such information at all. Tables 1 and 2 summarise this information on a global scale.

This is not a review of risk, because that is impossible without also discussing vulnerability and exposure to changing hazards. However, it provides a platform on which to begin such a discussion. Further, it is a basis for placing a price tag on the diverse impacts of climate change, with implications for mitigation and adaptation considerations at all levels of decision-making. It concludes with several key areas in which further work will improve upon quantification of climate-related impacts, and the applications of this to address the inequity at the heart of the climate crisis (Pelling & Garschagen, 2019; Stone et al., 2021; Raju et al., 2022).

2.2 Climate change and extreme weather impacts

2.2.1 Heat

Changes in extremes: The most dramatic changes in extreme weather induced by climate change are in the rate and intensity of heat and cold extremes. The rate and intensity of cold extremes are declining while heat extremes are increasing (Dunn et al., 2020), with dire consequences for communities around the world. By 2015, the chance of the most extreme daily maximum temperatures (above the 99.9th percentile) averaged over land had increased fivefold (Fischer and Knutti 2015a). Globally, as a direct result of climate change, previously very rare heat is now just unusual (Donat et al. 2016; King 2017; Dunn et al. 2020; Seong et al. 2021a), while, in some cases, events now considered 'extreme' reach temperatures that were formerly all but impossible (Rahmstorf and Coumou 2011; Imada et al. 2019; Sippel et al. 2020; Robinson et al. 2021). The 2021 IPCC report is unequivocal in stating that average and extreme heat are increasing on every continent and that this is due to human-caused climate change (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021):

- A heatwave that would once have had a chance of **1 in 10 to occur in any given year** in the pre-industrial climate will now occur 2.8 (1.8 - 3.2) times more frequently and be 1.2°C hotter. At 2°C of global warming, it will occur 5.6 (3.8 - 6.0) times more frequently and be 2.6°C hotter.
- A heatwave that would have had a **1 in 50 chance to occur in any given year** in the pre-industrial climate will now occur 4.8 (2.3 - 6.4) times more frequently and be 1.2°C hotter. At 2°C of global warming, it will occur 13.9 (6.9 - 16.6) times more frequently and be 2.7°C hotter.

For even rarer events and on local scales the changes are even more dramatic. The increasing regularity of formerly rare events is particularly consequential: societies tend not to prepare for events that were historically so unlikely that they have never occurred (Woo 2016). Societies are especially

vulnerable to the exceptionally extreme events that are now possible in a changing climate (Ciavarella et al. 2021). In addition to this global picture, regional trends in heat extremes are attributed to climate change in Asia (Dong et al. 2018; Yin et al. 2019; Chen and Sun 2021), Africa (Stott et al. 2011), Australia (Alexander and Arblaster 2017), Europe (Christidis and Stott 2016) and South America (Rusticucci and Zazulie 2021). A synthesis of current regional changes due to human influence are shown in Figure 1. I reproduce this figure and others from Working Group 1 (WG1) contribution to the IPCC AR6 (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021) to give context for our discussion of where attribution can add value to these global and regional pictures.

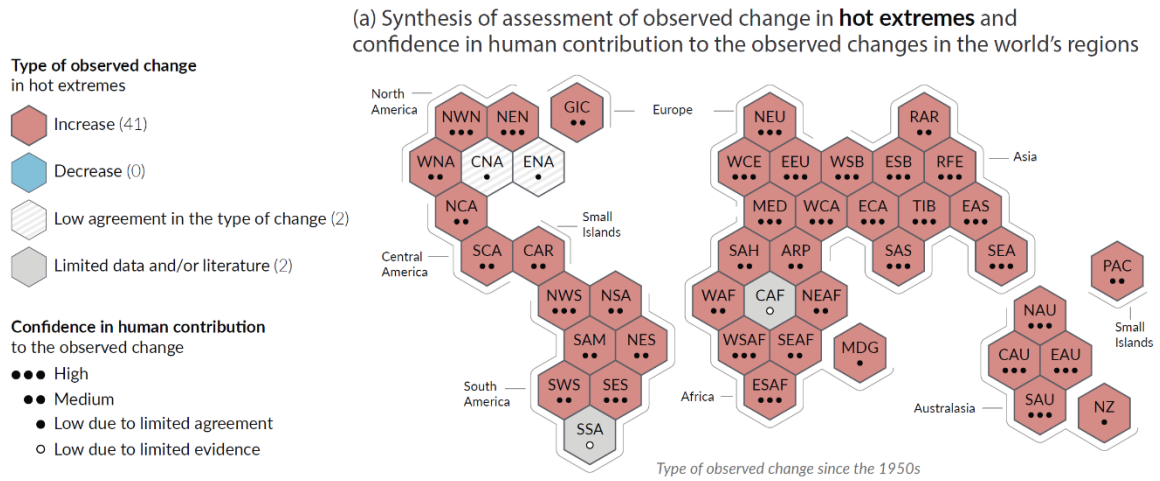


Figure 2.1: Synthesis of assessment of observed change in hot extremes and confidence in human contribution to the observed changes in the AR6 land-regions, excluding Antarctica.. The evidence is mostly drawn from changes in metrics based on daily maximum temperatures; regional studies using other indices (heatwave duration, frequency and intensity) are used in addition. From Figure SPM.3 of the WG1 contribution to the IPCC AR6. See (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021)*) for more details and* (Otto et al. 2021)*) for the dataset.*

Why it matters: The impacts of extreme heat range from infrastructure disruption and power outages to widespread morbidity and mortality, with cascading impacts between the two (Stone et al. 2021a). Here, I focus primarily on the health-related impacts because (where recorded) they are extremely

severe, both directly and through the indirect effects on labour productivity. The same discussion utilising event attribution could be extended to other impacts. The impact of increased temperatures on mortality is widely established in the epidemiological literature. As climate change intensifies heatwaves around the world, the risk of heat-related deaths increases unless exposed populations' vulnerability is reduced. The fraction of the burden of heat-related mortality that is due to climate change is large and growing, with 37% of heat-related deaths attributed to climate change worldwide (Vicedo-Cabrera et al. 2021), equivalent to tens of thousands of deaths per year. Increases in the number of hot days, and intensity of heatwaves results in a range of heat-related illnesses. Such illnesses include cardiovascular and respiratory complications, renal failure, electrolyte imbalance, and harm to foetal health (Moyce et al. 2016; Ebi et al. 2018; Parsons et al. 2021). Increasing temperatures and heatwaves have also increased the prevalence and range of temperature-sensitive pathogens, such as *Vibrio*, which can cause cholera and gastroenteritis (Ebi et al. 2017).

Increases in the occurrence of heat extremes result in substantial increases in mortality, and this effect is particularly pronounced the higher the temperatures. Climate change increases the likelihood of reaching very high temperatures, at which point the human body may no longer be able to cool itself. The theoretical limit for human survival is a 'wet bulb' temperature of 35 °C, at which point even the healthiest human in shade and with water would die from severe heat stroke in a matter of hours (Raymond et al. 2020). Both mortality and morbidity rise significantly at far lower temperatures than this upper limit, affecting the elderly, very young and those with pre-existing medical conditions, such as respiratory and cardiovascular illness (Michelozzi et al. 2009; Sugg et al. 2016; Watts et al. 2018; Green et al. 2019). Heatwaves are also strongly associated with rises in harmful pollutants such as ozone, particulate matter, sulphur dioxide, carbon monoxide and nitrogen dioxide, which further contribute to respiratory health impacts (Garcia-Herrera et al. 2010; Analitis et al. 2014; Li et al. 2017; Kalisa et al. 2018).

A direct consequence of the health impacts of heat is a loss of labour productivity during hot periods, as workers must slow down, take more breaks, and hydrate to remain safe (Sahu et al. 2013; Kjellstrom et al. 2016; Spector et al. 2019; Borg et al. 2021). In the US alone, labour productivity losses due to extreme heat cost around USD 2 bn annually (Zhang and Shindell 2021), while across the world total losses amount to USD 280-311 bn (Borg et al. 2021). These are concentrated in lower- and middle-income countries, in tropical and subtropical areas, and in heavy manual labour and outdoor industries such as agriculture and construction (Kjellstrom et al. 2016; Borg et al. 2021; Parsons et al. 2021). Across the world, the labour capacity of rural populations during summer months fell by 5.3% between 2000-2016 due to rising heat – in tropical regions capacity fell by up to 30% (Watts et al. 2018). While some adaptation policies have already been put into place, such as moving work hours earlier in the day, these measures may come with unintended consequences, and decrease in effectiveness as warming continues (Masuda et al. 2019; Parsons et al. 2021).

While there have been very few observations of wet bulb temperatures over the critical 35 °C threshold, the occurrence of dangerous humid heat extremes, exceeding wet bulb temperatures of at least 27 °C, has more than doubled since 1979 (Raymond et al. 2020). By another measure, 40% of the total land surface has already entered an “unusual” climate in the warmest months - that is, temperatures exceed a signal-to-noise ratio of 1 (Frame et al. 2017; Hawkins et al. 2020). Increases in severe heat hazards cause a disproportionate increase in the associated health risks because a disproportionately large fraction of the global population lives in hotter regions (Watts et al. 2018). On top of that, between 2000-2016, the number of vulnerable people (over 65 years) exposed to extreme heat increased by 125 million, reaching 175 million in 2015 (Watts et al. 2018).

Attributable impacts: Climate change amplifies the temperature of most heat extremes (Otto et al. 2016). Attribution research has found that the most extreme heatwaves have become substantially more likely, or even only possible at all (Imada et al. 2019), due to climate change. This includes, but is not limited to, events in Europe in 2003 (Stott et al. 2004a; Christidis et al. 2015a) and 2018 (Leach

et al. 2020), Russia 2010 (Rahmstorf and Coumou 2011; Otto et al. 2012), the US (Shiogama et al. 2014), China (Sparrow et al. 2018; Zhou et al. 2019), Argentina (Hannart et al. 2015), North Africa (Mitchell 2016), Australasia (Hope et al. 2016), South and Southeast Asia (Azhar et al. 2014; Wehner et al. 2016; Mazdiyasni et al. 2017; Christidis et al. 2018b; Imada et al. 2018), and across the world (Peterson et al. 2012, 2015; Herring et al. 2014b, 2015, 2016a, 2018, 2019a, 2020). In some cases, events were effectively impossible in the absence of climate change (Imada et al. 2019; Herring et al. 2019b, 2020, 2021; World Weather Attribution 2021a; Fischer et al. 2021), including the emerging possibility of simultaneous heat extremes across regions and continents (Vogel et al. 2019; Kornhuber et al. 2019).

Between the years 2000-2020, the disaster database EMDAT recorded approximately 157,000 deaths from heatwaves across the planet (presented in table 2.1 at the end of this chapter, alongside other hazard types)(EMDAT 2019), although it is acknowledged that this is likely to be a substantial underestimate due to reporting limitations and because deaths due to heat occur outside of officially-declared events (Otto et al. 2020a). Around 125,000 of these deaths occurred during just two events, the European heatwave of 2003 and Russian heatwave of 2010, which resulted in 70,000 and 55,000 deaths, respectively. Both of these events were made substantially more likely by climate change, as noted above (Stott et al. 2004a; Rahmstorf and Coumou 2011; Otto et al. 2012). In the case of the 2003 heatwave, this was made at least twice as likely to occur, due to climate change, and has since become 10 times more likely again (Christidis et al. 2015b). The Russian heatwave, meanwhile, was found to have been made 5 times more likely to occur by the climate change observed since 1960 (Rahmstorf and Coumou 2011). In the UK, estimates using simple hazard-based fractional attributable risk (FAR) methodology link around 1,500 excess deaths from three heatwaves directly to climate change (Clarke et al. 2021b). Another study on the 2003 heatwave used an end-to-end approach, combinining meteorological attribution with the effect of temperatures on mortality, to directly

attribute deaths in Greater London and Central Paris; 64 additional Londoners (~20% of the total) and 506 Parisians (~70% of the total) died due to the influence of climate change (Mitchell et al. 2016b).

CASE STUDY: Western Russia, 2010

From early July until mid-August 2010, an intense high-pressure system over Eastern Europe and Western Russia caused temperatures to soar above 30 °C throughout the region, breaking 40 °C in many major cities. An event of this magnitude was made approximately 3-5 times more likely by climate change (Rahmstorf and Coumou 2011; Otto et al. 2012).

This extreme heat led to widespread drought conditions that decimated 25% of the entire annual crop yield and also amplified wildfires across more than 10 million hectares of dried-out forests, steppe and peat regions (Barriopedro et al. 2011; Bondur 2011). This compounded an already growing fire hazard in rural Western Russia, resulting from changes in land use and sustainable management, among other factors (Goldammer 2010). The destruction of grain crops and subsequent export ban led to rising food prices domestically and abroad. Pakistan was Russia's fourth largest customer and experienced a 16% rise in the price of wheat, linked with a 1.6% rise in poverty (Welton 2010). The destruction of thousands of properties left over 3,500 people homeless. Harmful gases and aerosols from the fires became trapped in the stagnant high-pressure system, resulting in poor air quality in many major cities. This exacerbated the already-unprecedented public health crisis, particularly affecting those with severe asthma and heart problems. In the city of Moscow alone, around 5,000 more deaths were recorded than for the same period in the previous year, and across the whole country this was closer to 55,000 from a combination of heat and poor air quality (Barriopedro et al. 2011).

Underestimation of impacts: These Europe-focused results are far from a complete tally of climate change-amplified heatwave impacts. This is largely due to data limitations. Both assessments of health

associated with extreme heat (Green et al. 2019) and weather observations, crucial for assessing the link to climate change (Otto et al. 2020a), are concentrated within higher income countries. EMDAT lists 147 instances of impactful heat events from individual countries for the period 2000-2020, only an improbably low 58 of which are from all of Asia, Africa, South and Central America and the Caribbean combined (EMDAT 2019). Of the 157,000 total deaths recorded, only 10,000 – or 6.3% – were recorded in these regions, which together constitute almost 85% of the world's population, over 60% of the land mass, and many of the hottest and most humid climates. These data are subject to recording biases that limit the number of heatwaves registered to EMDAT to those that are officially declared by national meteorological services, many of which do not currently have formal heatwave definitions, and recorded locally as exceeding one of several impact thresholds; thus, they are limited by the capacity of governments or NGOs to attribute heat-related impacts. Further, this dataset focuses only on heatwaves, periods of relatively extreme temperatures, whereas many heat-related deaths in fact occur outside of heatwaves, when temperatures are also increased by climate change, but are not captured within these data (Gasparrini et al. 2015).

In the two most impactful European heatwaves recorded, the maximum recorded wet-bulb temperature peaked at 28 °C; temperatures frequently exceed this in other regions of the world such as south Asia (Raymond et al. 2020), with many more lethal heat events likely already occurring than are reported (Mora et al. 2017).

In addition to the attributable trends in exposure to extreme heat, we can elicit evidence from the few attribution studies that exist. For instance, in 2015 in the Indian city of Hyderabad, heat extremes over a 5-day period were made more than 30 times more likely by climate change (Wehner et al. 2016). Including this event, three devastating heatwaves in India in 2010, 2013 and 2015 resulted in the deaths of at least 5,000 people (Azhar et al. 2014; Mazdiyasni et al. 2017). Meanwhile in neighbouring Pakistan, also in 2015, the city of Karachi experienced an extreme heat event which by the same measure would have been effectively impossible without climate change (Wehner et al. 2016).

The impacts from heatwaves in hotter climates may be somewhat mitigated by factors such as the natural acclimatisation of populations – which might also be considered as longer-term impacts upon behaviour, culture and architecture – and age demographics (Gasparrini et al. 2015; Green et al. 2019). However, these mitigating factors are more than likely offset by greater population density, higher frequency of more intense extremes, and greater vulnerability in many of the regions with few reported impacts (Harrington and Otto 2018; Rohat et al. 2019). I am therefore confident that the reported deaths from heatwaves and extreme heat, and thus those linked to climate change, are a vast underestimate.

Is increased heatwave-related mortality offset by a reduction in cold extremes? Cold extremes are decreasing in frequency and intensity across most of the world and at continental and subcontinental scales (Christidis and Stott 2016; King 2017; Hu et al. 2020; Dunn et al. 2020). In the Arctic, the rise in heat extremes (Sui et al. 2017; Dobricic et al. 2020) and decrease in cold extremes (Sui et al. 2017) is especially pronounced, in line with its rapid warming (Box et al. 2019). Specific cold spells of recent years have displayed this decreased probability due to climate change, including in the UK (Christidis and Stott 2020), US (Bellprat et al. 2016), Europe (Peterson et al. 2012; Christiansen et al. 2018) and China (Sun et al. 2018).

On average, mortality and morbidity rates are higher in winter than summer months in temperate regions (Conlon et al. 2011; Ebi and Mills 2013; Gronlund et al. 2018), with a more complex relationship in locations across the tropics and subtropics (McMichael et al. 2008; Singh et al. 2019). The direct effect of cold on health remains obscured by the wide array of seasonal factors at play (Staddon et al. 2014a; Kinney et al. 2015; Hajat 2017), including cardiovascular disease which is only weakly linked to cold temperatures (Ebi and Mills 2013). For the effect of extremes specifically, there are two key factors to consider. First, temperature-mortality relationships are generally far steeper for extreme heat than extreme cold (Gronlund et al. 2018). Second, the most severe winter cold spells contribute little to overall winter mortality, and even in some temperate regions there is evidence

that climate change will not decrease winter mortality (Staddon et al. 2014b). Thus the reduction in frequency and intensity of cold extremes has likely not affected overall changes in mortality substantially, nor offset those from hot extremes (Ebi and Mills 2013) and the impact of increasing heat-related mortality are assessed to far exceed any reductions in cold-related mortality as a result of climate change (Huber et al. 2017; Gasparrini et al. 2017; Vicedo-Cabrera et al. 2018).

2.2.2 Rainfall and flooding

Changes in high rainfall extremes: By 2015, climate change increased the likelihood of daily precipitation extremes exceeding the 99.9th percentile of pre-industrial events by 18%, averaged over all land regions (Fischer and Knutti 2015a). A warmer atmosphere holds more moisture at a given pressure: the Clausius-Clapeyron relation states that the increase in moisture held at a given pressure is 6-7% per 1 °C. Extra water in the atmosphere combines with changes in weather patterns to affect rainfall extremes in a given region (O'Gorman 2015; Pfahl et al. 2017). In contrast to heat, these changes vary greatly across regions and seasons. For example, extreme rainfall is increasing in Northern Europe in winter but decreasing in the Southern part of the continent in summer.

Nonetheless, since the 1950s, heavy rainfall has become more frequent and intense across most parts of the world, which is now known to be mainly due to human climate change (Fischer and Knutti 2015a). It hasn't strongly decreased in likelihood anywhere. Globally, the IPCC reports that, in a given location, what would once have been a one-in-10-year rainfall event currently occurs 1.3 (1.2 - 1.4) times every 10 years and is 6.7% wetter. At 2 °C of global warming, this will be 1.7 (1.6 - 2.0) times per 10 years and 14% wetter (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021). Sub-daily extreme rainfall events are intensifying at a rate at or exceeding Clausius-Clapeyron scaling (Fowler et al. 2021), while regional attribution shows that deluges generally are becoming more frequent and intense especially across North America, Asia and Europe (Chen and Sun 2017a, 2021; Paik et al. 2020; Dong et al. 2021; Sun et al. 2021), though this may also be true in other regions with a lower availability of observational data.

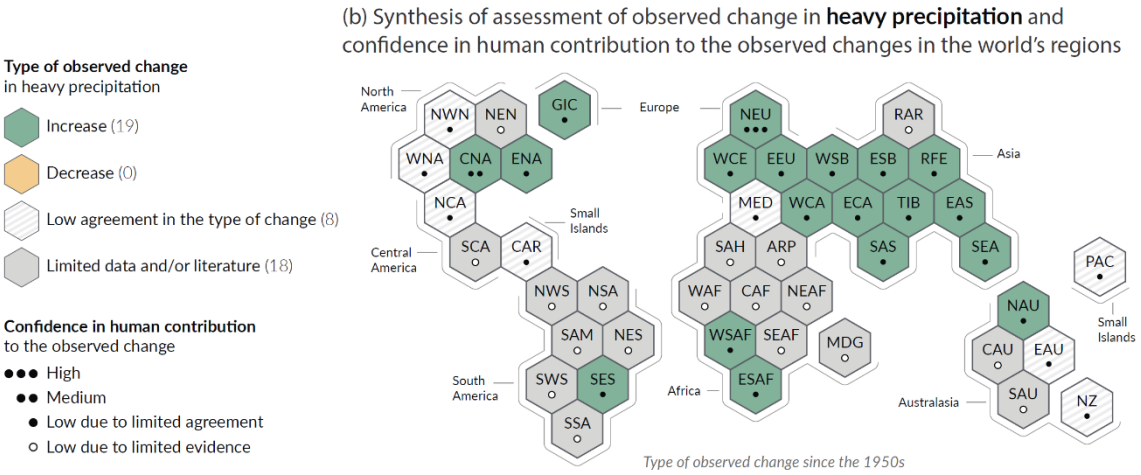


Figure 2.2: Synthesis of assessment of observed change in heavy precipitation and confidence in human contribution to the observed changes in the AR6 land-regions, excluding Antarctica. The evidence is mostly drawn from changes in indices based on one-day or five-day precipitation amounts using global and regional studies. From Figure SPM.3 of the WG1 contribution to the IPCC AR6. See (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021)*) for more details and* (Otto et al. 2021)*) for the dataset.*

Link with flooding: Flooding is a major source of the impacts that extreme rainfall has upon human societies. In general, changes in the risk of flooding due to heavy precipitation also depend on changes in other factors including the susceptibility of areas to flooding, land use change and river management (Ji et al. 2020), as well as other climate-related factors such as soil moisture, storm extent and snowmelt (Sharma et al. 2018; Wasko and Nathan 2019). As a result, there is high regional and sub-regional variation in trends in streamflow (Do et al. 2017; Gudmundsson et al. 2019), but many of the observed changes can only be explained by human influence on the climate (Gudmundsson et al. 2021). Evidence from attribution-science literature shows that growing numbers of floods have been made more intense by the effect of climate change on precipitation (Cho et al. 2016; Pall et al. 2017; van der Wiel et al. 2017a; Philip et al. 2018a; Teufel et al. 2019).

Why it matters: Flooding damages property and infrastructure, as evidenced by disaster data for the years 2000-2020 in which floods globally caused USD 610 bn in damage (Table 2). It also places people

in direct danger of injury and death. The flood events recorded in the EMDAT database led to 111,000 deaths and affected 1.66 bn people over the period 2000-2020 (Table 1)(EMDAT 2019). Indeed, flooding is the disaster that is recorded as affecting the greatest number of people - though this may be due to a bias arising from the variable ease of recording impacts for different disasters; heatwaves are more pervasive but ill-defined than flood extent, for example. One further study that considered only 'large floods' found that 255-290 million people were directly affected by flooding between 2000-2018, the population in areas affected by inundation grew by 58-86 million between 2000-2015, and the number of people affected by flooding continues to increase due to population increases and climate change (Tellman et al. 2021).

Floods impact both physical and mental health. Physical impacts result directly from dangerous water flows and inundation, as well as 'cascading impacts', in which the destruction of infrastructure limits access to services and utilities including clean water and sanitation, resulting in ill health (Ramana Dhara et al. 2013). In turn, this enhances the spread of and vulnerability to water-borne disease, including leptospirosis, cholera and other diarrhoeal diseases such as giardiasis, salmonellosis, and cryptosporidiosis (Marcheggiani et al. 2010; Ramana Dhara et al. 2013). The occurrence of such outbreaks following floods is well documented. This evidence includes an inventory of 87 extreme events between 1910-2010 (Cann et al. 2013a), known associations between flood events and gastrointestinal illness in the US (Patz et al. 2008; Uejio et al. 2014) and India (Bush et al. 2014), and has been observed in the aftermath of floods in Pakistan (Baqir et al. 2012), Mozambique (Devi 2019), China (Zhang et al. 2019), Ecuador (Carlton et al. 2014), the Solomon Islands (Jones et al. 2016) and many others (Fredrick et al. 2015; Levy et al. 2016). This is especially impactful in areas of pre-existing high vulnerability, such as those without access to improved sanitation and water sources, on top of other poverty- and conflict-related factors such as access to healthcare, education and early warning systems (Cann et al. 2013b; Davies et al. 2015).

In addition, vector-borne diseases such as malaria, dengue and West Nile Fever may spread further following flooding, as more widespread stagnant water bodies provide breeding grounds for mosquitoes (Ramana Dhara et al. 2013; Hinz et al. 2019). Finally, many diseases are also enhanced by the effect of warmth and high humidity, because this increases the longevity of many pathogens and mosquitoes (Moors et al. 2013; Levy et al. 2016; Hinz et al. 2019). The combination of climate change impacts on precipitation, temperature, and yet other factors that amplify the resulting impacts, such as societal capacity to deal with health impacts, create compound risks.

Other compound risks are also associated with flooding. For example, low-lying coastal areas are increasingly affected by high sea levels, due to storm surges and sea-level rise, which combine with heavy rainfall to amplify flood damages (Moftakhari et al. 2017; Bevacqua et al. 2019; Marsooli and Lin 2020). Similarly, tropical cyclones result in damage to infrastructure including power lines, water supplies and roads, increasing vulnerability to high temperatures as air conditioning is disabled, and access to clean water and healthcare are restricted (Lin 2019; Matthews et al. 2019; Yu et al. 2020a; Mejia Manrique et al. 2021).

The mental health impacts of disasters are also becoming documented and understood more widely, with an emerging literature (Watts et al. 2018; Hayes et al. 2018; Cianconi et al. 2020), especially on the impacts of floods (Tunstall et al. 2006; Stanke et al. 2012; Alderman et al. 2013; Azuma et al. 2014; Fernandez et al. 2015a; Burton et al. 2016; Waite et al. 2017). These impacts include post-traumatic stress disorder (PTSD), anxiety, depression and suicidal thoughts, among other conditions (Dodgen et al. 2016) and persist long after the disaster itself. First responders are severely impacted by the mental health effects of working in the aftermath of disasters, with local first responders most heavily affected (Osofsky et al. 2011; Rusiecki et al. 2014). These effects are more likely to occur in those with pre-existing mental health conditions (Dodgen et al. 2016; Hayes et al. 2018). Quantitative attribution of mental health impacts to climate change remains challenging. This is due to the diverse nature of such impacts, and because attribution studies typically consider one aspect of the causal chain

(climate-meteorological event or meteorological event-mental health impacts), not both (Hayes et al. 2018). However, a few cases exist in which mental health impacts are attributed to an event and the event itself is attributed to climate change. For example, the 2013/14 UK floods were made more likely by climate change (Huntingford et al. 2014; Christidis and Stott 2015; van Oldenborgh et al. 2015; Schaller et al. 2016; Kay et al. 2018) and caused increased psychological morbidity among those both flooded and disrupted (Waite et al. 2017).

Attributable impacts: Annual monsoons are a critical source of rainfall for at least 60% of the world's population in areas including south and east Asia, Australia, and east and west Africa (Li et al. 2016). The south Asian monsoon is of particular societal importance, providing 80% of the water to the subcontinent, which contains nearly a fifth of the world's population and is heavily reliant upon agriculture (Katzenberger et al. 2020). In the 20th Century, a decline in the East Asian summer monsoon rains was observed, with the most intense rains becoming shorter but more intense, including flooding and droughts (Burke and Stott 2017). Since 2000, the strength of south Asian monsoon rains has increased, with the most pronounced increases occurring in the most intense events (Katzenberger et al. 2020). This pattern covers all monsoon regions, to varying degrees, and crucially an associated increase in both drought and flooding (Burke and Stott 2017; Wang et al. 2021). In response to future warming, and if aerosol emissions are reduced, significant and substantial increases in monsoon rains are expected, resulting in growing flash flooding risks (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021), especially in East Asia (Samset et al. 2018). However, as increased precipitation is expected to occur over fewer days of more intense rainfall, worsening of droughts also becomes more likely (Burke and Stott 2017).

According to EMDAT, around 49,000 deaths due to flooding occurred in south Asia from 2000-2020, almost half of recorded global flood mortality (EMDAT 2019). The region has also suffered damages of around USD 104 bn, only around USD 4 bn of which is recorded as insured damages. Many of the deadliest and most destructive floods in this subset occurred during the monsoon season, including in

2000 (India and Bangladesh), 2007 (across south Asia), 2010 (Pakistan), 2017 (Bangladesh), and 2005, 2008, 2013, 2019 and 2020 (India). However, even outside of the monsoon season, rainfall extremes have been amplified by climate change (Rimi et al. 2018).

Outside of south Asia, the most impactful flood events in terms of both mortality and numbers of people affected by flooding also occurred primarily in low- and middle-income countries in Africa, including Sudan, Ethiopia, and Nigeria; South America, including Peru, Colombia and Brazil; and the Caribbean, including Haiti and the Dominican Republic. While few attribution assessments on specific events are available in these regions, there is nonetheless evidence of links between these types of events and climate change as described above. Further, trends in increased flooding have been identified in regions including parts of Brazil (Bartiko et al. 2019) and Ethiopia (Mamo et al. 2019), which combine with other factors to pose greater danger to people. For example, the Metropolitan Region of São Paulo has simultaneously undergone rapid urban expansion and an increase in the number of extremely heavy precipitation days. Such events were exceedingly rare in the 1950s, but by the 2010s occurred 2-5 times per year. This has placed people at a rapidly rising risk of flash flooding.

Not including tropical cyclones, extreme rainfall events with detected anthropogenic influence have occurred in Europe (Pall et al. 2011b; Schaller et al. 2016; van Oldenborgh et al. 2016; Otto et al. 2018b), the Mediterranean (Vautard et al. 2015), US (Herring et al. 2014c; Eden et al. 2016; van der Wiel et al. 2017b), parts of South America (Christidis et al. 2018a; De Abreu et al. 2018; Dalagnol et al. 2022), New Zealand (Rosier et al. 2015), southeast Asia (Yun et al. 2020), Japan (Kawase et al. 2020; Imada et al. 2020) and China (Burke et al. 2016; Sun and Miao 2018; Yuan et al. 2018b; Zhou et al. 2018). Collectively, these events represent financial losses and destruction of property of more than USD 60 bn.

In certain areas, attribution studies on rainfall have directly estimated the fraction of damages incurred due to climate change. For example, in the UK between 2000-2020 approximately USD 9 bn

in flood damages have been attributed to climate change (Clarke et al. 2021b). In New Zealand, USD 140 million in insured damages attributable to climate change occurred over 2007-2017, although this is likely a significant underestimate of overall costs (Frame et al. 2020b). These studies provide broad estimates using a simple hazard-based fractional attributable risk methodology. End-to-end attribution using hydrological models and taking account of exposure and vulnerability remains challenging (Schaller et al. 2016), though research using modelling chains (Kay et al. 2018) and a storyline approach (Schaller et al. 2020) is ongoing. While changing weather patterns can be complex in a given area, the general trend is increasingly extreme rainfall resulting in destructive flooding over a large portion of the world's surface.

2.2.3 Drought

Changes in extremes: Droughts are complex but extremely impactful events that affect billions of people worldwide (Table 1). There are many different types of drought with varying impacts. The main categories include meteorological, agricultural and hydrological drought. All are connected, and each simply refers to an anomalous moisture deficit in part of the hydrological system relative to some baseline, be it in precipitation, soil moisture, or groundwater reservoirs, respectively (Cook et al. 2018). The fingerprint of climate change on increasing drought has been observed in several drought-prone regions of the world, including California, the Pacific Northwest, parts of China, western North America, and the Mediterranean (Gudmundsson and Seneviratne 2016; Chen and Sun 2017b; Cook et al. 2018), as well as globally(Marvel et al. 2019). With the exception of the Mediterranean, which is already receiving markedly less precipitation, this is largely due to amplified temperatures driving evaporation and melting snowpack, reducing the meltwater contribution to river flows (Cook et al. 2018). Other smaller Mediterranean-like regions such as central Chile, the far southwest tip of southern Africa and southwest Australia have also dried due to climate change, and are now more prone to drought (Seager et al. 2019).

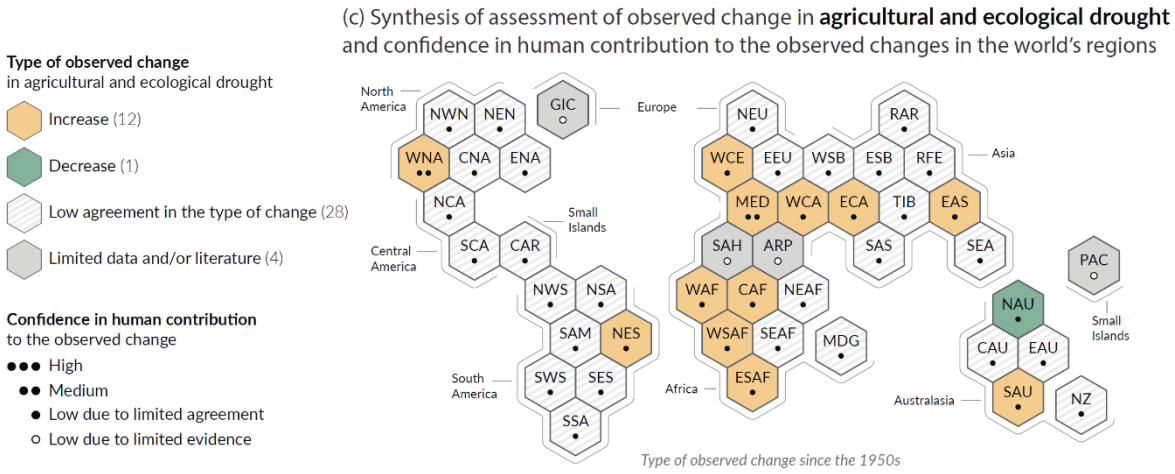


Figure 2.3: Synthesis of assessment of observed change in agricultural and ecological drought and confidence in human contribution to the observed changes in the AR6 land-regions, excluding Antarctica. These are assessed based on observed and simulated changes in total column soil

moisture, complemented by evidence on changes in surface soil moisture, water balance (precipitation minus evapotranspiration) and indices driven by precipitation and atmospheric evaporative demand. From Figure SPM.3 of the WG1 contribution to the IPCC AR6. See (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021)*) for more details and* (Otto et al. 2021)*) for the dataset.*

'Flash droughts' are a type of soil moisture, or agricultural, drought that occurs extremely rapidly, with little warning (Yuan et al. 2019) and can have severe consequences for agricultural productivity. In recent years, there has been a notable rise in such events in the US, China and South Africa (Cook et al. 2018). Meanwhile, some of the most catastrophic droughts in the world continue to occur in East Africa (Gebremeskel et al. 2019). No single drought there has been linked directly to climate change, partly due to a relatively short observational record, high uncertainties and high natural variability, especially for precipitation (Philip et al. 2018b; Uhe et al. 2018; Kew et al. 2021). There is limited evidence that anthropogenic warming of Western Pacific sea surface temperatures may contribute to more frequent drought (Funk 2012; Funk et al. 2019). More generally, the drying of the major rainy season in the region, the 'long rains'(Lyon and Dewitt 2012), is likely connected to climate change (Tierney et al. 2015; Hoell et al. 2017).

Why it matters: In 2019, there were approximately 690 million undernourished people. Food insecurity is linked to conflict, alongside climate-related shocks such as drought (FAO 2020). The least food secure regions of the world are the most vulnerable to drought, and thus any increase in drought severity due to climate change. In Brazil, an ongoing drought since 2019 has led to water scarcity, severe crop losses including corn and coffee, and amplified fire activity in the Amazon (Marengo et al. 2021). In south Asia, the changing patterns of monsoon rainfall as well as rising temperatures and other types of extreme weather have already caused a decline in food security (Bandara and Cai 2014). In East Africa, the major drought in 1984/85 led to a famine that caused the deaths of around 450,000 people. More recently, a drought in 2008-10 affected 13 million people, another in 2010-11 affected 12 million and caused the deaths of 250,000 people in Somalia alone. Since 2005, droughts have

increased in frequency in East Africa and caused substantial livestock death, disruption of livelihoods and rising food prices (Nicholson 2017a; Gebremeskel et al. 2019). In turn, this has contributed to internal migration and further socio-economic instabilities in the region (Gebremeskel et al. 2019). From South Asia across the middle east and most of Africa, hunger is a growing challenge that drought is exacerbating. More broadly, extension of drought across water-scarce regions is exceptionally costly through its impact on ecosystems, agriculture and wider society (Cook et al. 2018).

Attributable impacts: The fingerprint of climate change has manifested very clearly on several recent droughts. California provides an exemplary case. From 2011-2017, it suffered an extended drought, possibly the worst in a thousand years (Osaka and Bellamy 2020a). Even as this event unfolded, scientists demonstrated that various contributing factors were attributable to climate change, including reduced snowpack (Mote et al. 2016; Berg and Hall 2017) and warm dry years (Williams et al. 2015; Diffenbaugh et al. 2015). This drought was then alleviated by incredibly intense seasonal rainfall that led to destructive flooding, with damages of at least USD 1 bn (The Weather Channel 2017), in a compound event that has been linked to climate change (Simon Wang et al. 2017). Similar compound droughts and floods have occurred in the UK (Parry et al. 2013) and East Africa (Gebremeskel et al. 2019). Not only that, new research shows that the California drought was a smaller part of a larger mega-drought stretching from 2000-2018, which itself was pushed from a moderate event to the worst in 1200 years by climate change (Williams et al. 2020). From 2014-16, economic losses in the agriculture industry amounted to at least USD 5.5 bn, and the loss of 42,000 jobs (Howitt et al. 2014, 2015; Medellín-Azuara et al. 2016). Furthermore, during the first three years of the drought, hundreds of millions of trees perished due to water stress, wildfires and proliferating bark beetles; in parts of the Sierra Nevada almost half of all trees died (Fettig et al. 2019).

There are several other cases of drought across the world that have been shown to have been intensified by climate change. This includes South Africa 2015-17 (Otto et al. 2018c; Yuan et al. 2018a),

Europe 2016-17 (García-Herrera et al. 2019), Indonesia 2015 (King et al. 2016), New Zealand (Harrington et al. 2016) and Canada (Szeto et al. 2016).

The impacts of these droughts vary greatly in severity and form, being acutely related to exposure and vulnerability in the affected region. In Canada, drought conditions led to forest fires that created a serious public health risk. In New Zealand, economic costs of the 2013 drought totalled at least USD 1.3 bn. In Europe, drought costs an average of €6.8 bn per year (García-Herrera et al. 2019). Against this backdrop, the extreme 2016-17 event caused loss of many types of crops, including cereals, olives, tomatoes, wine grapes, and almonds, with losses of at least €2 bn in Italy alone (García-Herrera et al. 2019). Episodic drought is becoming more common in Brazil, and though the number of fatalities has fallen drastically, the number of people affected is still increasing; since 1990, hundreds of droughts affected over a billion people (Sena et al. 2014). In South Africa, economic losses totalled USD 400 million, cost tens of thousands of jobs and months of extreme water restrictions for citizens in late 2017 (Stanford University 2020). Cape Town also narrowly avoided 'day zero', when there would have been no water remaining in city pipes. Attribution research has demonstrated that climate change amplified all of these impacts.

CASE STUDY: Indonesia, 2015

In the dry season of July-October 2015, Indonesia experienced a combination of severe heat and extremely low precipitation that created drought conditions. This was partly due to the occurrence of a strong El Niño, which is linked to high temperatures and strongly linked to lower-than-normal precipitation rates in the dry season in Indonesia. In addition, the resulting land surface temperatures were also amplified significantly by anthropogenic warming (King et al. 2016).

The impacts of this drought were myriad and severe. Farmland drought affected over 111,000 hectares of crops (DMCDD 2015), which led to widespread loss of income, rises in food prices (Webb and Wadhwa 2016) and poverty (Reuters 2015). It triggered the worst fire season since 1997, resulting in air pollution that detrimentally affected the health of millions and caused in the deaths of over

100,300 people across Indonesia, Malaysia and Singapore (Huijnen et al. 2016; Koplitz et al. 2016). The impact on vegetation more widely disrupted local wildlife, causing thousands of long-tailed monkeys to attack and steal from villages in search of food (Rohmah 2015).

2.2.4 Wildfire

Changes in extremes: Wildfire risk is inextricably tied to dry and hot conditions, and is greatest during periods of 'Fire weather', classified using various metrics as some combination of high temperature, low humidity, lack of rain, fuel availability and high wind speed (Van Wagner 1987; Dowdy et al. 2009). The risk of wildfire has already substantially increased in many regions, including the western US, Alaska and Canada (Jarraud and Steiner 2012; Dennison et al. 2014; Balch et al. 2018; Goss et al. 2020), the Mediterranean (Abatzoglou et al. 2019; Barbero et al. 2020; Touma et al. 2021), Amazonia (Alencar et al. 2011, 2015; Abatzoglou et al. 2019; Touma et al. 2021), southeast Asia (Touma et al. 2021) and Australia (Dowdy 2018; Dowdy and Pepler 2018; Harris and Lucas 2019) (Figure 4).

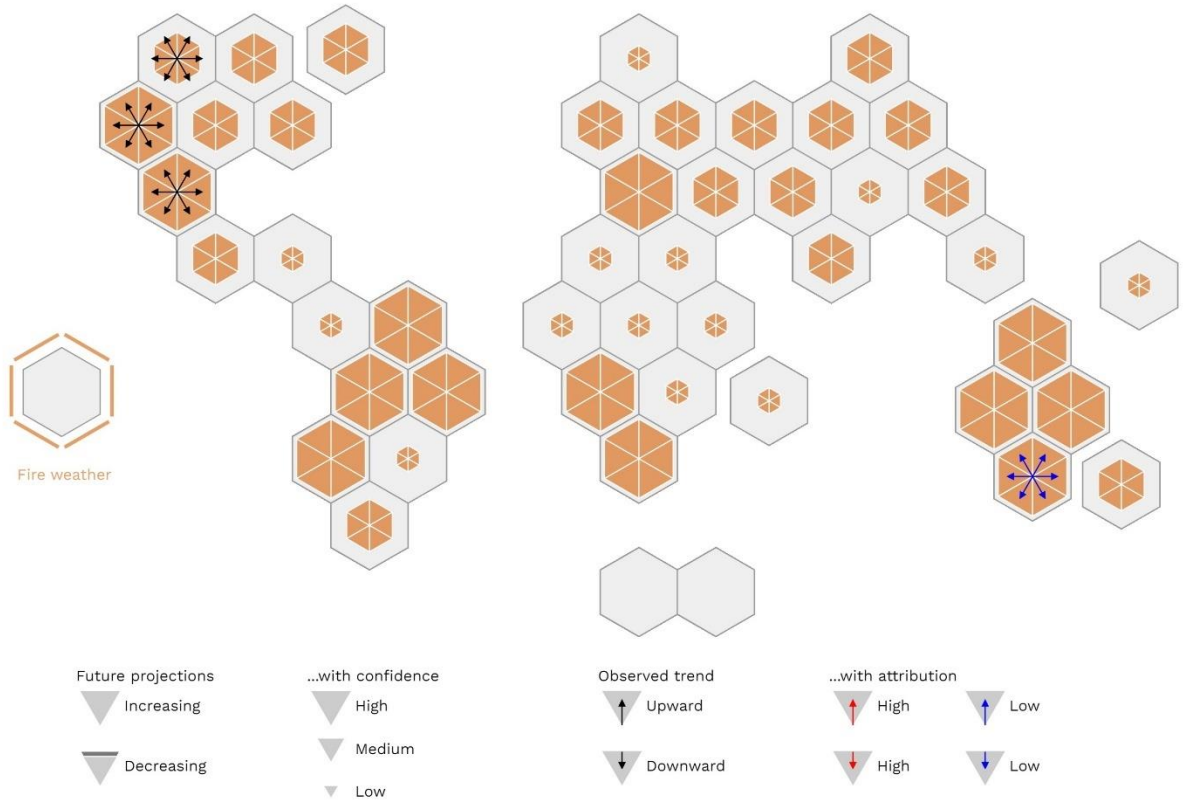


Figure 2.4: Synthesis of observed, attributed and projected changes in Fire Weather, defined as the conditions conducive to triggering and sustaining fires. This includes a combination of soil moisture, wind speed and direction, temperature, and humidity. From the Interactive Atlas of working group 1

of the sixth assessment report of the IPCC (Gutiérrez et al. 2021; Iturbide et al. 2021; Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021).

Recent blazes across the world have proved to be violent manifestations of this. For instance, in British Columbia in 2017 and 2021 severe hot and dry summers led to unprecedented forest fires. In 2017, the burned area was made 7-11 times larger by climate change and, equivalently, the event was made 2-4 times more likely (Kirchmeier-Young et al. 2019). Similar results were found in an analysis of fire risk in Western Canada, where fires as large as those that burned almost 600,000 ha near Fort McMurray, Alberta, in 2016, were found to have become 1.5-6 times more likely to occur as a result of climate change (Kirchmeier-Young et al. 2017a). In Sweden in 2018, extensive forest fires were made 10% more likely by climate change (Krikken et al. 2019). Using the same method, the record-breaking Australian bushfire season of 2019/20 was made at least 30% more likely by climate change (van Oldenborgh et al. 2020). From 1984-2015, over 4 million ha of burned area in the western US is directly attributed to climate change (Abatzoglou and Williams, 2016). In southern China, extreme wildfires of 2019 were made over seven times more likely by climate change (Du et al., 2021). In the southern Amazon 'arc of deforestation', climate change coupled with a record-high El Nino event to cause significant increases in the chance of fire weather (Li et al. 2021).

Why it matters: As in the case of extreme heat, I focus on the health impacts (both direct and indirect) of events, though they may also lead to destruction of property and ecosystems, among other impacts. Wildfires can cause direct mortality, although the total number of direct deaths are typically lower than for other extreme events (Table 1). However, wildfire smoke consists of fine particulate matter (known as $PM_{2.5}$ and PM_{10}) that reaches deep into the lungs when inhaled, can reach the bloodstream, and is likely more toxic than ambient particulates of the same scale (Aguilera et al. 2021). The hazardous air pollutants that constitute the smoke aggravate existing respiratory health issues, trigger new conditions and may also have links to cardiovascular health impacts (Reid et al. 2016; Matz et al. 2020; Chen et al. 2021), as well as adverse effects on pregnancy outcomes(Abdo et al. 2019). In

Canada, short term effects of wildfire smoke include 54-240 premature deaths and costs of USD 0.41-1.8 bn annually, while long-term chronic issues are responsible for 570-2,500 premature deaths and costs of USD 4.3-19 bn annually (Matz et al. 2020). A similar study for the US from 2008-2012 showed that short-term effects cost thousands of lives and additional hospital admissions for respiratory and cardiovascular illness annually, while long-term exposure cost tens of thousands of lives annually – the economic costs of these health burdens was estimated as USD 11-20 bn (2010$) per year for short-term, and USD 76-130 bn per year for long-term effects (Fann et al. 2018). Finally, across the world total attributable deaths to landscape fire smoke are in the hundreds of thousands (262,000 in La Niña years, compared with 532,000 during El Niño), with the worst affected areas being sub-Saharan Africa and southeast Asia (Johnston et al. 2012).

Attributable impacts: Severe impacts have also been recorded for attributed weather and fire events. For instance, during the anthropogenically amplified European heatwave of 2003, the central and Algarve regions of Portugal experienced the worst mega-fires in history (Tedim et al. 2013). The resultant smoke dispersed across Europe, increasing the concentrations of $PM_{2.5}$ by 20-200% in many places (Hodzic et al. 2007), where several hundred deaths were linked to air pollution in the UK and Netherlands alone (Solberg et al. 2008). Fires across Indonesia in 2015 led to over 100,000 excess deaths. Similarly, in Russia in 2010 smoke from burning forests and peatlands became trapped over population centres, exacerbating the public health crisis and causing up to 2,000 excess deaths in Moscow alone (Shaposhnikov et al. 2014). The Black Saturday bushfires in Victoria, Australia in 2009 were made more likely by climate change (Black 2016), and resulted in PTSD in a significant minority of the most affected groups (Bryant et al. 2014). Finally, the 2016 Alberta wildfires displaced over 80,000 people and caused over CAD 3.5 bn in insured losses. As noted above, these fires were made substantially more likely due to climate change. Across Canada, wildfires burn 2.1 million ha per year, approximately the area of Wales (Kirchmeier-Young et al. 2017b).

CASE STUDY: Australia, 2019/20

In the summer of 2019/20, New South Wales experienced the worst fire season on record, since dubbed the 'Black Summer fires'. In the 2019 fire year, the burned area totalled almost three times that in any of the previous 32 years (Canadell et al. 2021). This event was made at least 30% more likely by climate change (van Oldenborgh et al. 2020), which adds further evidence that dangerous fire weather in southeast Australia has emerged outside of the range of historical experience (Abram et al. 2021). Not only that, the sheer scale of the fires went beyond anything either simulated in CMIP6 models or widely discussed even within the large uncertainties associated with wildfire hazards;this led to calls for urgent improvement of both risk modelling and uncertainty interpretation for accurately informing society of such unprecedented risks going forwards (Sanderson and Fisher 2020). This case study thus illustrates a broader point about the urgent need to provide risk guidance acknowledging both known and unknown unknowns, especially in a changing climate (Sanderson and Fisher 2020; Clarke et al. 2021b).

These fires burned a record 19 million hectares of forest and woodland (Khan 2021), resulting in the direct destruction of 5900 buildings and tens of thousands of livestock being killed. An estimated 3 bn mammals, reptiles, birds and frogs were killed or displaced, making it "one of the worst wildlife disasters in modern history." (WWF Australia 2020), with fears of possible extinctions of endangered species (Filkov et al. 2020; Ward et al. 2020).

Across the region, levels of $PM_{2.5}$ exceeded the WHO guideline levels fourfold (Yu et al. 2020b). Smoke from the fires was responsible for "417 excess deaths, 1,124 hospitalisations for cardiovascular problems and 2027 for respiratory problems, and 1305 presentations to emergency departments with asthma" (Borchers Arriagada et al. 2020; Filkov et al. 2020). The costs associated with this totalled AUD 1.95 bn, approximately 10 times the annual health burden due to fire smoke (Johnston et al. 2021).

2.2.5 Tropical Cyclones

Changes in extremes: Trends indicate no significant change in the frequency of tropical cyclones globally, but a greater fraction of those that do occur are the most intense Saffir-Simpson category 4 and 5 superstorms (Walsh et al. 2019; Kossin et al. 2020), which usually dominate the societal impacts (Christensen et al. 2013). Tropical cyclones are also shifting poleward in most regions, affecting the areas impacted (Kossin et al. 2016). Further, a slowing in tropical cyclone movement has been observed (Kossin 2018; Yamaguchi and Maeda 2020), accompanied by deposition of higher rainfall intensities (Patricola and Wehner 2018b), affecting the severity of impacts.

There is substantial variability between basins. Increasing trends in the number of storms are most significant in the central Pacific, Arabian Sea and North Atlantic, and decreases are observed in the Bay of Bengal, the southern Indian Ocean and western North Pacific. This spatial distribution change is too large to be explained by natural variability alone and is linked to climate change (Murakami et al. 2020). In the North Atlantic, an observed increase in intensification rate is likely too large for natural variability (Bhatia et al. 2019), likewise for the significant slowing of translation speed over the US (Kossin 2018), while the observed increase in overall activity is significant yet not attributable to climate change (Ting et al. 2015). In the Bay of Bengal, despite the decreasing numbers, there is a clear increasing trend in the fraction of high intensity storms and overall cyclone energy (Balaji et al. 2018). Changes in overall activity are less certain in the west Pacific due to high variability, but northward shift in storm tracks since the 1980s is significant (Kossin et al. 2016; Lee et al. 2020), as is a slowdown of translation speed (Yamaguchi and Maeda 2020).

Additionally, notable recent seasons of high cyclone activity could not be explained without anthropogenic influence, including in the Arabian sea in 2015 (Murakami et al. 2017), in the western North Pacific in 2015 (Zhang et al. 2016; Yang et al. 2018; Yamada et al. 2019), and in the North Atlantic in 2017 (Murakami et al. 2018).

Why it matters: Tropical cyclones often cause flooding, including due to storm surges affecting coastal areas. In addition, storms generate high winds that fell trees, and destroy property and power lines, thus creating further disruption. For instance, in the wake of Hurricane Irma in 2017, services on Puerto Rico were hindered by blackouts after a partial collapse of the power system (Zorrilla 2017). When Hurricane Maria struck just two weeks later it caused devastation exacerbated by this additional vulnerability. Further, it extended the spatial and temporal aspects of disruption to services and the power grid across the island and for months into the future (Kishore et al. 2018; Kwasinski et al. 2019a). The subsequent reliance on generators led to worsening air quality in San Juan (Subramanian et al. 2018). The extreme rainfall also triggered over 40,000 landslides across the island, wiping out other power lines, roads and other structures (Bessette-Kirton et al. 2019). The storm's passage also severely damaged vegetation across the island, which took months to fully recover (Hu and Smith 2018). There were also more long-term impacts. For example, in 2017 in Puerto Rico, in the context of an already-struggling economy, the severity of the 2017 hurricane season may have led between 129,000 – 477,000 Puerto Ricans to migrate away from the island (Acosta et al. 2020).

Attributable impacts: Rainfall from both Hurricanes Maria and Irma was amplified by climate change (Patricola and Wehner 2018c). In Puerto Rico, these hurricanes resulted in widespread anxiety-mood disorders (Ferré et al., 2019; Scaramutti et al., 2019) especially prevalent among the most marginalised groups and the young (Orengo-Aguayo et al., 2019). Similar impacts have been observed during other events (Galea et al., 2007; Whaley, 2009; Rhodes et al., 2010). Additionally, at least 1,000, and potentially as many as 4,645, people died (Kishore et al. 2018; Santos-Burgoa et al. 2018). I note an illustrative pair of case studies is provided by the relative impacts of Hurricane Maria in Puerto Rico and Hurricane Irma in Cuba; both islands experienced devastating landfall which caused mass destruction of property and infrastructure that affected the entire population. However, in Cuba the loss of life was far lower and the recovery was much swifter, which in turn reduced longer-term impacts. This is due to an array of factors, including engaging the public in disaster preparation and

incorporating science into risk planning (Zakrison et al. 2020), which are crucial to consider in any direct end-to-end attribution of impacts.

Other high-mortality tropical cyclones include Typhoon Haiyan (Lagmay et al. 2015) and Cyclone Idai (Devi 2019), which are estimated to have led to over 7000 and 1300 deaths in southeast Asia and across south-eastern Africa, respectively. Typhoon Haiyan was shown to have been strengthened by climate change, increasing the height of the resulting storm surge by 20% (Takayabu et al. 2015). During Cyclone Idai, flooding destroyed over 800,000 hectares of croplands belonging to half a million households (Club of Mozambique 2019). In the Philippines, Haiyan severely impacted the livelihoods of 3.4 million coconut farmers and thus disrupted a major component of the nation's agriculture industry (Seriño et al. 2021). The deadliest cyclone in the global record in the 21st Century, representing nearly 70% of all recorded mortality for storms in the period, was Cyclone Nargis, which struck Myanmar in 2008 and caused over 138,000 fatalities (Fritz et al. 2009). This cyclone formed due to anomalously warm waters in the Bay of Bengal (Lin et al. 2009), where such storms are becoming less frequent but more intense due to climate change (Balaji et al. 2018).

In early 2022 in Malawi, Mozambique and Madagascar, tropical cyclones Ana and Batsirai triggered widespread flooding after causing extreme rainfall in the midst of a heavy rainy season. This led to a range of impacts, including destruction of thousands of homes and classrooms, as well as water supply systems, crops, roads, bridges, healthcare facilities and churches, and overall affecting hundreds of thousands of people. Rainfall from each was amplified by climate change, and the impacts were further compounded by high exposure and ongoing vulnerabilities in the region, including from recent flooding, conflict in northern Mozambique, and severe food insecurity in Madagascar (Otto et al. 2022b).

The extreme rainfall from Hurricanes Katrina, Irma, Maria, Harvey, Dorian, and Florence and Typhoon Morakot were each individually amplified by climate change (Van Oldenborgh et al. 2017; Wang et al. 2018a, 2019; Patricola and Wehner 2018b; Reed et al. 2020, 2021; Frame et al. 2020d). Furthermore,

analysis of specific drivers of Hurricane Harvey showed that such an event was linked with anomalously high ocean temperatures (both in the Gulf of Mexico and globally), therefore suggesting direct causality to global warming (Trenberth et al. 2018). Together, the six storms listed above caused almost half a trillion dollars in damage to property and infrastructure.

In the North Atlantic basin alone, it is likely that other hurricanes constituting damages in excess of USD 200 bn follow a similar pattern (EMDAT 2019). Furthermore, while Hurricane Sandy was not significantly intensified by climate change (Lackmann 2015), the probability of storm surges as high have more than tripled due to sea level rise (Lin et al. 2016). The added effect of climate change on this storm surge resulted in an extra USD 8 bn in damage and affected a further 71,000 people (Strauss et al. 2021b). It is reasonable to conclude that both storm surge and rainfall totals from all tropical cyclones are being amplified by climate change, while other aspects of such events vary between basins.

2.3. Discussion and conclusions

Developments in climate change attribution, improved understanding of the myriad impacts of extreme weather, and documenting its harms, have meant that an increasingly diverse and societally-relevant range of impacts can be assessed for their connection to anthropogenic climate change. This includes those occurring on local and regional scales beyond those assessed in the recent IPCC Sixth Assessment Report.

Hazard	Observed direct impacts			Attributable influence of climate change on hazard severity/likelihood (Confidence level)
	Deaths	Injured	Total Affected	
Heatwaves	157,000	193,000	320,000	Increase (High)
Cold waves and severe winter conditions	14,900	1.86 million	96.1 million	Decrease (High)
Floods	111,000	304,000	1.66 billion	Increase (Medium)
Droughts	21,300	N/A	1.44 billion	Increase (Medium)
Wildfires	1,570	7,260	3.38 million	Increase (Medium)
Storms	201,000	337,000	773 million	Rainfall Increase (High) Other impacts no change (Low)

Table 2.1: Direct physical health impacts of different types of disaster between 2000-2020, as recorded by EMDAT, and the attributable influence of climate change on each hazard (EMDAT 2019).

However, both the impacts of climate change and the current degree of understanding of these vary across hazards and regions. In order to adapt to changing risks effectively, and to optimise mitigation of further warming, it is crucial that understanding continues to develop and does so equitably. This review and other work (Otto et al. 2020c; Clarke et al. 2021b) provides a starting point for more systematic documenting of the costs (monetary and non-monetary) of human-caused climate change today and the losses and damages caused. In order to build on this, there are three areas in which scientific developments will add great value.

First, recording the impacts of extreme weather far more systematically around the world. A lack of data on past impacts of extreme events is a major barrier to mitigating future damages, simply because there is no direct evidence upon which to base the necessary measures. In particular, the impacts of extreme heat are chronically under-recorded in the global south. As explored by Harrington & Otto (Harrington and Otto 2020a) for heat in sub-Saharan Africa, this is likely due to institutional differences in the way impacts are recorded (government agencies vs NGOs), and would benefit from a collaborative effort to create databases for documenting mortality, morbidity and impacts on transport and power infrastructure, especially in cities. Furthermore, developing official heatwave definitions for nations currently lacking them would improve the chance that they are recorded in international disaster databases such as EMDAT, which includes a declaration of emergency in its list of entry criteria.

Second, improve the coverage of attribution for more regions around the world, for a more diverse range of hazards, and with a focus on event definitions that are most pertinent to the impacts upon people. Attribution allows us to identify whether and to what degree climate change influenced a given event, as well as a trajectory of change over time. This is just part of the full picture of risk, as

explored below. However, it remains useful to link between lived impacts and global climate change for the purposes of communication, adaptation and mitigation. It is therefore important everywhere.

Hazard	Observed direct impacts		Attributable influence of climate change on hazard severity/likelihood (Confidence level)
	Insured Damages (USD)	Total Damages (USD)	
Heatwaves	10,000	13.4 bn	Increase (High)
Cold waves and Severe winter conditions	4.63 bn	31.3 bn	Decrease (High)
Floods	74.1 bn	610 bn	Increase (Medium)
Droughts	21 bn	119 bn	Increase (Medium)
Wildfires	51.3 bn	94.3 bn	Increase (Medium)
Storms	499 bn	1.30 trillion	Rainfall Increase (High) Other impacts no change (Low)

Table 2.2: Direct damages of different types of disaster between 2000-2020, as recorded by EMDAT, and the attributable influence of climate change on each hazard (EMDAT 2019). *Note that these values are likely to be substantial underestimates of the true magnitude of damages.*

Attribution studies on individual events are currently lacking for a number of regions and hazards. This includes key flood events highlighted earlier in this review as some of the most impactful, in South Asia; in Africa, including Sudan, Ethiopia, and Nigeria; in South America, including Peru, Colombia and Brazil; and the Caribbean, including Haiti and the Dominican Republic. Attribution of extreme heat is

limited across South America and Africa largely due to a lack of research capacity across the world. For tropical cyclones, while rainfall and storm surge heights are increasingly well understood, especially in the North Atlantic, changes in intensity are not. Further, basins with some of the most devastating storms of the past, such as Cyclone Nargis in the Bay of Bengal and Cyclone Idai in the southwestern Indian Ocean, remain understudied. Finally, for wildfires, the IPCC AR6 documents regional observed changes. However, these are large spatial averages that may dampen the signal of individual attribution studies if they only apply to smaller subregions. Further, additional attribution work would add value in vulnerable and drought-prone regions such as Amazonia, the Mediterranean and Southern Africa.

Going forwards, the coverage of attribution studies can be improved in several ways: operationalising attribution and recording impact information as part of national weather services; incorporating local experts into any attribution analysis; building capacity for local experts to conduct such analyses in the future; improving understanding of compound event attribution, especially for drought; utilising the existing body of attribution literature to make statements without requiring new analysis in regions that are already well understood; creating a standardised language for impacts and risk.

The third and final area for future work involves a broader consideration of risk, rather than simply hazards and impacts. The context of a disaster, in the form of the exposure and vulnerability of affected individuals, infrastructure, agricultural systems and property, is crucial to a more complete understanding, whether this is included in quantitative analysis (Otto et al. 2015b; Ebi et al. 2017), or provides a way to frame a study and define an event that is suitable for a particular use (Stone et al. 2021b). For instance, East Africa is frequently subjected to droughts with devastating humanitarian consequences. Despite substantial research into these events, no significant connection to climate change is detectable. In part, this is due to a dearth of observational data. However, the reality in the region is that high levels of vulnerability due to poverty and socio-cultural factors, and very high regional exposure are already significant drivers of disasters.

One consequence of this is that even a relatively small climate change signal would lead to vastly-amplified impacts in the region - this framing tells part of the story. Most importantly, however, it also shows that to reduce risks it is more pertinent to tackle these non-climate drivers head-on, rather than blaming the external forces of 'nature' or 'climate' (Raju et al. 2022).

Therefore, in the illustrative case of East Africa, expending additional resources purely to identify a climate-related signal from the noise is relatively unimportant, and headlines about climate change driving drought in the region are actively unhelpful as they divert attention from governance and other factors that may be addressed sooner to reduce risks more and in a shorter timeframe. Instead, in order to mitigate impacts, the focus of research and resources ought to be the development of reliable seasonal forecasting to enable active preparation and adaptation measures, the effective distribution of forecasts, and other measures to reduce vulnerability (Gebremeskel et al. 2019; Coughlan de Perez et al. 2019). In this situation, attribution provides a crucial source of information if it is framed in such a way to identify all key drivers of impacts, not simply answering the climate question or considering meteorological extremes (Stone et al. 2021b; Raju et al. 2022).

A recent study on famine in Madagascar exemplifies this approach (World Weather Attribution 2021b). Analysis found that low precipitation totals, which contributed to the crisis, were not significantly changed in likelihood or magnitude by human-caused climate change. Instead, the main drivers of the famine were food insecurity due to poverty, compounded by outbreaks of pests and COVID-19 restrictions. This information has great utility for risk reduction, which promises significant near-term co-benefits yet may be overlooked in analysis focused solely on climate change. Building on this, the study also notes an emerging future connection to climate change, which will likely only amplify such droughts significantly at global warming levels of greater than 2°C. This could be important information for mitigation going forwards.

This work is in line with other analyses in which climate change is found to be the single most important driver of an event. For example, in Siberia in 2020, the extreme heat would have been all

but impossible without human-caused climate change (World Weather Attribution 2021c). In essence, to address climate change appropriately, it is important to understand all of the key drivers of an event that may be hidden behind the headlines - neither ignoring climate change nor focusing solely upon it.

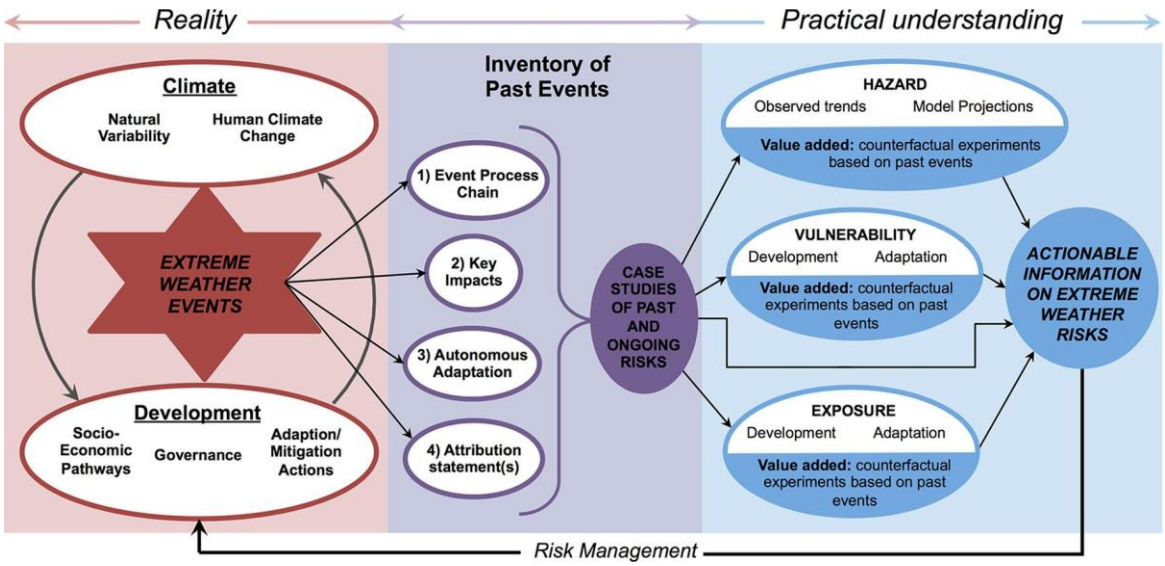
Chapter 3 - Inventories of extreme weather events and impacts: Implications for loss and damage from and adaptation to climate extremes

Abstract

Extreme and impactful weather events of the recent past provide a vital but under-utilised data source for understanding present and future climate risks. Extreme event attribution (EEA) enables us to quantify the influence of anthropogenic climate change (ACC) on a given event in a way that can be tailored to stakeholder needs, thereby enhancing the potential utility of studying past events. Here I set out a framework for systematically recording key details of high-impact events on a national scale (using the UK and Puerto Rico as examples), combining recent advances in event attribution with the risk framework. These 'inventories' inherently provide useful information depending on a user's interest. For example, as a compilation of the impacts of ACC, I find that in the UK since 2000, at least 1500 excess deaths are directly attributable to human-induced climate change, while in Puerto Rico the increased intensity of Hurricane Maria alone led to the deaths of up to 3670 people. I also explore how inventories form a foundation for further analysis, learning from past events. This involves identifying the most damaging hazards and crucially also vulnerabilities and exposure characteristics over time. To build a risk assessment for heat-related mortality in the UK I focus on a vulnerable group, elderly urban populations, and project changes in the hazard and exposure within the same framework. Without improved preparedness, the risk to this group is likely to increase by ~50% by 2028 and ~150% by 2043. In addition, the framework allows the exploration of the likelihood of otherwise unprecedented events, or 'Black Swans'. Finally, not only does it aid disaster preparedness and adaptation at local and national scales, such inventories also provide a new source of evidence for global stocktakes on adaptation and loss and damage such as mandated by the Paris Climate Agreement.

Graphical Abstract

Schematic showing how inventories of past events help to inform the risk framework by highlighting ongoing vulnerabilities and providing an experimental basis for changing exposure and hazard.



3.1. Introduction

Extreme weather of increasing intensity and frequency is the sharp edge of climate change (Coumou and Rahmstorf 2012; Fischer and Knutti 2015a), posing a broad spectrum of evolving risks to societies around the world. Unprecedented heat waves threaten food supply chains (Welton 2011) and pose a severe public health risk (Mitchell et al. 2016a; Arbuthnott and Hajat 2017), particularly to maladapted populations (Shaposhnikov et al. 2014; Heaviside et al. 2016). Rainfall and wind extremes from stronger storms lead to flooding and destroy property, lives and livelihoods (Houze et al. 2011; Schaller et al. 2016; Van Oldenborgh et al. 2017). This inflicts drastic impacts on the health, both mental and physical, of those affected (Paranjothy et al. 2011; Fernandez et al. 2015b) as well as heavy economic disruption (Chartteron et al. 2016; Pregnolato et al. 2017). Moreover, multiple extremes may occur simultaneously or in rapid succession in the same location, thus exacerbating the severity of lived impacts (Zscheischler et al. 2018). Such 'compound events' are exceptionally difficult to plan for and are now undergoing dedicated study (AghaKouchak et al. 2014; Leonard et al. 2014; Zscheischler et

al. 2020). The subtleties of changes in extremes in an irrefutably warming world are far from fully established, yet the overall signal and austere implications for society are clear (Hoegh-Guldberg et al. 2018).

However, anthropogenic climate change is far from the only contributor to changing extreme weather risks faced by people and property. Exposure and vulnerability to hazards are permanently in flux due to an ever-changing interplay of natural and human forces (Cardona et al. 2012). Furthermore, these contributions to risk all interact in a non-linear fashion and over diverse spatiotemporal scales (Birkmann and von Teichman 2010). As such, while many individual contributing factors are reasonably predictable in a given locale, it is critical that their simultaneous evolution and relative magnitude are better understood. This would ensure that the science is best placed to inform future planning, given stakeholder interest (Duvat et al. 2017; Martín et al. 2017; Ahmadalipour and Moradkhani 2018; Byers et al. 2018).

This work develops a new framework to improve understanding of changing risks from extreme weather. In the remainder of this section I home in on the most relevant literature upon which to build this framework and lay out the thought process behind its development. It could be argued that the exploration of climatic risks is largely a challenge for the impacts- modelling community, utilising projections of climate and socioeconomic development. However, in spite of recent developments, the field of literature assessing climate impacts still often focuses on trends in the mean in climate projections, rather than the drivers of risk from extremes (Hoegh-Guldberg et al. 2018). In part, this is due to the large uncertainties in projected hazards, which forms the basis for all impacts projections and thus forms a weak foundation for further action. It is therefore proposed that additional work focusing specifically on rare but impactful events could add significant value. In line with this, I began with the young but expanding field of Extreme Event Attribution (EEA).

EEA enables researchers to estimate the change in likelihood and intensity of a specific, real-world weather event as a result of anthropogenic forcing in the climate system (Allen 2003). By necessity,

this is built upon a rigorous foundation of evidence relating to the event in question, a process that is steadily becoming formalised (Otto et al. 2020c). As a result, EEA provides a tangible bridge between the global phenomenon of climate change and the scales at which people live and decisions are made (Sippel et al. 2015). Moreover, through the choice of 'event definition(s)', it builds directly on lived experience of the event. Thus it enables effective communication of this link to non-expert stakeholders, from civil society to policymakers (Otto et al. 2015a; Jézéquel et al. 2019a), in turn forming an easily interpreted and more robust evidence base for planning resilience. Unfortunately, EEA studies are currently conducted on an ad-hoc basis, in part due to discrepancies in data availability in different regions (Huggel et al. 2016) but also the lack of comprehensive, coordinated efforts (Stott et al. 2016). They are also highly dependent upon the event definition used (Otto et al. 2016), and for some hazards struggle with deep uncertainties (Shepherd 2016).

In short, EEA cannot (nor does it set out to) provide a silver-bullet method for attaining deep understanding of all changing risks from extreme weather. Nonetheless, as time passes by, the continued lack of serious mitigation effort means that the number of realisations of anthropogenically-amplified extreme weather is growing cumulatively (Peterson et al. 2012, 2015; Herring et al. 2014a, 2015, 2016b, 2018, 2019c, 2020); there is already a substantial body of case studies from which to learn. This remains a vastly under-utilised resource, despite the evidence that a "societal actor's prior experience of similar extreme weather events influences adaptive measures and preparedness for future extremes. An adequate description of the physical mechanisms and implications of relevant analogues from the past can positively influence adaptive capacity." (Hazeleger et al. 2015). It is therefore critical that results from EEA are integrated with the knowledge of impacts collated by the insurance sector and NGOs, as well as insights from the Disaster Risk Reduction (DRR) community that deal more closely with the relationship between the meteorological extreme and experienced impacts. Collating such knowledge will optimise the potential practical applications of the science in a useful timeframe, particularly if efforts to build resilience are ramped

up. It will also become ever more effective, and therefore pertinent, as EEA evolves into a standardised operational service (Stott et al. 2016).

Moreover, in addition to EEA, new approaches to risk analysis that capitalise on the wealth of information provided by case studies of past events are constantly emerging. For example, 'storyline' methods (Shepherd 2015) enable exploration of the causal chain leading to an event (Daron et al. 2019), and are used to create bespoke narratives for various stakeholders (Hazeleger et al. 2015). This is complementary to the probabilistic approach as it is possible to gain useful information even when EEA analysis falls victim to prohibitively large uncertainties (Shepherd 2016). Finally, it has also been proposed that exploring the physical boundaries of plausibility surrounding past events and near misses could provide insight into the possibility of highly destructive unprecedented events, or 'black swans' (Woo 2016, 2019).

Overall, I conclude that a deeper knowledge of past events can underpin future understanding of, and preparation for, trends in extreme weather risk. Currently, however, a range of sources, including governments (Public Health England 2013), reinsurance companies (Munich RE 2016, 2018), media outlets, academic publications and NGOs (Muller 2014) all keep records of past events and their impacts on an ad hoc basis. Even the most comprehensive and systematic hazard databases such as EMDAT (Guha-Sapir et al. 2014) are not built for the task of quantifying all loss and damage or relating this to anthropogenic climate change, much less disentangling all relevant drivers of disasters (Gall 2015).

In order to bring together the relevant knowledge, I propose a standardised framework for recording historical impactful extreme weather events in an inventory structure. In particular, details of past events must be recorded alongside their key impacts, as well as other factors that fed into these impacts and finally any existing attribution literature to highlight the contribution from anthropogenic climate change (ACC). Critically, wherever possible the recording of impacts must include both quantifiable data and qualitative information, and through both the immediate- and long-term.

Furthermore, I suggest that such inventories provide maximum utility if compiled at the national scale and completely open-access as this is where the majority of stakeholders who are concerned with managing risk operate (Hoegh-Guldberg et al. 2018). In cases where risk management is largely the responsibility of more local powers, it is nonetheless beneficial for such policymakers to have access to other case studies outside their own jurisdiction but within a shared climatology. The national approach also aligns most closely with the remit of the Paris Agreement on adaptation, which aims to "follow a country-driven, gender-responsive, participatory and fully transparent approach" (Article 7).

To demonstrate the framework I present a inventories of past extreme weather events for the UK and Puerto Rico in the period 2000-2019. The UK was selected as the ideal initial location to explore this concept due to its substantial body of attribution literature, well-documented hazards and excellent record of observational data. Puerto Rico is presented as a counterpoint to this, being subjected to highly destructive tropical storms that present an array of additional challenges. Though the observational record of these impactful events is strong thanks to the island's status as a US territory, the EEA literature for this region is extremely limited and the overall consensus on changing risks from climate change is still deeply uncertain. Furthermore, the deficiency of official estimates of mortality from Hurricane Maria (Kishore et al. 2018) highlighted possible systematic failures in the recording of such information from other disasters. The territory is therefore an emblematic case of ongoing and urgent risk management in the presence of high uncertainty.

The remainder of this chapter is set out as follows. In section 2 the process of creating the inventories is explained and excerpts are presented. The main body of the chapter is dedicated to the potential utility of this inventory concept. In section 3 I focus on the applications of the work at national and sub-national scales, with an emphasis on risk management. This is further divided into two subsections: in 3.1 I explore results that are largely emergent from completed inventories, then in 3.2 I describe and present further analysis that uses inventories as a foundation. In section 4 I discuss the

implications of the work to the international community. Finally, in section 5 I summarise our findings and propose pathways for future work to build on this.

3.2. The Inventory

3.2.1 Process: 'How to Build an Inventory of Extreme Weather Events'

EMDAT is a global hazards database that provides information on impactful historical disasters, including meteorological, hydrological, epidemiological and even technological events (Guha-Sapir et al. 2014). Events are included in the database if the impacts meet at least one of the following criteria: 10 or more reported deaths, 100 or more people reported affected, a state of emergency declared, and/or a call for international assistance. Using the 'disaster list' feature, and specifying the UK and Puerto Rico as countries and the period 2000-2019 (inclusive) as the timeframe, I submitted a download request for all possible event and impact data. This data forms the basis of the inventory and a sample of data used for four UK events is provided in the appendices.

We then undertook a restructuring of the inventory to align with our central aim of providing a tool for exploring extreme weather events in more detail. I recognise that, in order to build up an accurate picture of how various factors contributed to the eventual impacts, it is critical to view the development of an event as a multi-stage causal chain. This 'event narrative' system facilitates the application of distinct framings for various analyses. For example, both a frequentist approach to the changing likelihood of the meteorological extreme and a highly conditional approach for probing different drivers of risk into the future would be supported in this system.

In the inventory, the 'event narrative' is divided into 3 components. Firstly, the meteorological conditions: here, the large-scale synoptic situation and ensuing formation of the often-extreme meteorology that triggered the event are detailed. Secondly, factors that compounded or helped to mitigate the eventual impacts on people are added. This could include topography, land-use, existing adaptation measures or the presence and effectiveness of warning systems, among a plethora of others. Finally, the narrative is concluded with details of any notable actions that were taken following

an event. This includes both those to manage the longer-term impacts such as rehabilitation, and those to mitigate similar impacts in the future such as adaptation or improved warning systems.

Furthermore, to gain a more accurate perspective of the multitude of risks that extreme events pose to people and property, a wide range of impacts, both qualitative and quantitative, are considered. Thus, several of the specific impact data fields from EMDAT were amalgamated into a 'miscellaneous impacts' category with a broader scope to include both primary and secondary impacts, where documented. This contains notable data, such as numbers of homes flooded, people left without power and the local uptick in reported mental health issues, and also qualitative information where no quantities are quoted in reports. For example, during the UK summer drought of 2003, there were 'fish fatalities and stress on other aquatic fauna'.

Finally, a section was created for EEA literature, which highlights the anthropogenic forcing component of the event. In order to provide maximum clarity, this section was subdivided into two. Firstly, the quantitative attribution statement itself. This takes the form of either a frequentist perspective, in the form of a FAR (fractional attributable risk) or PR (probability ratio) value, or a magnitude perspective, given by an amplification factor or magnitude change due to ACC. While the frequentist perspective enables a simpler calculation of expected attributable damages from comparable events over a long time period, the magnitude perspective provides both a clearer way of partitioning the effect on individual meteorological phenomena from a larger event and a causal link between ACC and lived impacts. The second subsection features a detailed explanation of the event definition and framing used in each study. Finally, as a point of clarification, 'risk' in the context of FAR refers only to hazard probability. This is distinct from the definition used throughout this work, which refers to an overlap of hazard probability, exposure and vulnerability. As such, FAR will only be used where absolutely necessary in reference to the studies that employ it.

With the restructuring complete, the process of 'filling in' the inventory began. This involved two aspects. Initially, I searched for events that may have been missed by EMDAT but which were, by the

criteria above, still considered impactful. Secondly, I drew upon a whole range of sources to 'fill in the gaps' in the inventory. These sources included academic papers from a range of fields including health impacts and EEA, official government reports and those from external government bodies (e.g. the Met Office, CEH, NOAA), reports from local councils, financial loss data from risk consultancies, other NGOs such as charities and disaster response organisations, and finally, failing other sources, media reports. While this system does not make the long-standing challenge of data curation easier or quicker, it both enables and encourages the collation of data from diverse sources and highlights where data is lacking.

Additional qualifying events were discovered through systematic research of the existing ones, which largely originated from the databases of National Met Services. For the UK, EMDAT provided 48 events and the final inventory contains 62, for the Puerto Rico, EMDAT provided 15 events and there are now 17. Furthermore, some new events, particularly windstorms ([CSL STYLE ERROR: reference with no printed form.]), lacked data on anything other than direct insured damages. It was therefore decided that a fifth criterion should be included; damage to property (insured or uninsured) and/or lost economic output over $75 million. While it seems unlikely that any such event would fail to meet at least one of the other criteria, deficiencies in data reporting make this necessary in the framework to avoid rejecting important events. Inventories for both the UK and Puerto Rico can also be seen in the appendices.

Below is a brief step-by-step guide for creating inventories:

- Download data from EMDAT using 'disaster list' feature and select location and timeframe of interest
- Restructure table into inventory format and re-organise data
- Fill in missing data with additional research into each event, adding any new qualifying events. Note: Some national Met Services provide an invaluable source of information on past events often missed by EMDAT.

- Review attribution literature and fill in results – specifically, I suggest:
    - Begin with BAMS special reports
    - Follow up with Google Scholar or other literature databases using targeted keyword searches
- Repeat upon the occurrence of new events and conduct a literature search for other events of the same type (as new literature may have come to light)

3.2.2 Inventory Definition

Overall, this inventory is a framework for recording historical events that are defined as impactful using a predefined threshold, and its purpose is highlighting the most relevant drivers of the impacts of these events, with implications for studying future risk through the lens of changing hazard, exposure and vulnerability.

There are several factors involved in defining which events are included in the inventory where criteria thresholds are to some degree arbitrary. For example, the losses crucially depend not only on the level of vulnerability and exposure but also on whether the event was forecasted and if the forecast was acted upon. Over time the implications of a static impact threshold method might also need to be questioned given the existence of adaptation measures. For instance, if such measures were successful in mitigating the final impacts of an event to below the required threshold, it would fail to be recorded. The inventory is therefore strictly defined as including impactful events above existing adaptive capacity at the time of occurrence. This definition adds a level of inherent bias in event selection, which may be important in the case of comparing different regions. In addition, some potential 'near-miss' case studies will be excluded. However, since the primary aim of the inventory is to provide a useful tool for highlighting and managing current and evolving risks, this is viewed as a necessary bias; the alternative would require some far more arbitrary definition of 'impactful'.

Furthermore, the inclusion of EEA may create the impression that the inventory is a way of providing an overall assessment of the cost of climate change through its influence on impactful weather events. However, this is not the case. While trends and individual events can be linked to climate change through attribution science, simply adding up the fingerprint on all events that have happened is insufficient to provide a comprehensive picture of the 'social cost of carbon'. There are many possible events, such as severe cold spells, that in some counterfactual scenario may have been sufficiently impactful to be recorded in the inventory, but as a result of anthropogenic forcing were made less extreme. Thus, in its ideal form, the inventory provides no more or no less than a breakdown of historical impactful events into various known factors that contributed towards the eventual impacts, including the anthropogenic climate forcing. As such it has significant value as an evidence base for engaged parties to identify actions that could enhance disaster resilience, and also to assess the losses and damages from anthropogenic climate change that have truly occurred.

3.3. Stakeholder Applications

The majority of stakeholders interested in extreme weather risks operate at the national and sub-national scales. Previous research involving stakeholder participants suggests that "[EEA] might become a useful tool in the day-to-day work of adaptation planners or to bolster investment decisions" (Sippel et al. 2015). Thus for such prospective users, I propose two overarching benefits of this inventory. Firstly, it provides an assessment of historic extreme weather events resulting in losses and damages, alongside their relation to ACC. This allows for the first time an assessment of the impacts of climate change that have actually occurred and also a timeline of changes in these attributable losses and damages. Critically, this will help to close the gap between the tools currently used to inform climate policy and the actual damages being done, as highlighted by Frame et al. (Frame et al. 2020c). Secondly, it offers the means for disentangling and identifying the drivers of changing hazards and losses, and allows linkages with how they are projected to change, at policy-relevant scales. The inventory therefore provides the evidence base necessary for a practical resilience framework (de Bruijn et al. 2017), specifically in 'adopting a system's approach' and 'remaining resilient into the future'. It also moves towards addressing stakeholder concerns about EEA, including how useful it is for policy in isolation (Osaka and Bellamy 2020a) and its lack of consideration of vulnerability and exposure (Parker et al. 2017).

3.3.1 Assessing extreme weather resulting in climate-related losses

3.3.1.1 Hazard Overviews

The inventory presents a detailed but, due to the nature of different impacts of extreme weather and our current understanding of local climate change, a partly incomplete and conditional picture of recent events. However, perfection is not necessary to add value; in spite of its caveats, the inventory is the most complete picture we have. In particular, we can assess the contributors to different

hazards, including the meteorology, compounding factors and key impacts involved as well as where existing vulnerabilities may lie, what additional work is required and, critically, an overview of the anthropogenic contribution to loss and damage. Below I present a brief summary of heat waves in the UK as an example (additional example summaries, floods in the UK and tropical storms in Puerto Rico, are found in appendix A).

Example: UK Heatwaves

Summary

In the past two decades, four major heat waves in the UK, in 2003, 2006, 2013 and 2018, are responsible for the premature deaths of an estimated 5615 (4084 – 7146) people, mostly in urbanised areas, in addition to travel and agricultural disruption, outbreaks of wildfires in forests and moorland and other widespread health impacts. Over 80% of the mortality occurred in 2003 and 2006, with 2234 (1936 – 2532) and 2323 (2008 – 2638) excess deaths, respectively, though there is not enough quantitative data on other impacts to compare the overall severity.

Meteorological Drivers

These events are generally caused by anomalous high-pressure systems over Northern Europe (figure 3.1), amplified by feedback from a dry and/or heavily urbanised land surface, and typically aligned with a positive summer North Atlantic Oscillation (SNAO).

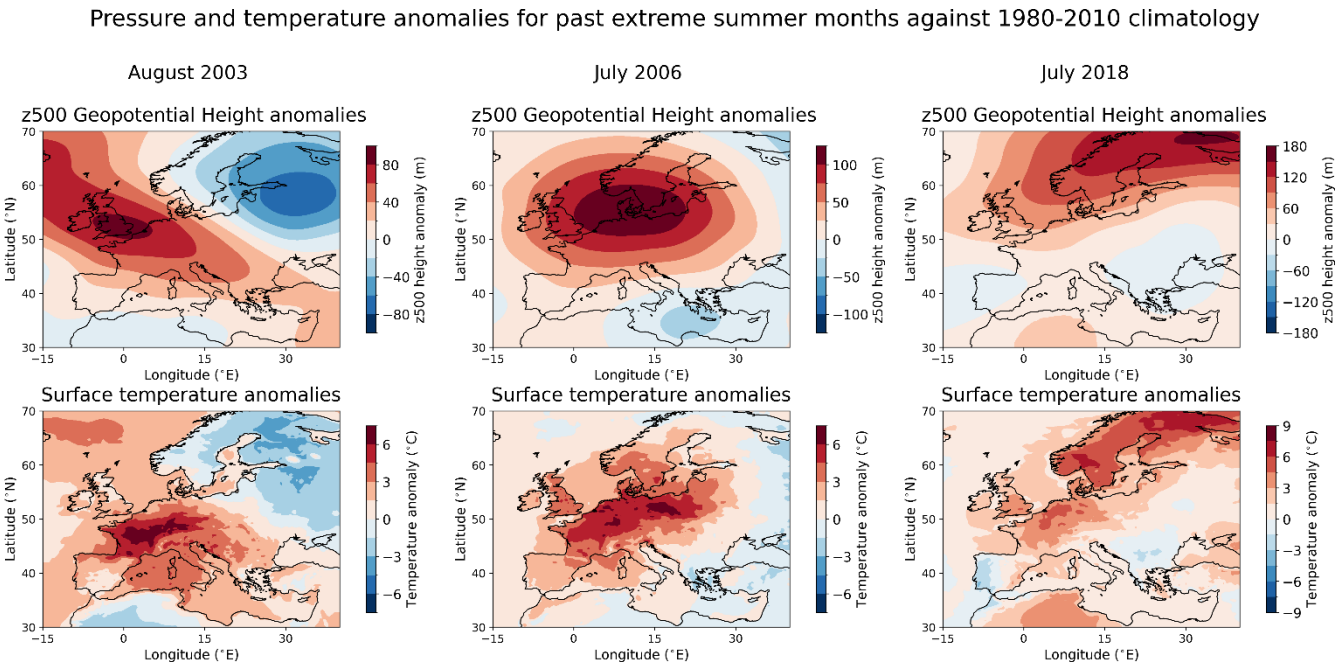


Figure 3.1: Pressure (top row) and surface temperature (bottom row) anomalies over Europe during major heatwave months in the UK: August 2003 (left), July 2006 (centre), and July 2018 (right). The anomalies are calculated with respect to the climatological period 1980-2010. The data is from the gridded observational product E-OBS (Haylock et al. 2008).

Anthropogenic influence

EEA studies for the 2003, 2013 and 2018 events show that events of such magnitude were made 2-30 times more likely by ACC, depending on the event itself and the definitions used. Furthermore, the 2006 event was an extreme of comparable magnitude and a similar causal history to the others, and thus is highly likely to fall within this range. This increase in probability is in agreement with analysis of trends in both mean and extremes of heat to date, with a projected further increase in frequency and magnitude of such events in the future. Finally, an updated study of the 2003 event shows that the probability of similar events has substantially increased again in the time since it actually occurred (Christidis et al. 2015c).

Action taken

The UK created a heatwave plan after the 2003 event, the implementation of which may be responsible for the significant reduction in mortality in 2013 and 2018 relative to the earlier events. In May 2018, seasonal forecasts that predicted the dry conditions to come over Northern Europe were shared with government contingency planners. However, the prediction for surface temperatures showed no significant deviation from the trend over the same region and thus underestimated the hot conditions (McCarthy et al. 2019).

Existing vulnerabilities and further work

In 2018, most of the statistically significant regional mortality rates were recorded among 65+ year olds in London, which suggests an ongoing vulnerability of those specific groups to heat extremes (Public Health England 2019). Furthermore, in the UK Climate Change Risk Assessment (CCRA) trends in heat-related mortality and related impacts are considered but the risks from individual extreme events, particularly those without current precedent for the UK, remain largely unaccounted for (Committee on Climate Change 2016). More work must therefore be undertaken to study the current and future risks for urban and ageing communities and to acknowledge the potentially devastating impacts of highly extreme summers in risk assessments, in addition to the overall trend.

3.3.1.2 Direct Quantification

These overviews incorporate the most substantial quantitative and qualitative impacts for each hazard, robust descriptions of changing meteorological extremes from EEA and other scientific understanding, and finally links between these that include relevant compounding factors. However, we can also use this framework to create a more explicit assessment of loss and damage related to ACC. For any event with an attribution statement, the ACC-related impacts can be approximated by multiplying the total quantifiable impacts with the best-estimate FAR value. For example, the attributable insured losses I_{att} from a flood could be approximated as $I_{att} = I_{total} \, x \, FAR$, where I_{total} is the

known total insured losses of the event. This approach was taken in the pathfinder report commissioned by the New Zealand treasury to approximate the fingerprint of ACC on extreme weather impacts in the country (Frame et al. 2020a) and has subsequently been applied in the context of US hurricanes (Frame et al. 2020c). This method could equally be applied to any quantified impacts from an event, including overall economic loss or mortality.

Event	FAR	Total Mortality	Attributable Mortality
2003	> 0.5	2234 (1936 - 2532)	1117 (968 - 1266)
2018	0.5	863 (227 - 1499)	432 (114 - 750)

Table 3.1: Estimated attributable mortality from UK heatwave events with quantitative attribution statements combining the FAR statements with an assessment of loss of life.

In Tables 3.1-3.3 I present estimates of attributable impacts for major events in the UK and Puerto Rico. These figures should be interpreted in the context of the uncertainties on each value, the variation in how FAR values were calculated, and that there are events with no data. In addition, this calculation only provides a first-order estimate with clear caveats. Namely, it utterly neglects non-linear effects, such as the relationship between temperature and human health, and thresholds, such as overtopping flood defences or the destruction of critical infrastructure. As set our previously, it also represents a change in frequency for events above a given magnitude threshold, and thus a change in the expected loss over a long time period for similar events. The losses calculated here ought to be interpreted in light of this. Therefore, while not equivalent to a direct impact attribution, FAR is a useful metric for a variety of purposesincluding public understanding and risk management, and thus for inclusion in an inventory.

Here, the total attributable mortality on heatwaves is likely an underestimate; both FAR values quoted are thought to be underestimates and there is no FAR estimate for the destructive 2006 event, which

is likely to have been amplified by ACC. Moreover, framing the attribution statement as an increased intensity and considering the non-linear health implications may yield a higher mortality fraction. By contrast, the estimate for Hurricane Maria is highly likely to be an overestimate. The FAR value is based upon an analysis of observational data of long-term climate trends, and therefore is not directly linked to ACC. Furthermore, it is a statement for the most extreme rainfall observed over part of the island and does not include wind-driven impacts.

Event	FAR	Total Damages ($m)	Attributable Damages ($m)
Autumn 2000	0.6 (0.2 - 0.85)	5900	3540 (1180 - 5015)
Summer 2007	≥ 0.5	8448	≥ 4224
Winter 2013/14	0.30 (~0 - 0.38)	1500	450 (~0 – 570)
Winter 2015/16	0.37 (~0 - 0.6)	2176*	805.1 (~0 - 1306)

Table 3.2: Estimated attributable damages from UK flood events with quantitative attribution statements combining the FAR statements with an assessment of total monetary damage.

**Converted from GBP using conversion at the time of occurrence according to https://www.exchangerates.org.uk/GBP-USD-spot-exchange-rates-history-2016.html (accessed 23/09/2020)*

Event	FAR	Total Damages ($m)	Attributable Damages ($m)	Total Mortality	Attributable Mortality
Hurricane Maria, 2017	0.79* (> 0.02)	68000	53720	4645 (793 - 8498)	3670 (626 - 6713)

*Table 3.3: Estimated attributable impacts from Hurricane Maria in Puerto Rico combining the FAR statement with an assessment of total monetary damage and loss of life. *FAR statement of intense rainfall related to long term climate trends.*

In effect, I propose using inventories of past events to create high-level syntheses of our understanding of each hazard as well as calculating the anthropogenic influence on the total impacts.

These could then feed into a comprehensive assessment of all hazard-related impacts for a given nation or region, with the current influence of ACC highlighted. Such an assessment would provide a valuable communication tool for describing and tracking the state of the climate and ongoing vulnerabilities, applicable to policymakers and the wider public alike.

3.3.2 Exploring drivers of past impacts and informing future risk assessment

A further strength of the inventory is in providing rich case studies that can serve as probes of changing risks. In this case, inventories provide a foundation for further analysis. Here I illustrate this through two types of experiment in which actionable information is gleaned from considering how the contributing factors in past events, including hazard probability, exposure and vulnerability, are likely to evolve in different hypothetical scenarios and the implications of this for the impacts. Crucially, such experiments are flexible and can be tailored to the needs of different stakeholders. This methodology fits firmly within the 'storyline' framework described previously (Hazeleger et al. 2015; Shepherd 2016). There is also an important distinction between insights naturally emergent from the inventory and those that requires further work - in this section I provide examples illustrating both.

3.3.2.1 Assessing Future Risks

Events of the recent past are, by definition, plausible. It is therefore feasible to create case studies of future weather by nesting these factual events in modified worlds (Rasmijn et al. 2018; van der Schrier et al. 2018). A trivial case could be placing past events in the context of changing exposure using a simple proxy of changing population, such as the number of people exposed to tropical storms in the Caribbean and eastern US. A more interesting experiment could integrate socioeconomic development scenarios with migration flux into cities and the associated heat island and run-off effects, plus infrastructure and adaptation changes. Then, the experienced impacts in each counterfactual scenario could be modelled, based on a factual meteorological event (Glotter and Elliott 2016). For example, by placing the current and future exposure and vulnerability of residents

of London and Paris in the context of the disastrous heatwave of 2003, the risk of heat-based mortality in the two cities in the 2020s could be assessed. Finally, by utilising climate modelling the meteorology of past events could be tweaked to align with the future climate of each development scenario, thus creating an array of future risk pathways. To continue the example above, this would involve studying the change in magnitude of a heatwave of the same return period in each city and each scenario, and modelling the added effect of this upon mortality.

Projections already exist globally for a variety of forcing scenarios (the representative concentration pathways – henceforth RCPs) and socioeconomic development scenarios (shared socioeconomic pathways – henceforth SSPs) that can provide a physically consistent basis for such work. Experiments may even consider the cost-benefit trade-off in these futures by weighing up the changing risks with other development considerations.

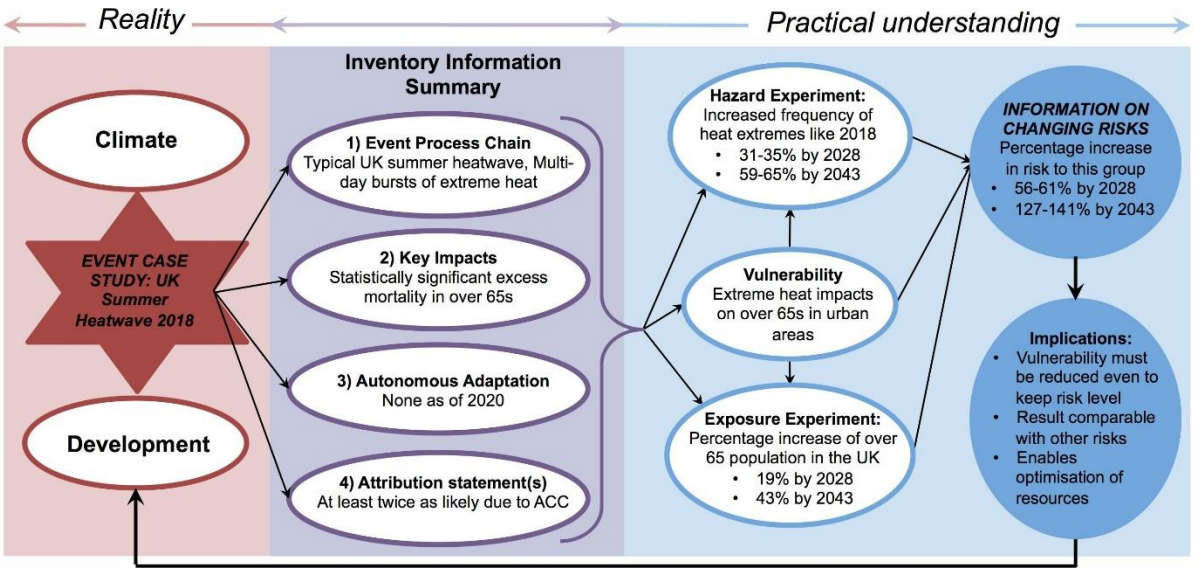


Figure 3.2: Case study using the inventory framework using an impactful event of the recent past, the 2018 UK summer heatwave. The 2018 UK heatwave from the inventory is used to highlight a key source of ongoing vulnerability, then the risk framework is applied to this through analysis of

changing hazard and exposure. Presented are the results for the entire UK region - see table 4 for complete results.

Case study: Changing mortality risk in UK heatwaves

Introduction

From the inventory we can identify that mortality in summer 2018 was triggered by short pulses of extreme heat and was particularly rife among older populations (over 65s) residing in London and other large cities. This immediately highlights an ongoing risk to a specific group of people in the present day. Here I build on this insight and undertake a simple experiment exploring how the changes in both the hazard, in terms of the probability of similar extreme heat events, and exposure, in terms of the number of individuals in elderly urban populations, are changing over multiple policy-relevant timescales: 10 and 25 years after 2018. This will enable us to estimate the trajectory of risk assuming constant vulnerability, thus providing an evidence base for adaptation policies to reduce vulnerability accordingly (figure 1).

Data and methods

In order to assess the contribution from changing probability of extreme heat, I define an event as the annual maximum of 3 day mean of daily maximum temperature (TX3x) exceeding the observed 2018 threshold, over two spatial scales. Critically, this metric is closely linked to mortality (D'Ippoliti et al. 2010; Van Oldenborgh et al. 2019). First, I investigate the historical trends in this metric using daily maximum temperature data from three gridded observational and reanalysis datasets: the ERA5 reanalysis product from the European Centre for Medium-range Weather Forecasts at 0.25° resolution from 1950 (Hersbach et al., 2020); the multi-source weather product MSWX at 0.1° resolution from 1979 (Beck et al., 2022); the European high resolution gridded dataset E-OBS at 0.1 ° resolution from 1920 (Haylock et al., 2008).

Next, future risks are assessed as follows. The event magnitude at each scale was determined using the observational dataset E-OBS (Haylock et al. 2008), detrended according to globally-averaged mean surface temperature (Hansen et al. 2010a) as in(Leach et al. 2020). This delivered event definitions of 25.76 °C for the entire British Isles region (-10.6-2°E, 49.8-59 °N), and 29.72 °C for the region centred on South East England (-2 - 2 °E, 50.5-53 °N) - see table 3.4 and figure 3.3.

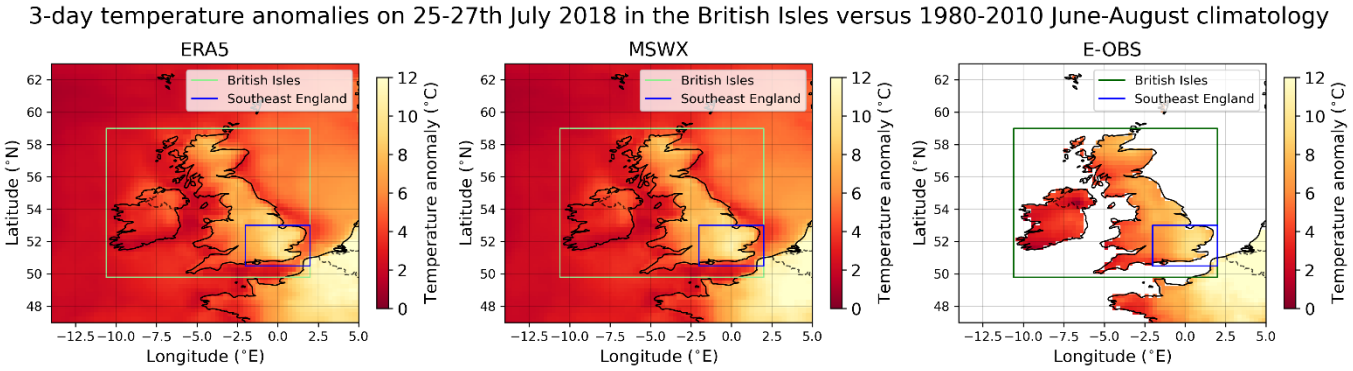


Figure 3.3: Temperature anomalies for the hottest consecutive three days in late July 2018 over the British Isles, for three observational datasets, and calculated with respect to the mean climatology for June-August 1980-2010. The larger domain for the entire British Isles is defined as the land areas bounded by the green box, and the smaller domain over southeast England is land areas within the blue box.

I then identified the model event magnitudes corresponding to the same return periods as the observed events, using the period 2016-2020 with 16 ensemble members in the EC-Earth model (Hazeleger et al. 2012), and 2020-2022 with 100 ensemble members in MaRIUS (Guillod et al. 2018), as only data from 2020 onwards was available. Equating the events through return periods minimised the error from model bias, assuming reasonable consistency in the bias itself. All uncertainties were estimated using a bootstrapping technique for the event magnitudes, which then corresponded with a range in return period values for a given model distribution.

For the estimates of future hazards, I focused on the changing return periods of events equivalent to that of 2018. This is the most directly applicable metric to this risk analysis, rather than studying the changing magnitudes of yet more severe events, because we know the 2018 event to be

fundamentally plausible. An extension to this analysis could therefore instead focus on the changing magnitudes of constant return period events.

Alongside the hazard analysis, the changing exposure of elderly urban populations was studied using subnational population projections from the Office for National Statistics (ONS) (Office for National Statistics 2019). I calculated the fractional population growth, fractional change in the percentage of elderly people and thus the absolute fractional change in the elderly population, both in London and the wider UK (table 4). The estimates of exposure for 2028 and 2043 were then combined with the change in probability of extreme heat events like 2018 in each model, giving estimates of the change in risk for the populations in each region.

Results and Discussion

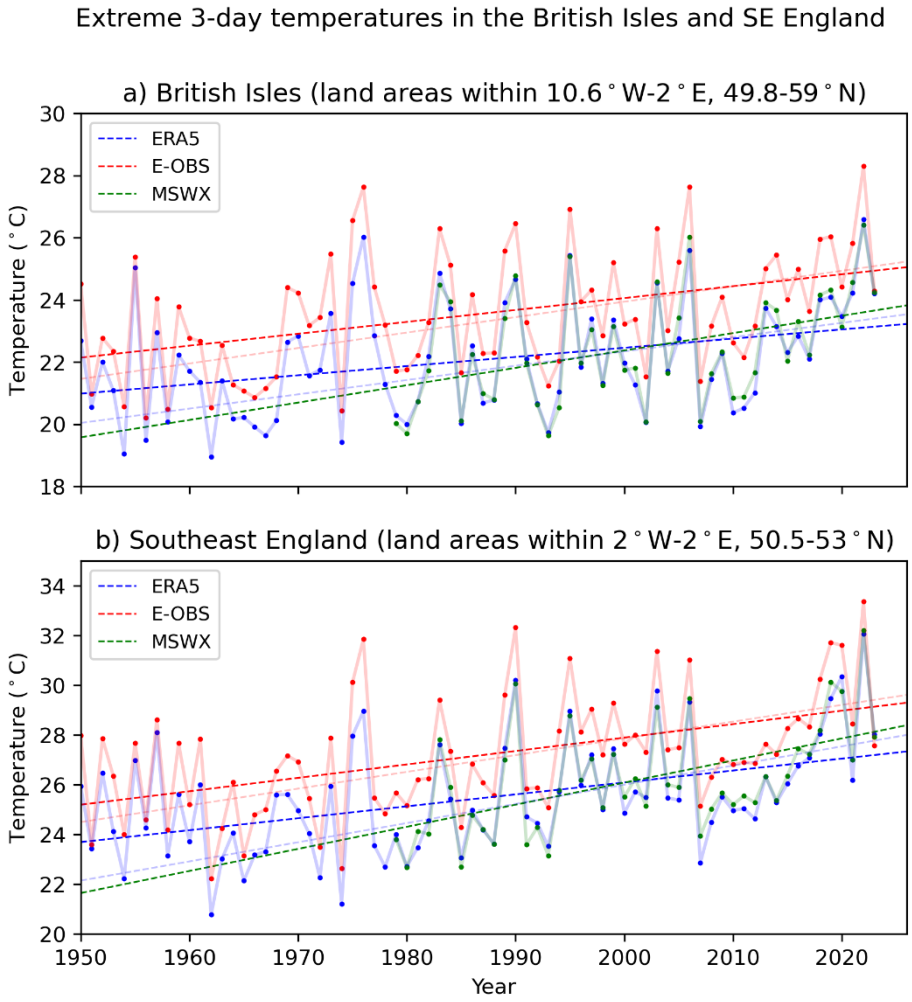


Figure 3.4: Time series and trends in extreme heat events in the British Isles (top) and smaller region in southeast England (bottom), using three observational datasets ERA5, MSWX and E-OBS. The dashed lines show trends calculated through linear regression of each dataset, with lighter red and blue for the same datasets over the period 1979-2023 only.

Trend analysis across both regions clearly highlights a significant increase in the intensity of 3-day heat events (figure 3.4). The estimated trends in extremes are summarised in table 3.4. This shows that over the period 1950-2023, 3-day heat extremes in the British Isles became approximately 0.3-0.4 °C hotter per decade, and around 0.5 °C per decade in SE England in which extremes are already generally

hotter. Since 1979, the increase has accelerated to 0.45-0.55 °C per decade in the British Isles and 0.7-0.9 °C per decade in SE England.

Period	Dataset	Trend and standard error (°C / decade)	
		Southeast England	British Isles
1950 – 2023	EOBS	0.54 (0.11)	0.38 (0.10)
	ERA5	0.48 (0.11)	0.29 (0.09)
1979 – 2023	EOBS	0.67 (0.22)	0.50 (0.20)
	ERA5	0.77 (0.22)	0.46 (0.19)
	MSWX	0.89 (0.21)	0.56 (0.19)

Table 3.4: Observed trends of temperature extremes over the British Isles and Southeast England calculated through linear regression of the annual maximum of 3-day maximum temperatures over each of the domains. The results are provided for two periods, 1950-2023 and 1979-2023 to investigate the influence of the earlier period on the overall shallower trends for ERA5 and EOBS datasets. The standard error on each estimate is also shown in brackets.

Based on E-OBS, the impactful event of 2018 was not unlikely at the time of occurrence, with return periods of about 4 years over the British Isles and 3 years in the hottest region over South East England (table 3.5). This suggests that even in the 'present day' climate defined in this experiment there is already a substantial risk. The magnitude of events corresponding with these return periods in the two models differ largely with each other and with observations, with EC-Earth being too cold while Marius is too hot. Nevertheless, the models show remarkable agreement in the change in return period for the event at both spatial scales and both time horizons consistent with the observations. (Massey et al. 2015) and references therein did show that the dynamics of large scale temperature extremes are reasonably well represented (see also (Guillod et al. 2017)), which increases our confidence that future changes in return period are reliable in spite of the magnitude biases, and given the model is only compared to itself with respect to magnitude. This reasoning does however not hold

for more localised heatwaves (city or county scales) where badly represented atmosphere-land feedbacks lead to an underestimation of increasing trends (Vautard et al. 2019a). Consequently, using the models for the two large regions of interest there is strong evidence to expect an increase in this hazard, with 2043 return periods down to ~2.4 years for the British Isles event and ~2 years for the South east England event.

The subnational population data project increases in overall population and the fraction of older people, both across the entire UK and in London. This further compounds the increasing risk from the hazard itself, leading to an overall increase in heat-related mortality risk of over 50% by 2028 and up to 150% by 2043 in both regions. In the case of constant vulnerability, this indicates the potential loss of many hundreds of lives per year even in the absence of other, record-breaking heat extremes. It therefore highlights the urgency of measures to reduce vulnerability.

Region	Observed event		Model events with same return period		Future return periods of 2018 event (years)			Population changes						Risk factor for constant vulnerability	
	Magnitude (°C)	Return period (years)	Model	Magnitude (°C)	2018	2028	2043	Fractional change in total population		Fractional change in over 65s		Total exposure change factor		2028	2043
								2028	2043	2028	2043	2028	2043		
British Isles*	25.76	3.91 (5.82- 2.77)	Marius	28.92 (28.15 - 29.63)	3.91 (3.41 - 4.50)	2.99 (2.68 - 3.35)	2.32 (2.12 - 2.55)	1.04 (UK)	1.09 (UK)	1.14 (UK)	1.31 (UK)	1.19 (UK)	1.43 (UK)	1.56 (UK)	2.41 (UK)
			EC-Earth	21.27 (20.96 - 21.54)	3.91 (3.04 - 5.13)	2.89 (2.22 - 3.96)	2.46 (1.95 - 3.23)							1.61 (UK)	2.27 (UK)
South East England**	29.72	3.08 (4.44-2.33)	Marius	33.04 (32.21 - 38.50)	3.08 (2.79 - 3.49)	2.72 (2.49 - 3.04)	2.10 (1.95 - 2.30)	1.05 (London)	1.10 (London)	1.20 (London)	1.54 (London)	1.26 (London)	1.70 (London)	1.43 (London)	2.49 (London)
			EC-Earth	24.13 (23.81 - 24.40)	3.08 (2.51 - 3.88)	2.22 (1.85 - 2.76)	2.07 (1.74 - 2.53)							1.75 (London)	2.53 (London)

*Table 3.5: Changing hazard and exposure of vulnerable populations to 2018-like heatwaves over two spatial scales, using two different climate model ensembles alongside subnational population projections. 5-95% confidence intervals for event magnitudes and return periods are included in brackets. *Data refers to the entire British Isles region unless otherwise specified in the table. **Data refers to the entire SE England region unless otherwise specified in the table.*

3.3.2.2 Black Swans and Dragon Kings

In a changing climate, the probabilities of events at the tail of the distribution generally increase most rapidly (Fischer and Knutti 2015a). Thus there is an ever-greater possibility of totally unprecedented events with no analogue in living memory. Until recently, a subclass of these events, dubbed 'Black Swans' (Taleb 2007), was thought to be impossible to predict except in hindsight due to the presence of epistemic uncertainty. However, the recently proposed method of 'downward counterfactuals' (Woo 2019) capitalises on the historical record, utilising stochastic simulations of past events and near misses to probe the physical plausibility of the formerly unexpectable.

In essence, this methodology is a tool that pushes back the boundary of the unknowable. In doing so, it allows us to consider many (but of course not all) Black Swans as 'Grey Swans' or 'Dragon Kings' (Wheatley et al. 2017); those events without precedent that can nonetheless be understood to be feasible given the appropriate conception – in other words, those governed largely by aleatoric, or statistical, uncertainty (Sornette 2009; Paté-Cornell 2012) At this point the distinction between Dragon Kings and Black Swans is largely philosophical and, while this nuance is still important in terms of identifying the necessary methodology, here the key point is practical; assessing the risk of destructive and unprecedented events. Therefore, the term Black Swans will be employed for the remainder of this work to describe events that were or may yet be utterly unprecedented, whether strictly anticipatable at the time or not. Recent examples include the Russian heatwave of 2010, European heatwave of 2003, Hurricane Katrina in the US, Hurricanes Irma and Maria in Puerto Rico, and the 2010 floods in Pakistan.

To return to the inventory, studying such events could be perceived as a weakness because, by definition, unprecedented events will not be accounted for in the recent past. However, past events do provide a foundation of plausibility from which potential 'black swans' could be discovered and "the larger the number of notable historical events in the recorded past, the more extensive is the

combined coverage of extreme events spanned by the space of downward counterfactuals" (Woo 2019). There are two complementary perspectives through which this may be achieved.

Firstly, past catastrophes from different regions pose a warning. In 2003, Europe experienced an unprecedented heatwave that resulted in the deaths of tens of thousands. Then, in 2010, this occurred in Russia. Although both events, like all extremes, had natural causes as well (Dole et al. 2011), they were made substantially more likely by anthropogenic climate change (Stott et al. 2004a; Rahmstorf and Coumou 2011; Otto et al. 2012; Christidis et al. 2015c). Merely acknowledging its physical plausibility in a variable and warming world, in the aftermath of such an event to the west, could have motivated preparation for such an eventuality. In this case, little physical insight will be gleaned regarding the plausibility of such events due to the fundamental nature of differing climatologies and exposure and vulnerability in different regions. Nevertheless, inventories provide a basis for systematic inclusion of potential Black Swans in risk assessments, particularly highlighting where similar vulnerabilities may lie in other regions and providing 'lessons learned' in the aftermath of disasters. Inventories provide a foundation for this with little additional work required, enabling other nations to take factual black swan events into account in climate risk assessments in a systematic manner.

Secondly, we can ask if events of the past could have been far more devastating given slightly different, but still plausible, circumstances. For example, for an event in which a town's flood defences narrowly held back a river, how much greater would the magnitude of rainfall have needed to be for it to have escalated from negligible impacts to highly destructive? I have already acknowledged that using an impact-based threshold eliminates most 'near-misses' from the inventory. Nevertheless, given some plausible perturbations to the antecedent conditions, all events may be simply 'near-misses' of a more destructive counterfactual version of themselves.

Example: UK heatwave

In 2003, the UK experienced the periphery of a heatwave that caused untold suffering across Europe. Though this was enough to cause the premature deaths of thousands, the UK has never experienced a truly catastrophic event such as in mainland Europe or Russia. Nevertheless, there exists some threshold at which the impacts would be amplified to these levels. This is complex, because the mortality associated with temperatures vary by region and by season. However, as with Russia, the UK has a relatively low threshold for severe impacts. In London, for example, studies show that the risk of mortality follows a sharp exponential rise with temperature (Baccini et al. 2008). It is therefore critical that the likelihood of such events, however low, are explored and an appropriate level of preparation put in place.

To do so, projection analysis of anomalous events such as these must be undertaken, with attribution studies alongside to isolate the key drivers such as ACC. Past events such as 2003 form a strong physical basis for such experimentation. For example, asking: how would events with the same return period as the 2003 event look in a warmer world? Then, what is the plausibility of a high-pressure system similar to 2003 forming slightly further north, thereby bringing more extreme temperatures to the UK and Scandinavia? Finally, how do the answers to these questions change in different climate and development scenarios?

Example: Puerto Rico Hurricanes

For Puerto Rico the twinned hazard of Hurricanes Irma and Maria was a black swan; no direct precedent existed for an event of such catastrophic impacts. However, in hindsight there was sufficient reason to anticipate such a hazard through counterfactual thinking. Even in recent memory the mainland US and other Caribbean islands experienced massive destruction from tropical storms, while Puerto Rico itself experienced severe impacts from storms such as Jeanne in 2004 and Irene in 2011. In part, the impacts of the event may have been mitigated by additional preparedness following analysis of the risk of such an occurrence.

Now, the nature of black swan events means that we are forced to consider how it may have been even worse. The event was already compounded by the fact that Irma struck just weeks before Maria, saturating the soils of the island and degrading some infrastructure. But what if Irma had also made landfall, thereby causing further destruction and crippling resilience ahead of Maria? From historical records, model runs and physical reasoning, such as the rate of recharge of sufficient ocean heat content, is there good reason to discard the possibility of two concurrent strikes? If not, what is the probability of such a compound event occurring in the future? The occurrence of this event indicates the non-negligible plausibility of yet worse circumstances, which in turn strongly suggests the benefit of considering additional risk in rebuilding and future crisis management.

Finally, it is critical that the lessons of this event are not limited to Puerto Rico; it has direct implications for every island in the Caribbean as well as the eastern seaboard of the US, where, in the absence of this lesson from Puerto Rico, the concurrent strike of powerful cyclones may still be considered a black swan. Beyond this, extrapolations may be made for other regions, as discussed previously. In particular, the plausibility of such concurrently striking storms may need to be assessed in other basins.

3.4. Global Policy Implications

On top of the national interest, creation of inventories of the impacts of human-induced climate change across the world would be of significant interest to the broader international community. This is evident by looking through the lens of the Paris accord. In particular, inventories have the potential to aid two areas of the agreement that currently present unique challenges: adaptation (Articles 7 and 14) and loss and damage (Article 8). Additional utility could also be argued for other articles subsections, such as ‘Technology transfer’ in Article 13, though I do not explore such links here.

Article 7 sets out the global goal on adaptation of “enhancing adaptive capacity, strengthening resilience and reducing vulnerability to climate change”, and goes on to develop a framework for such action. Among other aspects, this includes strengthening international cooperation in a number of ways, including “Sharing information, good practices, experiences and lessons learned”. Article 14 then introduces the global stocktake system to monitor the implementation of the agreement, stating that it shall do so “in a comprehensive and facilitative manner, considering mitigation, adaptation and the means of implementation and support, and in the light of equity and the best available science”. Taken together, this is a clear mandate for global research efforts to better understand and systematically track adaptive capacity (Tompkins et al. 2018) and for decision makers to ratchet this up in line with this evidence.

Article 8 acknowledges “the importance of averting, minimizing and addressing loss and damage associated with the adverse effects of climate change”. It proposes that nations “enhance understanding, action and support … on a cooperative and facilitative basis with respect to loss and damage”. It further highlights key areas where work and cooperation is needed, including “Events that may involve irreversible and permanent loss and damage; Comprehensive risk assessment and management; Non-economic losses; and Resilience of communities, livelihoods and ecosystems.” Since Katowice 2018, the stocktaking process in article 14 additionally “may take into account” the loss and damage considerations from article 8, though will not explicitly take stock of loss and damage.

Despite the existence of this accord, and the explicit task to include adaptation and Loss and Damage in the global stocktake underpinning the agreement, there is still no established system for tracking adaptation and vulnerability to climate change or the associated loss and damage. This is for an array of reasons, from the perceived and very real political barriers (Boyd et al. 2017) to the disparity in data between regions and the difficulty in assessing non-economic impacts (Serdeczny 2019).

Inventories of past events are a logical starting point to provide a foundation for this, in particular as impacts relating to extreme weather are already recorded in various ways, albeit not comprehensively (Harrington and Otto 2020b). In particular, past extremes explicitly highlight existing vulnerabilities. This is particularly pertinent in cases where rebuilding strategies in the wake of a disaster failed to reflect the risk of similar or even more destructive future events.

The proposed inventory builds on approaches that have been proposed that bypass the political and ethical questions surrounding compensation, which science alone can never answer, instead utilising attribution science in a broader pragmatic way to identify drivers of loss and damage that assist in optimising resources for minimizing risk (James et al. 2019). Additionally, it does this on a policy-relevant horizon and in collaboration with other science that considers the longer-term picture.

In section 3 I furthermore discussed how inventories provide a transparent and bottom-up approach to understanding climate-related loss and damage from extreme weather. I clarified that, while this is distinct from a full 'social cost of carbon' estimate, it is complementary to the top-down approach to calculating specific loss and damage, as applied to impacts from Hurricane Harvey ((Frame et al. 2020a)). Though the inventory method is still limited by geographical biases in both the availability of information and prevalence of science such as attribution (Otto et al. 2020a), it is nonetheless the most complete option we have. It also highlights such biases, providing evidence for the need for a more representative distribution of analysis and research. Furthermore, inventories have capacity to handle non-economic and even purely qualitative losses, as well as facilitating the assessment of present and future risk as in section 3. Taken together, this might be a valuable tool and evidence base to inform the Warsaw International Mechanism, specifically for the aim of "enhancing knowledge and understanding of comprehensive risk management approaches to address loss and damage", for which there is a dedicated working group.

Alongside this, addressing present and future loss and damage is inextricably intertwined with identifying key areas for and optimising adaptation. For example, inventories provide case studies of

adaptation being to some degree unsuccessful, thus contributing to the 'experiences and lessons learned' element that is core to international cooperation. Also, the standardised nature of the system facilitates this sharing of information across borders (though language barriers remain a key challenge) and helps to keep the process fair and transparent.

Our inventory system is simply a natural extension of this pragmatic approach to adaptation and loss and damage, and additionally complements recent work e.g. by Germanwatch (Eckstein et al. 2019) that utilised hazard databases stored by reinsurance companies to calculate a global climate risk index (CRI) for every nation. The integration of EEA helps to clarify the 'climate risk' aspect, distinguishing the specific 'anthropogenic climate risk'. Furthermore, inventories include more impact information, on the scale of individual regions, than the re-insurance datasets used to construct the current indices. Finally, some catastrophes could be inferred to pose a level of risk to all nations in the same region. For example, largely due to Hurricane Maria, Puerto Rico is placed at number 2 in the entire world for climate risk. However, in accordance with black swan methodology, the destructiveness of this event indicates a clear risk to all Caribbean islands and the eastern coast of the US going forwards.

We do not claim that inventories present a full solution to this challenge. The most successful adaptation measures are inherently excluded from the database as a direct result of using an impacts-based threshold (section 2.2), while the impacts of slow-onset and irreversible events require completely separate bodies of work. Rather, inventories provide a transparent line of evidence for tracking and understanding adaptation measures for extreme weather risks on a global scale. Similarly while hazards continue to grow in a warming world we are only starting to understand our vulnerability if by recording it (Harrington and Otto 2020b). The more we compile this information the faster we can learn and understand the impacts and avoid future Loss and Damage.

3.5. Conclusions

The body of literature linking individual extreme weather events to ACC grows every year. Thus far, this has remained largely distinct from efforts to prepare for and adapt to disasters, and to take stock of the resulting loss and damage in the aftermath. Here I set out a framework for recording extreme weather events and the associated attribution work in a standardised inventory to better utilise this science in real time and at the scales risk assessments are made and adaptation is implemented. It is a pragmatic approach utilising existing data and concepts at local and national scales that bypasses interdisciplinary hurdles and addresses a clear need for such information to understand climate-related losses and identify vulnerabilities. Key challenges remain, including language barriers, ensuring user understanding around attribution statements and communicating uncertainties. However, even its current form may provide tangible benefits. For instance, such a system facilitates a bottom-up approach to assessing climate risk. Studying factual events of the recent past enables us to build risk analysis around lived experience at local scales, while counterfactual analysis of historical events can help to expose plausible, more severe catastrophes. Assessing risk in this way inherently places vulnerability front and centre, thereby aiding in optimisation of resource deployment for disaster preparedness and adaptation. To evaluate and improve the practical utility of this inventory concept for a variety of stakeholders, formal feedback and development are now required. The national inventory further provides a framework to identify losses and damages as well as progress in adaptation to feed into the global stocktake requested by the Paris Agreement as well as the Sendai Framework on disaster preparedness.

Chapter 4 - When don't we need a new extreme event attribution study?

Abstract

The influence of anthropogenic climate change on the frequency and intensity of extreme weather events is becoming increasingly well understood. Extreme event attribution studies now exist for hundreds of events over the past few decades. However, there remain large heterogeneities in the number of attribution studies across the world and for different hazards, as well as limited capacity to conduct new studies. In this study, I suggest that there is more information to draw from past attribution studies about recent events. This is because, even though anthropogenic forcing continues to increase, many new events share meteorological characteristics with previously attributed ones. Here, I explore the possibility of using related studies and other lines of existing evidence such as projections and trend analysis to create rapid, low-resource attribution statements. To do this, I discuss the potential use cases for attribution results, including raising awareness of climate risks, preparing adaptation measures, and attributing climate loss and damage. Then I discuss the considerations necessary to fulfil these uses in three cases studies, including a heatwave in the UK, a tropical storm in the Caribbean, and a drought in East Africa. To conclude, I highlight the regions and hazards for which information can be drawn without new quantitative analysis, and those in which it remains urgent. This could aid prioritisation of limited resources for research into less well understood regions and hazards.

4.1. Introduction

Anthropogenic interference in the climate system is increasingly manifesting as altered intensities and likelihoods of extreme weather events (Seneviratne et al. 2021). The science of extreme event

attribution (EEA) is the toolbox used to understand and quantify these changes in intensity and likelihood of individual extreme events attributable to human-caused climate change. For any given observed event, multiple possible event definitions exist, each of which relates to slightly or significantly different aspects of the extreme, e.g. a tropical cyclone could be characterised by wind speed or associated heavy rainfall. Estimates of the influence of anthropogenic climate change (ACC) also differ depending on the event definition, including spatiotemporal factors, as illustrated in recent heatwave attribution (Leach et al. 2020) and multiple studies of rainfall from Hurricane Harvey (Van Oldenborgh et al. 2017; Emanuel 2017; Risser and Wehner 2017; Wang et al. 2018b). Similarly, the framing of the attribution study and methodological decisions also play an important role in the overall estimate of the role of climate change (Otto et al. 2016).

After more than a decade of development of this science, consensus on various best practices are beginning to emerge. For example, using multiple definitions for a given event informs understanding of the dependence of the result on this choice, as well as providing utility to a wide range of prospective stakeholders (Otto et al. 2012; Kirchmeier-Young et al. 2019; Leach et al. 2020). More broadly, the conditions required for ranking the quality of evidence provided by studies are now well established (Otto et al. 2020c) and standardised protocols are being laid out by the community (Philip et al. 2020; van Oldenborgh et al. 2021). In addition, combining quantitative approaches referenced above and narrative or storyline approaches (Shepherd 2021b) can address different stakeholder needs.

As the science is further refined, its reliability and credibility grow. Moreover, our ability to attribute different extreme meteorological events increases and the cumulative number of attributed events increases every year (Herring et al. 2021; Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021). However, there is limited capacity for producing attribution studies. Relatively few resources are available and attribution studies are still produced on an ad-hoc basis, with an overwhelming focus on the global north. This is for a variety of reasons including historical data availability, climate model performance

and the prevalence of local experts, as set out by Otto et al. (Otto et al. 2020b). Critically, attribution is not yet undertaken systematically in a single region of the world (Clarke et al. 2022). This not only prevents the provision of valuable information in the wake of weather-related disasters but also hinders a comprehensive overview and understanding of climate change impacts, and thus loss and damage (Stott et al. 2016; Parker et al. 2017).

By their nature, event attribution studies are tailored to specific events. However, over the course of several years in a given location, multiple events can occur that share common characteristics. For many meteorological hazards, certain synoptic circumstances are effectively a necessary precondition for occurrence. Thus, I posit that attribution studies for specific events contain far more information, about other hazards of the same type, than is currently utilised.

Even in an ideal world with sufficient capacity to undertake many studies, it may be both inefficient and unnecessary to study afresh every event that occurs. The untapped information in past studies can be combined with improved recording of hazards and impacts (Clarke et al. 2021a), and ever-increasing knowledge of trends in extremes and large-scale detection and attribution studies (Seong et al. 2021b). This has the potential to facilitate attribution scientists making expert judgements for very rapid, low-resource attribution statements. As no quantitative analysis is required for such a statement, and a literature review is necessary during the formulation of any attribution study, such a derived statement would be lower in cost by definition.

Important considerations when deriving statements for new events based on past attribution studies include both how comparable different events are, and the intended use of the attribution results. First, not all events in the same region of the same type will have a comparable influence from human-caused climate change, at least not on a quantitative basis. For instance, extreme seasonal rainfall events in the UK have elicited a variety of statements: the wet summer of 2012 was not influenced significantly (Sparrow et al. 2013); the wet winter of 2013/14 had a possible link but was ultimately inconclusive (Christidis and Stott 2015); autumn 2000 rainfall-driven floods in England and Wales, and

winter 2014 floods in southern England were made more likely (Pall et al. 2011c; Schaller et al. 2016). This arises partly due to the seasonality itself, which plays a significant role in the link between many extremes and climate change (Stott et al. 2016), and more broadly the choice of event definition in each case (Leach et al. 2020; van Oldenborgh et al. 2021).

Second, the uses for attribution results are becoming increasingly diverse. When an extreme event occurs, a variety of stakeholders raise questions that are answered using attribution science. For example, 'what was the role of climate change in this event?', and 'what are the implications for disaster risk reduction or for loss and damage from climate change?'.

In this chapter, I examine when and under what circumstances some common questions can be answered rapidly based on past attribution studies and other information sources, such as projections. In particular, when can we use attribution literature to provide information to interested stakeholders? And how can we do so in a transparent manner that facilitates reproducibility?

To explore this challenge, I assess the statements that can be made for two region-specific case studies of heatwaves in the UK and tropical storms in Puerto Rico (section 2). I then comment more generally on where and for which hazards new studies offer value, or if drawing insights from existing studies allows for sufficiently reliable conclusions on the role of climate change (Section 3). The conclusions of this study provide an assessment of where the attribution community could prioritise limited resources to add the greatest value.

4.2. Different uses of attribution results

In this section, I discuss three distinct applications for attribution results. The most important aim is to determine the minimum useful information that each of these applications requires and then when it is possible to meet these requirements with past studies. This is not a comprehensive list of possible applications but covers some of the most likely uses to benefit from rapid and low-resource attribution statements, as opposed to more detailed scientific analyses.

4.2.1 Raising awareness of climate change risks

In the aftermath of an impactful weather or climate-related event, the general public, and by extension the media, increasingly raise the question of the role of climate change (Ettinger et al. 2021). It is important to provide a robust scientific answer, as often the question is answered un-scientifically, leading to either over- or under-estimating the role of climate change (Stott et al. 2016; Painter et al. 2020; van Oldenborgh et al. 2021). Attribution science shows that not all events are influenced by climate change, and in some cases a conclusive finding can't be made, but that many are, with destructive effects (WWA 2020). This balanced view is important to promote informed awareness of the most pressing challenges and a realistic understanding of the impacts of climate change. Therefore, as a minimum for a new event, a general statement of the influence of climate change is required - whether it affected the likelihood of an event of this magnitude, or affected the magnitude of an event of this likelihood, or played an insignificant role.

Attribution also provides an opportunity for communicating the impacts of climate change to the general public, through connecting knowledge and experience (Zanocco et al. 2019; Kubin et al. 2021; Ettinger et al. 2021). For instance, it provides a direct comparison between the event that people experienced and how a similar one would have played out in a counterfactual world of no anthropogenic interference in the climate system. This demands a numerical estimate of changes in probability or magnitude and/or use of a storyline approach (Shepherd 2016; Shepherd and Lloyd 2021). Research also suggests that incorporating vulnerability and exposure information - the other drivers of extreme impacts - is important for providing a useful narrative (Ettinger et al. 2021). Doing so demonstrates how natural hazards can trigger disasters, and may also raise awareness of how climate and society are related (Wallace 2012).

In summary, to raise awareness and connect people's experience of extreme weather with global climate change, qualitative assessments of its role (increase/decrease/no change) are needed as well as contextual information of the weather event and its impacts.

4.2.2 Adapting to climate change risks

Attribution elucidates the degree to which climate change is driving current weather risk, for a specific class of hazards bounded by the event definition used, in a given region. As a result, it is frequently suggested that it provides a basis for planning measures to prevent further harms (Stott and Walton 2013; Otto et al. 2015c; Schwab et al. 2017). For this purpose, it is of particular importance to provide a quantitative attribution statement, along with an associated uncertainty range, as it may be used as evidence to justify and optimise the allocation of finite resources (Schwab et al. 2017). Therefore, as a minimum, this usage requires an estimate of the influence of climate change on the frequency or intensity of the event. The former is derived from a probability ratio, given by

$$PR = \frac{p_1}{p_0}, \tag{4.1}$$

Where p_1 and p_0 are the respective probabilities of an event of a given intensity in a climate with and without anthropogenic forcing. The latter may be derived via the same methodology used to generate (1), but as a difference in intensity between events of equal frequency in different climate, in which case providing both will in most cases be plausible and maximise utility. Intensity changes may also be derived using a storyline approach, conditioned on event occurrence, which may highlight anthropogenic influence on specific aspects of a given event (e.g. Reed et al., 2020). There are several arguments challenging the use of attribution in adaptation, including: the limits of hazard-only analysis; perceptions of high uncertainties in attribution results among decision makers; the lack of information about the future. Here I consider these in turn to further refine the threshold for actionable information.

First, it has been argued that since the probability change only describes a change to meteorological risk, it has very limited utility. This is because it is understood by some scholars to be completely blind to all social structures and political and ethical factors relevant for assessing blame for the realised impacts (Hulme et al. 2011; Lusk 2017). However, event attribution studies increasingly include

contextual information on exposure and vulnerability, potentially enhancing their utility (Stone et al. 2021b; van Oldenborgh et al. 2021) and even in early stages used impact information to identify the event definition. For example, analysis of severe, drought-driven food insecurity in Madagascar showed that climate change did not significantly alter the likelihood of low precipitation that contributed to the disaster. Instead it showed that low rainfall struck a region with low levels of pre-existing food security, which was further compounded by Covid-19 restrictions and pest infestations (WWA 2021). The attribution result, coupled with the qualitative analysis of other drivers of impacts that is a crucial element of modern event attribution (Philip et al. 2020), therefore inherently focused attention towards understanding these other factors. In doing so, it provided a statement that may be used to enhance adaptation and resilience planning.

In addition, even if attribution is indeed limited to purely meteorological factors, a deeper understanding of this can lead directly to risk reduction through the motivating and informing development of improved early warning systems, which can contribute to adaptation by reducing vulnerability. The degree to and time in which an event was not only forecast, but forecastable, is a crucial aspect of reducing vulnerability. While early warning systems are not a panacea for mitigating extreme weather impacts (Hillbruner and Moloney 2012; Gwimbi and Siimane 2021; Engelbrecht and Vogel 2021), they remain a key component of integrated disaster risk reduction strategies (Banwell et al. 2018).

Second, recent studies suggest that decision makers remain doubtful about using attribution for planning, due to the perceived high uncertainties and current lack of a role for such information (Young et al. 2019; Osaka and Bellamy 2020b). However, high uncertainties are found in climate projections, which are traditionally used to inform adaptation, and uncertainties in attribution studies are generally no larger. Still, quantifying the uncertainty is crucial for decision makers to determine whether the quantitative attribution is suitable for their needs in allocating resources.

While stakeholders and scholars such as the authors cited above are used to uncertain projections, expectations for attribution studies have not been established and are thus consistently measured against what is desirable, not what is possible. Most importantly, attribution studies and projections are most effective in combination, as explored by recent studies (Otto et al. 2018a; WWA 2021) and later in this section.

Third, critics argue that attribution only provides a snapshot of climate-influenced risk - it does not directly provide information on future changes, which is clearly of significance for planning (Lusk 2017). However, this view may neglect potentially important information. Clearly, it is more useful to know whether a hazard has already changed in probability, than to have no idea. For certain event types, such as extreme heat and extreme rainfall conditioned on specific synoptic circumstances, it is also often trivial, based on physical reasoning and existing climate projections, to extrapolate forwards qualitatively from an attribution statement. For these cases, we can state that the direction of change already observed (be it an increase or decrease) will most likely continue as long as the anthropogenic forcing does. An attribution statement that demonstrates a statistically significant change is not only a snapshot, but for many cases in which thermodynamic effects dominate, an indication that a trajectory of change very likely existed at the time of occurrence and plausibly will persist.

In addition, and in accordance with the argument presented above, assessments of future changes in the same class of events have also become a more regular feature of attribution studies (Otto et al. 2018a; van Oldenborgh et al. 2021). This could address potential concerns about the wider applicability of attribution results. For instance, the Brahmaputra floods of 2017 that affected millions of people were not made significantly more likely by climate change (Philip et al. 2019). However, at 2°C of global warming, the probability of such a rainfall event as brought the flood will increase by roughly 70% and the associated extreme river discharge by around 50% (Philip et al. 2019). A useful development from this would be in estimating the relative attribution statements for a class of event across multiple emissions pathways, to enable local planners to fairly evaluate possible measures for

long-term resilience. This also has the added benefit of informing mitigation decisions by showing their direct implications on plausible events.

Overall, it will be beneficial for derived statements used for adaptation to explicitly address future changes based on physical reasoning and other work such as trend analysis, and that it is likely in the case of thermodynamically-dominated events, without additional evidence to the contrary, the frequency and/or intensity increases will continue to grow over time. Where possible, derived statements should draw upon studies that have projected the change in attributable fraction, with reference to multiple global warming levels.

In summary, to inform adaptation quantitative attribution information is preferable. While the sign of change is more useful than nothing, direct quantification, including uncertainty estimates, has far greater utility. In addition, any assessment of the role of vulnerability and exposure and if and how likelihood/intensity will continue to change with higher warming levels, greatly increase the utility of attribution for adaptation.

4.2.3 Estimating climate Loss and Damage

Through its influence on extreme weather, among other factors, climate change is responsible for loss and damage to people, society and nature around the world (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021). However, our knowledge of these growing costs is not well-defined nor compiled systematically, and its true extent is unknown (James et al. 2014; Clarke et al. 2022). Attribution provides one way to quantify the influence of climate change on the likelihood and intensity of an impactful event, and thus connect global change with individual losses in a way that could contribute to a systematic inventory of attributable impacts (Otto et al. 2020c; Clarke et al. 2021a). Assessing loss and damage is therefore another potential use case for derived attribution statements. Though it is

worth mentioning that this faces a number of challenges, including the unequal capacity for attribution in different regions and for different event types (Jézéquel et al. 2019b)

Themethodology behind attributing impacts is still in development. Direct attribution of weather impacts is challenging, often requiring multiple steps of modelling and analysis, with compounding uncertainties (Perkins-Kirkpatrick et al. 2022). For example, attributing impacts of flooding involves modelling changes in meteorological extremes, how these affect surface hydrology, and the implications for the number of flooded properties, as explored in Pall et al. (Pall et al. 2011c; Schaller et al. 2016) and Schaller et al. (Schaller et al. 2016). Cascading impacts, such as the spread of disease and those arising due to the disruption to key services, are even more complex to causally attribute.

The fractional attributable risk (FAR) statistic (Allen 2003; Perkins-Kirkpatrick et al. 2022) provides a very simple albeit limited method of attributing impacts (Clarke et al. 2021a), as the FAR statement refers to a class of events above a certain magnitude, while the actual impacts are from a single realisation (Perkins-Kirkpatrick et al. 2022). Furthermore, the relationship between event magnitude and impacts, such as heatwave temperature and mortality, is almost never linear and may involve critical thresholds (Mitchell et al. 2016b; Vicedo-Cabrera et al. 2021). Evidently, since a shift in hazard magnitude does not necessarily translate into an equivalent shift in impact magnitude, the FAR method does not constitute a causal attribution.

Nonetheless, for the purposes of estimating attributable impacts across many events, it forms a useful first-order approximation. Therefore, as a minimum, the use case of attributing impacts requires a numerical estimate of the influence of climate change in the form of a FAR statement (or a similar method, such as a comparison of event probability density around the event threshold itself (Harrington, 2017). Additionally, it would be useful to have an attributed change in magnitude rather than probability, and to understand the nature of the relationship between the magnitude of the event and the subsequent impacts. This would show whether the FAR-based attribution of impacts

was likely an over- or under-estimate and enable an order-of-magnitude estimation of the attributable impacts.

Finally, attribution may also be applied in the growing area of climate litigation, including lawsuits seeking compensation for climate change-related loss and damage or to show admissibility for inadequate mitigation (Stuart-Smith et al. 2021). In most such cases, the threshold for legal liability requires demonstrating causation; that a specific harm to the plaintiff resulted from specific actions of the defendant (typically a corporation or nation state) (Lusk 2017). Some scholars and stakeholders suggest that extreme weather attribution is insufficient to satisfy such a condition in legal systems – this is for a range of reasons including the unreliability of models, the range of methods used in attribution, and that it is difficult to trace an attribution to climate change to the specific actions of a defendant (Stott and Walton 2013; Hulme 2014; Lusk 2017). Most such lawsuits to date have been unsuccessful (Lusk 2017; Stuart-Smith et al. 2021). However, this is more often due to legal hurdles preceding the review of evidence, or because plaintiffs present evidence that does not draw upon the latest attribution science that is able to demonstrate causality in many cases (Stuart-Smith et al. 2021). Furthermore, common law in England, Wales and the US also provides precedent for probabilistic evidence when strict causal links are impossible (Marjanac and Patton 2018). Therefore, for such a use, dedicated causal attribution analysis of the impacts are required to provide a firm basis for a new case. However, an expert judgement of attribution based on past studies could add a complementary line of evidence to an existing case.

In summary, to assess loss and damage from anthropogenic climate change a quantitative attribution statement is needed as well as information on the role of vulnerability and exposure, and the relationship between event magnitude and impacts. For the purposes of attributing legal liability for the impacts of a given event, a dedicated study is most likely required.

4.3. Case studies of deriving new attribution statements

In this section I look at three illustrative case studies to ultimately answer the following questions:

- Under what conditions is it possible to draw useful information about a given event from past attribution studies?
- What are the practical steps required to obtain this information?

I begin to address these two questions through the structure of these case studies, developing the process through which the available evidence is evaluated and new information derived.

I first discuss a heatwave in the UK, for which there are several studies relating to similar events with consistent conclusions. I then consider tropical storms that impacted Puerto Rico in the recent past, for which there are several studies relating to various aspects of these complex hazards. I discuss how any event in this period may be influenced by climate change based on the existing studies. Finally, I discuss droughts in East Africa, for which several studies give a range of messages, including a small anthropogenic signal, a lack of one, or not enough evidence to confidently determine either way. Section 3 is dedicated to answering the first question.

4.3.1 UK Heatwave 2006

In 2006, anticyclonic conditions dominated over Northern Europe as a ridge of high pressure persisted for several weeks, bringing clear skies and consequently high solar radiation at the surface. This was the hottest month on record over most of the UK (Prior and Beswick 2007; Perkins-Kirkpatrick et al. 2022), and of all heatwaves between 2000-2019 this event had the highest recorded mortality (Green et al. 2016). 2022, with its extraordinary hot and dry summer will have probably exceeded these, though numbers are still outstanding at the time of writing (WWA 2022).

4.3.1.1 Relevant past studies

Other notable summer heatwaves occurred in 2003, 2013, 2018 and 2022 in the UK, each with attribution statements (Stott et al. 2004b; Dong et al. 2014; Christidis et al. 2015c; McCarthy et al. 2019; Leach et al. 2020; WWA 2022), shown in figure 4.1. In each of these cases, as in 2006, anticyclonic conditions and clear skies led to high surface temperatures. Furthermore, as in 2003 and 2013, high surface temperatures were maintained by a southerly and southeasterly airstream. This is somewhat in opposition to 2018, when anomalously high SSTs in the coastal waters surrounding the UK played a large role. In addition, in 2006, 2013 and 2018, a positive phase of the Summer North Atlantic Oscillation (SNAO) resulted in a northward shift of the North Atlantic storm tracks and

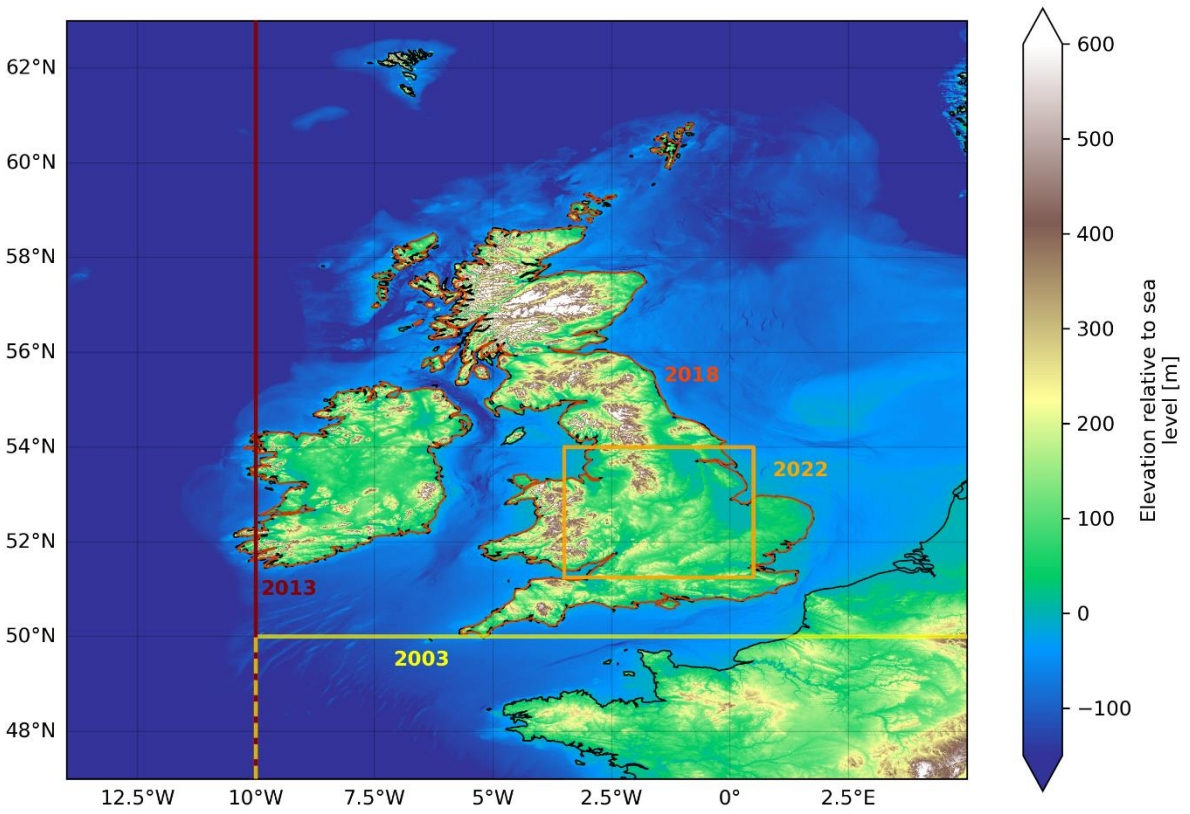


Figure 4.1: Domain of attribution studies for extreme heat in the UK. Some of the domains extend beyond the map and/or do not cover the UK (in the case of 2003), but do attribute the same meteorological event that affected the UK. The 2003 domain covering most of western Europe is

highlighted in yellow, the 2013 domain is in dark red and extends eastward. 2022 is shown in orange, while 2018 is the British Isles land surface, highlighted in red.

therefore drier conditions over the UK. The ground was also especially dry in 2006 due to the prevalence of below-average rainfall for the previous two winters. As a result the capacity of the land surface to cool through evaporation was limited and, coupled with high radiative inputs, formed a positive feedback leading to high surface temperatures (Clarke et al. 2021a).

In all these recent cases the observed temperature anomalies were higher than they would have been in the absence of anthropogenic forcing. In 2003 the temperature anomalies over Europe were utterly unprecedented and shown to have been extremely unlikely (return time of at least thousands of years) in simulations of the world as it might have been without anthropogenic climate change. Similarly unprecedented extreme temperatures (higher though as they were occurring with almost 20 more years of rapid global warming) were reached again in 2022. In simulations of today's climate an event like 2003 is to be expected with a probability of up to 10% in any given summer (Christidis et al. 2015c) while 2022 summer temperatures are on the order of 1%. In 2013 (Dong et al. 2014) and 2018, studies showed that natural variability did play a role in the events but were insufficient to fully explain the observed temperatures (McCarthy et al. 2019).

When deciding if a new attribution study is needed, and thus when comparing attribution studies, it is important to consider whether events are within the same 'class' i.e. belonging to the same category of hazard creating the same meteorological conditions that may result in impacts (Perkins-Kirkpatrick et al. 2022). This consists of two parts. First, as above, I ensure that the events resulted from similar meteorological synoptic conditions and geographical context. Second, I check the event definitions (variable used, temporal and geographical scales) in past studies are useful in the context of the new event.

For instance, while the seminal study for the 2003 event has been updated using modern methods and modelling, and the event itself affected the UK, it has nonetheless been discounted for use here because the study does not include temperatures over the UK (Stott et al. 2004b; Christidis et al. 2015c). Conversely, there are numerous studies for the 2018 event that provide probability ratio (PR) – the ratio between the probabilities of event occurrence in 'factual' and 'counterfactual' (with anthropogenic forcings removed) scenarios - estimates over a range of spatiotemporal scales over the UK. For instance, Leach et al. (Leach et al. 2020) provide three metrics for extreme heat over the UK: the annual maximum of the 90-, 10- and 1-day running mean surface air temperature (henceforth T90x, T10x and T1x, respectively). Further, while the 2013 study does not provide a direct PR to quantify the effect of climate change, it attributes the seasonal warmth event to causal factors including changes in SSTs, Arctic sea ice extent and direct warming (Dong et al. 2014).

As a final qualification, I use the methodology of Otto et al. (Otto et al. 2020c) to rate the quality of evidence provided by the attribution studies utilised here, and find that both Leach et al. (Leach et al. 2020) and Dong et al. (Dong et al. 2014) are of at least 'medium quality'.

4.3.1.2 Deriving useful attribution statements

a. Direction of change

It is clear that recent (2003 onwards) UK summer heatwaves have increased in frequency and magnitude due to climate change. Since most attribution studies apply to classes of events, and there is substantial evidence to suggest that the 2006 event was part of the class attributed by previous studies, as defined by its causal history, including seasonality, synoptic conditions and region, and the event definitions used, it is trivial to conclude that this statement applies to this event.

Other analyses reinforce this conclusion. In 2007, the IPCC stated that it was more likely than not that climate change had increased the risk of heatwaves (IPCC 2007). Trend analysis shows that short heat

extremes in Northern Europe warmed by roughly 0.33 °C per decade, or 2.3 °C in total from 1950-2018 (Lorenz et al. 2019). Therefore, despite this event having occurred at a lower level of anthropogenic forcing than 2 out of the 3 available attribution studies, it was clearly made more likely and intense by climate change. Alone, this is a useful statement for raising awareness of climate impacts.

b. Quantification

To make quantitative estimates, I consider the event definitions used in each of the past studies: on a seasonal scale, 2018 was more extreme than 2006, suggesting that the T90x value for 2006 has a lower PR; in contrast, July 2006 remains the hottest July since records began; it was hotter than July 2018, both overall and in the hottest single days and short multi-day bursts (Cornes et al. 2018; Hollis et al. 2019) and hotter than 2022 despite the extraordinary heat observed in 2022. As such, the values of T10x and T1x in 2006 were more extreme than 2018 by at least 1°C each, suggesting higher PR values.

PR values from 2018 are likely to be overestimates for a given similar-magnitude event from 2006 because anthropogenic forcing has continued to grow significantly in the 12 years between these events (Christidis et al. 2015c; Diffenbaugh 2020). Further, the models used for the 2018 estimates display lower variability than the observations (Leach et al. 2020).

Taking these factors together, I conclude that the maximum probable seasonal value for 2018 forms an upper bound for 2006, which we can be highly confident of, thus giving a final range of possible values of: $1 < PR_{T90x} << 84$. This PR cannot be pinned down with any additional confidence, but gives an order of magnitude estimate, which is sufficient given that the seasonal extreme of 2006 was the least remarkable of the three statistics considered here.

For the 1- and 10- day events, the two key factors for deriving the attribution statement - relative event magnitude and anthropogenic forcing level - act in opposition on our estimate of PRs for 2006 relative to 2018. However, the largest attributable fractions occur for the most extreme events

(Fischer and Knutti 2015b). In all likelihood the greater magnitudes of the 2006 event more than offsets the anthropogenic forcing discrepancy, assuming no drastic shift in the shape of the distribution of extremes (Christidis et al. 2015c), suggesting that the 2006 PRs are larger than for 2018. Thus, for the purposes of making a concrete statement, the lower bounds of the 2018 uncertainty ranges form conservative estimates for the best guess at the 2006 PRs. I therefore confidently conclude that the 2006 PRs obey the following: PR_{T1x} >= 2.9, PR_{T10x} >= 3.2 (Leach et al. 2020).

These estimates form a basis for adaptation and estimating loss and damage when combined with the impacts of this event, in particular that 2689 (2229–3149) people died (Green et al. 2016; Clarke et al. 2021a). None of the studies provide estimates of changing magnitude due to global warming, which makes it challenging to relate the lived experience of elevated temperatures with the attribution statements available; the only possible messages are that 'events like this one will occur at least 3 times more often', and 'this event was hotter than it would have been without climate change', with further reference to the impacts. Further information on exposure and vulnerability drivers of the impacts would supplement all of these applications. In addition, adaptation also requires deeper understanding of future changes in the hazard.

c. Future changes and/or trajectory

None of the attribution studies considered attempt to project future changes in hazard probability due to continued greenhouse gas emissions. Nonetheless, there are two ways to build a clearer picture. First, there is no reason to believe that the trajectory presented by the attribution studies will not continue to hold. Thermodynamic arguments suggest that event magnitudes will increase at an accelerating rate with additional warming, while little evidence exists to show that dynamic changes in event formation are occurring (Mitchell et al. 2016b). It is therefore reasonable to conclude that the derived attributable increases will continue to grow at least at the same rate with warming.

Second, we can use projection analysis to check this claim. The UKCP18 projections show that average daytime summer temperatures will increase by 0.57°C to 0.78°C per decade in major UK cities, under

the RCP8.5 warming scenario (Eunice Lo et al. 2020). Clarke et al. (Clarke et al. 2021a) project that the chance of heatwaves at least as extreme as the 2018 event will increase over both the British Isles and Southeast England, under different warming pathways and time horizons. Since changes in probability are higher for more extreme events, it is likely that T1x and T10x conditions seen in 2006 will grow at a rate at least as fast as those seen in 2018. Over Northern Europe at 1.5°C global warming, CMIP6 projections show an increase of 0.5°C in annual daily maximum temperatures compared to the modern level (of approximately 1°C); at 2°C global warming, the difference is an additional 1.5°C, suggesting an acceleration of hot extremes (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021).

d. Vulnerability and exposure context

During the 2006 heatwave, over 86% of mortality was in people over 65 years of age (Green et al. 2016), indicating a clear vulnerability of older people to heat-related health impacts. This was similar to 2003, in which 88% of deaths were from this age group (Green et al. 2016), and 2018 in which over 65s in urban areas were significantly impacted (Clarke et al. 2021a). Since 2004, Public Health England has released a heatwave plan annually, featuring a tiered warning and communication system, and preparatory measures for national, local and health authorities (Williams et al. 2019). In 2006, daily mortality was slightly lower than in 2003 (Green et al. 2016), possibly as a result of these new measures. A major overhaul of the heatwave plan in 2012 and subsequently severely reduced mortality in the 2013 heatwave (Green et al. 2016) may also indicate the effectiveness of these existing adaptation measures.

Nonetheless, significant mortality in 2018 suggests ongoing vulnerabilities to extreme heat. Moving forwards this will be further compounded by increases in the frequency and magnitude of this hazard, and exposure to it, which continues to rise due to an ageing population, urbanisation and migration to cities (Williams et al. 2019; Eunice Lo et al. 2020; Clarke et al. 2021a).

Across several major European cities including London, higher mean temperatures are associated with a greater-than-linear rise in mortality (Baccini et al. 2008; Gasparrini et al. 2015; de' Donato et al.

2015; Mitchell et al. 2016b; Vicedo-Cabrera et al. 2019). This effect has already been observed and is projected to rise further across England and Wales, with the strongest rate of increase in mortality for more extreme temperatures (Huang et al. 2022).

Perkins-Kirkpatrick et al. (Perkins-Kirkpatrick et al. 2022) show that approximately 17% of mortality on a single July day was attributable to anthropogenic influence (due to the change in magnitude of a 1-in-4 year event). Extrapolating this over the estimate for all heatwave-related mortality for 2006 gives an estimated attributable mortality of 395 deaths. Mitchell et al. (Mitchell et al. 2016b) show very similar results for the 2003 heatwave, with ~20% of mortality in London directly attributable. The mortality rate in 2003 across London was ~4.5 per 100,000 people, which is remarkably similar to the wider event across the entire UK, with mortality of ~3.8 per 100,000 people. This increases our confidence in the above estimate for overall 2006 mortality.

In summary, this case study shows that it is possible to rely on past attribution studies to derive new information; see table 4.2 for a full summary of the derived results.

4.3.2 Tropical Storms in Puerto Rico

As recorded in the disaster database EMDAT (EMDAT 2019) and in Clarke et al. (Clarke et al. 2021a), 10 tropical cyclones substantially impacted Puerto Rico from 2000-2019, all between June and December. Irma and Maria, the two most impactful, occurred within a two-week period in September 2017. Irma tracked around 90 km north of the island, bringing high winds, storm surges leading to inundations of 30-60 cm along coastal regions, and extreme rainfall totalling 25-45 cm in some elevated locations. This led to widespread disruption to electricity and water lines as well as the collapse of some weaker structures. Before the island fully recovered, Maria made landfall as a category 4 storm. The resulting rainfall was the highest from any storm and the most intense single rainfall event, both since 1956, with over 1.5m over 48 hours in some areas. Coupled with extreme

storm surge and winds at the high end of category 4, this led to thousands of deaths, tens of thousands of landslides that blocked roads, the destruction of 70000 homes with a quarter of a million damaged, island-wide loss of power transmission and distribution infrastructure and water supplies that affected all 3.4 million residents, as well as disruption to other key medical services (Kwasinski et al. 2019b; Clarke et al. 2021a). The loss of services, mental health impacts and heavy net migration away from the island were sustained for months to years afterwards. Combined, these two events caused damages of at least US$ 90B, the overwhelming majority of which came from Maria (Pasch et al. 2017). Two of the other storms, Jeanne in 2004 and Irene in 2011, caused US$ 750M in damages and the latter affected over a million people, while very little quantitative impact data is recorded for the other events (Clarke et al. 2021a).

4.3.2.1 Relevant past studies

Of the 10 impactful tropical cyclones to affect Puerto Rico, only Irma and Maria are the subjects of attribution studies. One found that ACC substantially increased the rainfall totals from Hurricanes Katrina, Irma and Maria in an area 1.5^{o} x 1.5^{o} about the centre by 4, 6 and 9%, respectively (Patricola and Wehner 2018b). However, no human influence on hurricane intensity was discerned. Another study analysed rainfall observations and found a significant increase (best estimate factor 4.85) in the probability of Maria-like extreme rainfall over the most affected parts of Puerto Rico, due to long-term climate trends (Keellings and Hernández Ayala 2019).

Events that affect Puerto Rico are also a subset of events that occur in the wider North Atlantic region, such as major Hurricanes Harvey, Florence, Dorian and Sandy, which have all elicited attribution study (Van Oldenborgh et al. 2017; Trenberth et al. 2018; Reed et al. 2020, 2021; Strauss et al. 2021a). For Harvey, a probabilistic study of extreme rainfall from the event concluded that ACC increased the probability of the rainfall totals observed over Texas by a factor of 3 (1.5-5), or that, equivalently, the rainfall totals themselves were increased by approximately 20% (15-38%) (Van Oldenborgh et al. 2017;

Risser and Wehner 2017; Wang et al. 2018a). Other work posits that the observed rainfall simply could not have occurred in the absence of ACC (Trenberth et al. 2018).

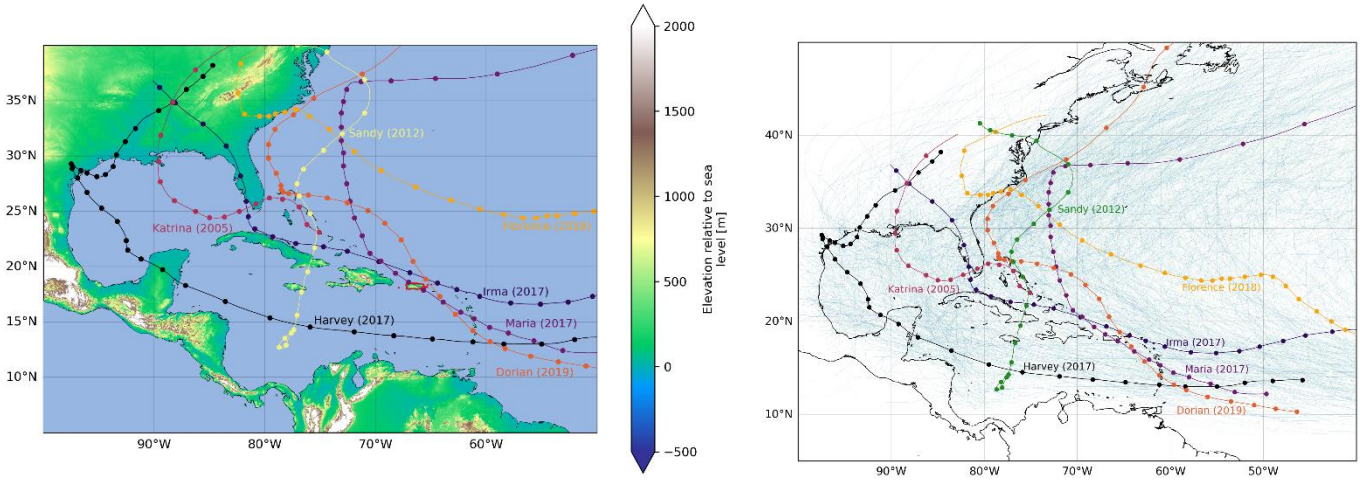


Figure 4.2: Storm tracks for the hurricanes with attribution statements in the North Atlantic basin from IBTrACS (Knapp et al. 2010). *Each hurricane and its year of occurrence are highlighted. Left: Storm tracks plotted over a map of elevation relative to sea level, with Puerto Rico highlighted in red. Right: All recorded historical storm tracks in the basin across a slightly wider domain.*

Total overland rainfall from Hurricanes Florence and Dorian were increased by 4.9% (0.3-9.5%) and 7% (5-10%), respectively, by anthropogenic influence (Reed et al. 2020, 2021). The intensity of Sandy was not influenced significantly by climate change (Lackmann 2015), but the extent of the floods resulting from storm surges was increased due to sea level rise. The ensuing damages totalled an additional $8.1B ($4.7B–$14.0B) and affected 71 (41 - 131) thousand more people due to anthropogenic sea level rise (Strauss et al. 2021a), and such occurrences will increase in frequency with further warming (Sweet et al. 2013).

4.3.2.2 Deriving useful attribution statements

a. Direction of change

In the North Atlantic basin, there are several studies that show clear anthropogenic influence on extreme rainfall totals and storm surge height from tropical cyclones (Van Oldenborgh et al. 2017; Trenberth et al. 2018; Reed et al. 2020, 2021; Strauss et al. 2021a). These appear to be largely due to the influence of increased atmospheric moisture content described by the Clausius-Clapeyron relation, sea level rise, and extreme ocean heat content. To determine how applicable these conclusions are to other events we must first consider the degree to which other events are similar.

Almost every tropical storm to affect Puerto Rico in recent years, including Irma and Maria, has undergone a similar formation process: in 80% of events to affect Puerto Rico from 2000-2019, as in 72% of all NA tropical cyclones between 1995-2015, an African Easterly Wave (AEW) - a low-pressure disturbance associated with the African Easterly Jet - departed the west coast of Africa (Russell et al., 2017), then typically moved westwards under the influence of a sub-tropical ridge, convection became increasingly organised and the low strengthened further, it underwent rapid intensification over a region of warm surface waters and low vertical wind shear, reached maximum intensity around the Caribbean sea and deflected increasingly northwards as the ridge weakened (Clarke et al. 2021a). The remaining ~20% of cyclogenesis in the basin is triggered by other low-pressure disturbances, or 'seedlings', throughout the basin, which go through a very similar subsequent development process. Patricola et al. (Patricola et al. 2018) show that occurrence of tropical cyclones is largely independent of changes in AEW occurrence, suggesting that attribution statements are applicable across events with different seedlings.

Trend analysis adds another line of evidence. In the North Atlantic basin, there has been an observed increase in measures of aggregated cyclone activity, such as the 'Power Dissipation Index' and the 'Accumulated Cyclone Energy' (Emanuel 2005; Holland and Webster 2007; Walsh et al. 2016) but not normalised damages (Weinkle et al. 2018) and mixed results for occurrence frequency (Landsea 2007; Murakami et al. 2020) since 1970. These trends are difficult to attribute to ACC due to the high multi-decadal variability exhibited in the NA basin (Walsh et al. 2016) and changing coastal exposure and

vulnerability, though a fraction of recent historical damages in the US from tropical cyclones have now been attributed to ACC (Estrada et al. 2015).

Even though we can't make a generalisation of anthropogenic influence on Atlantic tropical storm hazards overall, we can do so for specific aspects including extreme rainfall and storm surges - these aspects of all recent north Atlantic hurricanes were amplified by ACC. Based on the evidence above, I conclude that for any North Atlantic hurricane the extreme rainfall totals were made higher and that storm surges reached further inland due to anthropogenic warming. Hurricane Katrina in 2005 is the earliest event for which an attribution statement is available, thus I suggest that the above statement is reasonable for events from roughly 2000 onwards, as it represents a time period of comparable anthropogenic forcing. Though the signal may have emerged earlier, such as for Hurricane Georges in 1998, there is no evidence either way for this. Overall, this retrospective attribution of events is equivalent to attributing additional events as they occur, and has important ramifications for the communication of the influence of climate change.

b. Quantification

The conclusion above can be written as PR > 1 for the rainfall totals of each event that affected Puerto Rico this century. More detailed probabilistic attribution statements were estimated for the rainfall of Harvey and Maria. For Harvey, comprehensive attribution analysis that utilised a range of methodologies, including counterfactual dynamical modelling, showed a probability ratio of 3 (1.5-5) for such extreme precipitation. Further, observation-based analysis for the most extreme precipitation totals within the two storms returned probability ratios of 9.6 (3.5+) for Harvey and 4.85 (~1-~12) for Maria. Maria was the most intense storm to affect Puerto Rico, and thus has the greatest probability ratio within a probabilistic framework. Since it is also one of the most recent, we can assume that all other events in this period likely obey the following relation: 1<PR<~12. Based on the limited number of estimates I cannot improve on this very broad probabilistic estimate for other storms, and I advocate caution when estimates are based off such a limited number of studies. However, attribution

studies for tropical storm rainfall tend to focus more on magnitudes. This may be within the same probabilistic framework as a frequency estimate (Van Oldenborgh et al. 2017), or may be a conditional statement of magnitude change assuming that the dynamical drivers of an event occur (Patricola and Wehner 2018b). In the latter case, while this sacrifices our ability to attribute the overall influence of climate change, it also vastly reduces the noise of dynamical variability and the deep uncertainties on these changing drivers, and thus enables greater confidence (Shepherd 2016).

From those studies, it is clear that rainfall intensities have been increased by roughly a Clausius-Clapeyron scaling factor of ~7% K^{-1}, with a probable range of 4-9%. Hurricane Harvey was an exceptional case with magnitudes of 15-38% greater than the counterfactual event and far beyond Clausius-Clapeyron scaling. Harvey stalled over Houston due to blocking by high pressure, while record ocean heat content in the Gulf of Mexico continued to fuel the storm, potentially providing higher moisture flux through both moisture content and circulation velocities (Van Oldenborgh et al. 2017; Risser and Wehner 2017; Trenberth et al. 2018).

Harvey may be the canary in the coal mine for tropical storms making landfall on the US coast, or even across the North Atlantic region. Preliminary evidence suggests that probability ratios for extreme rainfall across the southeast US coast are very consistent across specific event magnitudes (Risser and Wehner 2017). Meanwhile, while trends in translation speeds for tropical cyclones globally are highly uncertain, limited evidence points to a slowdown across the contiguous US (Kossin 2018; Hall and Kossin 2019). For severely affected small developing islands such as Puerto Rico and the wider Caribbean, while individual events such as Dorian have exhibited stalling behaviour, there is currently no evidence to suggest a similar trend exists (Vosper et al. 2020).

Overall, we can conclude that for tropical cyclones that affect Puerto Rico (and the wider region), it is likely that the most extreme rainfall has become up to an order of magnitude more likely, and, equivalently, is amplified in intensity by at least Clausius-Clapeyron scaling.

c. Future changes and/or trajectory

A number of studies project future magnitude changes from tropical cyclones. A significant uptick in Harvey-like storm intensity and frequency in southeast Texas is projected by mid-century (Wang et al. 2018a), and by 2081-2100 the annual probability of Harvey-like rainfall over Texas is expected to be ~18% under an RCP8.5 scenario, up from 1% in 1981-2000 (Emanuel 2017). Across the Caribbean, the fraction of stalling hurricanes is not projected to significantly increase at 1.5°C or 2°C global warming, but the probability of extreme hurricanes increases significantly across most of the region. In Puerto Rico, for example, the return period of a Maria-like event decreases from 115 years in the present climate to 75 years at 1.5°C and 43 years at 2°C (Vosper et al. 2020). Furthermore, by 2100, under RCP4.5, 6.0 and 8.5, Maria-like rainfall events are projected to become 21.8%, 23.4% and 36.9% more intense than the historical event, respectively. For Katrina and Irma, increases vary from 7.1-16.5% and 17.5-27.8% across the same set of projections (Patricola and Wehner 2018b). There is also evidence to suggest significant increases in wind speed intensity; in 2100, wind speeds from storms like Katrina, Irma and Maria will be 6.0-13.8 knots faster, depending on the RCP scenario (Patricola and Wehner 2018b).

Projected future changes in hurricane frequency from both GCMs and downscaled models also vary (Emanuel 2013; Trenberth et al. 2018), point to a slight decrease in frequency, with a larger fraction of the most intense storms (category 3-5 on the Saffir-Simpson scale) (Sobel et al. 2016; Seneviratne et al. 2021). The latter forecast is of the utmost importance, given that the overwhelming majority of damages are due to these super-storms (Weinkle et al. 2018; Clarke et al. 2021a).

To conclude, it is very likely that rainfall from present and future tropical cyclones will be amplified by at minimum the Clausius-Clapeyron scaling factor, and thus at the upper end or greater than the derived range from 2000-2019. Across different RCP scenarios, the variation in future rainfall intensity increases by approximately 10-15%. Furthermore, storm surge heights are increasing nonlinearly with warming as sea levels rise, and an anthropogenic influence on wind speeds emerges. Compound

flooding hazards will thus be influenced by multiple nonlinear factors (Masson-Delmotte, V., P. Zhai, A. Pirani et al. 2021).

Without further attribution study of specific, more localised hazards, this provides a foundation for adaptation planning. However, hazards translate into impacts only where people and property are exposed and vulnerable, which has been highlighted by a number of recent events.

d. Vulnerability and exposure context

Maria was the costliest hurricane ever recorded on Puerto Rico by at least an order of magnitude, the second being Georges in 1998 (Pasch et al. 2017). The event therefore most clearly highlights existing, ongoing vulnerability and exposure on the island. Increasingly, Maria is becoming understood as an 'unnatural disaster', being "directly shaped by existing socioeconomic and racial inequalities" (Garciá-López 2018), linked to extractivism, economic recession and austerity, and forced migration, and having the greatest impacts on those in poverty, in isolated communities and infirm and disabled (Lloréns 2018).

A combination of sustained high winds and extreme rainfall, which triggered mudslides and flooding, led to disruption of power and water services to all 3.4 million residents of the island (Keellings and Hernández Ayala 2019). Unprecedented river flooding affected the northern side of the island, especially from the La Plata river, while the southeast, east and northwest suffered severe damage due to wave action and storm surge, affecting marinas, harbours, and coastal buildings, homes and roads (Pasch et al. 2017). The loss of critical infrastructure on an island-wide scale led to cascading impacts on health, through shortages of basic supplies, exposure to vector-borne diseases, high heat and humidity, loss of jobs and school closures (Ferré et al. 2019), as well as disruption to services including care and medication (Niles and Contreras 2019).

Poverty was (and remains) rife in Puerto Rico, with approximately 45% of the population below the federal poverty level, compared with an average of 15% across the US, and this had a significant bearing on the magnitude and distribution of the impacts of the event (Niles and Contreras 2019). Severe damage to homes disproportionately affected renters, low-income households, and especially low-income renters, with the implication that minimum structural standards were insufficient to withstand such an event (Ma and Smith 2020). Further, health issues - both physical and mental - in the wake of the disaster occurred disproportionately more amongst the economically disadvantaged, as well as older and younger people, those living in more isolated areas, and those with chronic health conditions and disabilities (Morris et al. 2018; Ferré et al. 2019; Niles and Contreras 2019; Scaramutti et al. 2019; Orengo-Aguayo et al. 2019). This was compounded by historical underfunding of health services and welfare on the island, though outreach work by healthcare workers operating at a community scale helped to meet people's urgent needs (Morris et al. 2018; Niles and Contreras 2019).

The impacts of and responses to Maria in Puerto Rico have been juxtaposed with those in Cuba after the landfall of Hurricane Irma, an event of comparable meteorological magnitude in these locations, respectively (Clarke et al. 2022). The most striking difference was in the long-term impacts, which were far lower in Cuba due to evidence-based risk planning that engaged with the public, and a swift and effective response that minimised disruption (Zakrison et al. 2020). In contrast, in Puerto Rico, planning for climate vulnerabilities did not account for landfall by a category 4 hurricane, while the federal aid response to Maria was widely viewed as insufficient (Walsh-Russo 2018).

Last, it is informative to consider adaptation put in place since the event transpired. At a community level, housing groups are building more resilient and extreme weather-resistant infrastructure such as storm-safe roofs, though this is expensive and capacity is still limited compared to the scale of the adaptive transformations required (Walsh-Russo 2018). In terms of planning for future disasters, planners such as the Puerto Rican Climate Change Council are shifting from a 'top-down' approach used prior to Maria towards a more 'bottom-up' approach. In other words, local communities will

drive the adaptation strategies of local government, while communication channels between national/regional and local government are also being improved (Walsh-Russo 2018).

As for heatwaves in the UK, this case study shows that it is possible to rely on past attribution studies to derive new information; see table 4.2 for a full summary of the derived results.

4.3.3. Case Study: Drought in East Africa

In 2022 Kenya, Uganda, South Sudan, Somalia, Ethiopia and Djibouti (figure 4.3 for reference) all experienced severe droughts, with a fourth rainy season in a row failing. 2022 is not an uncommon year, as droughts in East Africa are frequent and devastating, often resulting in severe humanitarian consequences. In recent decades, major disasters linked to drought occurred in 1974-75, in Ethiopia and Sudan in 1984-85, and more recently in the Horn of Africa in 2010-11, 2014 and 2016, Ethiopia in 2015, Kenya in 2016, and the ongoing region-wide drought in 2022, to name a few (EMDAT 2019; Gebremeskel et al. 2019; Toreti 2022).

While some scholars suggest that drought is broadly becoming more frequent in East Africa (Lyon and Dewitt 2012; Nicholson 2017b; Gebremeskel et al. 2019; Funk et al. 2019; Haile et al. 2020), overall trends in drought indicators are both very local and seasonal if they exist at all (Seneviratne et al. 2021). The relationship to potential climate change influences is therefore unclear, while the ongoing severe impacts are undoubtedly related to the high vulnerability in the region (Uhe et al. 2018; Haile et al. 2020). To begin to untangle this simultaneously important and complex picture, several of the most impactful events in the most recent decade have been studied for their link with climate change. Of the 10 attribution studies that broadly cover drought events in the region, the results are highly diverse and largely inconclusive (table 4.1).

4.3.3.1 Relevant past studies

Some studies found evidence of anthropogenic influence in aspects of the assessed droughts. For instance, anthropogenically-amplified temperatures in East Africa itself and across the Western Pacific were found to have contributed to rainfall and soil moisture deficits in an area comprising much of Ethiopia, Kenya and Somalia, based on both observations and CMIP5 models (Funk et al. 2015b). Further, while ensemble modelling shows no attributable change in rainfall deficits during the 2014 long rains (March-May), anthropogenic climate change did increase temperatures and net incoming radiation. Both were not excluded to have played a role in the observed drought over a

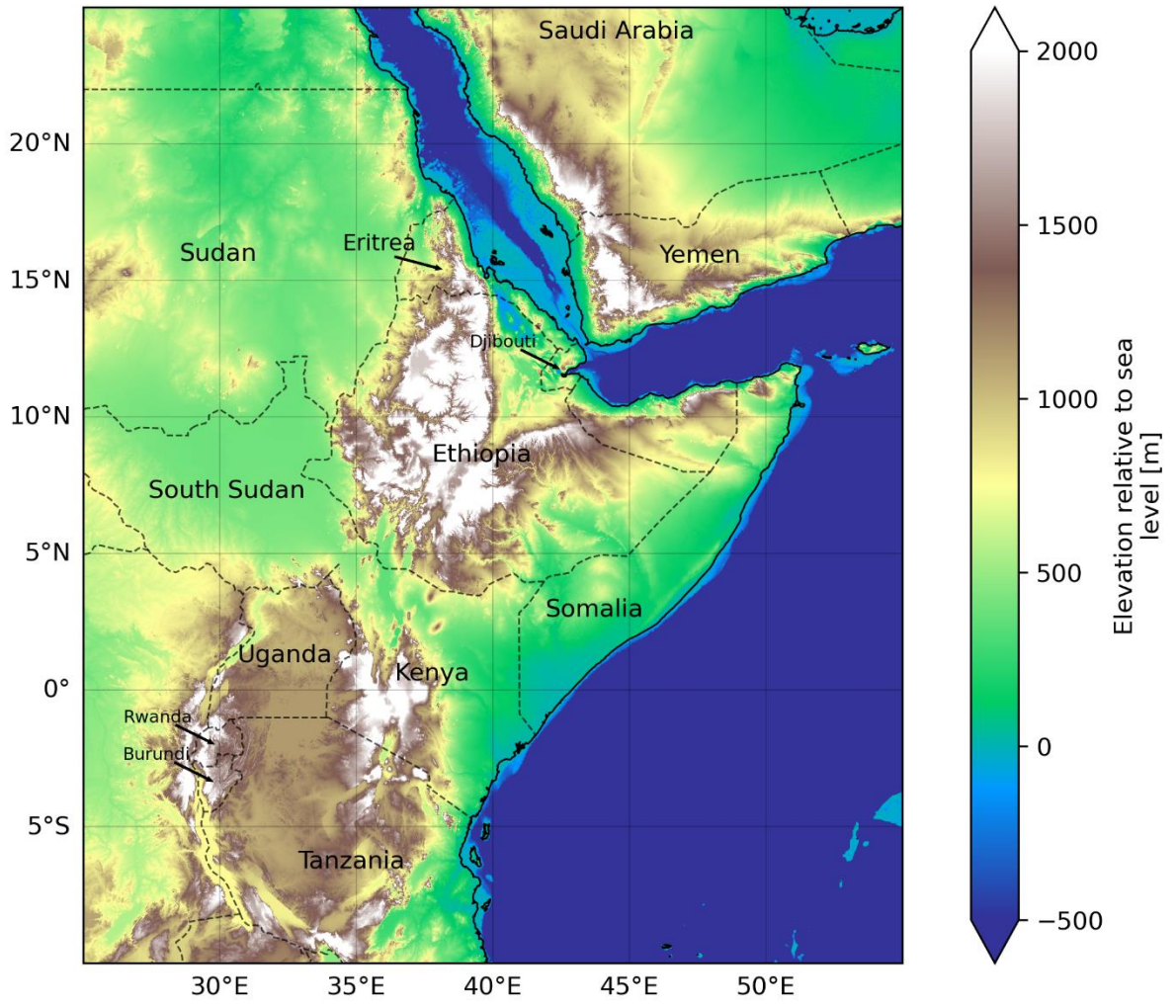


Figure 4.3: Elevation map of East Africa with the nations wholly or mostly contained within the domain labelled, for reference with table 4.1.

Study	Event definition			Attribution results
	Spatial domain	Temporal domain	Variable(s)	
Funk et al., 2015	Greater Horn of Africa	April-June 2014	Soil moisture	Increase due to ACC and pacific SSTs
Marthews et al., 2015	Area between Ethiopia, Kenya and Somalia	March-June 2014	Precipitation, temperature, net incoming radiation	No signal in rainfall deficits, possible increase due to temperatures and net incoming radiation.
Funk et al., 2019	Area including much of Ethiopia, Kenya and Somalia	March-June 2017	Precipitation	SSTs warmed human influence doubled likelihood of rainfall deficits
Philip et al., 2018b	Northern and Central Ethiopia	February-May and June-September 2015	Precipitation	No role for ACC
Funk et al., 2016	Northern Ethiopia	June-September 2015	Precipitation	Warming of SSTs enhanced deficit
Funk, 2012	Area between Ethiopia, Kenya and Somalia	March-May and June-September 2011	Precipitation	Warming of SSTs enhanced deficit
Lott et al., 2013	Kenya and Somalia	March-June 2011	Precipitation	Warming made dry long rains more likely
Otto et al., 2018a	Somalia	July 2010 – June 2011	Precipitation	No role for ACC
Peterson et al., 2013	Kenya and Somalia	March-May 2012	Precipitation	Not explained by ENSO SSTs, no direct assessment of ACC
Uhe et al., 2018	NW Kenya	October-December 2016	Precipitation, temperature	No role for ACC
WWA, 2016	Somnalia and Somaliland	October-November 2016	Precipitation	No role for ACC

Table 4.1: Summary of attribution studies on recent droughts in East Africa. Key elements of the event definition(s) used are detailed, including the spatiotemporal domains and key variables studied, as well as the attribution results.

border region between Ethiopia, Kenya and Somalia (Marthews et al. 2015). In 2017, the failure of the long rains from March-June was forecast well in advance, and according to a single-model study the probability of such a drought was doubled due to anthropogenic warming of Western Pacific SSTs (Funk et al. 2019).

Assessments of the role of climate change for the drought in Ethiopia in 2015, in which tens of millions of people required urgent humanitarian assistance due to severe food insecurity, are inconclusive. The strong El Nino increased the severity of the drought, but anthropogenic forcing was found to have played no role in the precipitation deficit observed across the "belg" (February-May) and "kiremt" (June-September, JJAS) rains in northern and central Ethiopia (Philip et al. 2018b). A separate study focusing on rainfall reductions in northern Ethiopia, for the JJAS period only, found that anthropogenic warming of El Nino SSTs and local air temperatures did enhance this deficit and the ensuing runoff, thus amplifying food insecurity (Funk et al. 2016). Mixed results also arise from studies of the 2011 drought across the region. While Lott et al. (Lott et al. 2013) show that human influence made the dry long rains more probable across Kenya and Somalia in the Hadley Centre model, Funk (Funk 2012) did not find an attributable influence for dry regions covering parts of several nations in south-central East Africa.

Other droughts in the region have not been found to be influenced substantially by climate change. The includes the very dry July 2010 – June 2011 in Somalia, which resulted in a record death toll due to famine (Otto et al. 2018a), as well as the dry short rains (October-December) in 2016 in southeast and northwest Kenya, in which over 3 million people required food aid. In the latter case, a strong La Nina did have a significant influence on the low rainfall, while the influence of higher temperatures on soil moisture through evaporation was not significant, though other effects of temperature such as on water demand were not accounted for (Uhe et al. 2018).

Finally, some studies were unable to produce conclusive results either way. Across Kenya and Somalia in 2012, below average March-May rainfall hampered recovery from the severe droughts of 2011 and

before, compounding the impacts further. This rainfall deficit could not be explained by the observed ENSO SST variations alone, thus suggesting but not directly attributing an anthropogenic influence (Peterson et al. 2013). And in Somalia and Somaliland (a climatologically-distinct region of northwestern Somalia) in 2016, failures of the autumn rains, which resulted in a rapid onset of food insecurity, were linked partially to the La Nina conditions but not to anthropogenic influence (WWA 2016).

4.3.3.2 Deriving useful statements

a. Direction of change

Clearly, there is no overarching pattern of change in East African drought that is currently attributable to climate change (Seneviratne et al. 2021). By looking at individual climate-related drivers, we can state that there is limited evidence that anthropogenically-amplified sea surface temperatures in the Western Pacific could lead to a causal reduction in East African rainfall, and amplified temperatures in the region itself result in increased evaporation (Dai 2011; Marthews et al. 2015; Funk et al. 2016, 2019). However, the former is a highly conditional attribution and thus not easily generalisable, and the latter is a minor effect given the aridity of the region (Kew et al. 2021). The effect of increased water demand due to temperature rises may also contribute to impacts but remains poorly understood (Gebrechorkos et al. 2018).

Additionally, there is high natural variability at the scales of individual nations and even subnational regions (Gebrechorkos et al. 2020). Further, any detected and attributed signals are minor in comparison with this natural variability, suggesting that anthropogenic forcing is likely not a major driver of recent droughts and their impacts. Thus, at current warming levels, it is possible to say without undertaking an attribution study that while anthropogenic influences cannot be excluded to

play a role in exaggerating the impacts, they are small compared to natural variability. The severe impacts of these droughts are largely driven by the high vulnerability and exposure in the region.

b. Quantification

The high natural variability in the region, comparable lack of observational data and adequate climate models make the derivation of concrete attribution statements, quantitatively and qualitatively, impossible (Otto et al. 2020b). Bespoke studies are required in each case, incorporating an understanding of the underlying dynamical mechanisms and their representations (Otto et al. 2018a). Uhe et al. (Uhe et al. 2018) state as much from their study of the 2016 Kenya drought: "this indicates attribution results for a particular drought cannot be easily generalised to other droughts and highlights the importance of a case-based approach to an attribution analysis of individual events."

However, this exercise remains useful. The intractable nature of attribution for drought in the region highlights other drivers of impacts. In addition, weak signals in the present may yet become more significant depending on future emissions pathways, so are important to identify.

c. Future changes and/or trajectory

The IPCC AR6 WG1 report states that there is low confidence in the attribution of changes for all types of drought (Seneviratne et al. 2021). Studies looking at future changes of drought corroborate these findings. At 1.5 ^{o}C and 2 ^{o}C of global warming, the probability ratios for low rainfall in Somalia like that observed in 2010/11 show no clear signal. However, this is split by season, with a drying Jan-June and a wetting July-December, suggesting that various dynamical mechanisms may be at play (Otto et al. 2018a). Similarly, rainfall anomalies for February-September in north and central Ethiopia are not projected to become significantly more probable by 2050 under an RCP8.5 scenario (Philip et al. 2018b).

For the Greater Horn of Africa, projections show that by 2100 the area experiencing drought conditions may increase by 16%, 36%, and 54% under RCP 2.6, 4.5, and 8.5, respectively, alongside

increases in drought intensity (Haile et al. 2020). Many of the countries showing an increase are those outside of the area considered in the studies above, such as Djibouti, South Sudan, Sudan and parts of Tanzania. However, increases in drought conditions are also anticipated in Somalia, large parts of Ethiopia and eastern and northwestern Kenya. These changes are especially pronounced for drought conditions characterised by the Standardised Precipitation-Evapotranspiration Index (SPEI), which unlike the Standardised Precipitation Index (SPI) considers the effect of rising temperatures upon evaporation. On the other hand, decreases are expected for wetter regions such as Rwanda, Uganda, the Ethiopian highlands and southwestern Kenya (Haile et al. 2020). In many parts of the Horn of Africa, increasing drought is only observed in projections when the effect of temperatures is included; otherwise drought mostly decreases (Spinoni et al. 2020).

Global climate models show sub-regional variations in trends of meteorological drought in broad agreement with attribution studies, which show results that are highly conditional on the event definition, the region and the time of year. The pattern of change broadly follows the "wet gets wetter, dry gets drier" paradigm (Haile et al. 2020; Ayugi et al. 2022), and there is limited evidence of major changes in drought hazards around mid-century (Haile et al. 2020; Seneviratne et al. 2021). Understanding location- and event-specific changes continues to require tailored attribution studies (Uhe et al. 2018).

d. Vulnerability and exposure context

East Africa has a rapidly increasing population and is extremely vulnerable to frequent drought. High natural variability of seasonal rainfall can make drought unpredictable and result in compounding events when multiple rainy seasons fail, such as in Kenya and Somalia in 2012 and ongoing in 2022 in several countries. Vulnerability arises due to existing extreme poverty, high endemic rates of malnutrition, poor governance and an array of other factors across the region (Peterson et al. 2013). For instance, in Kenya, the majority of livestock and a significant minority of the population live in arid or semi-arid areas (Uhe et al. 2018). Across Somalia, decades of conflict and unstable regimes have

resulted in very low resilience of households to shortages and global food price rises, as well as restrictions to the flow of aid, compounded by underlying structural issues (Maxwell and Fitzpatrick 2012; WWA 2016). In Ethiopia, high population growth and density makes the area increasingly vulnerable to hydrological drought as the potential for water storage is limited and increasing extraction stretches resources (Philip et al. 2018b). Currently, ongoing conflict around the Tigray region is responsible for a growing humanitarian crisis, compounded by repeated failures of the rainy season in the Somali region of Ethiopia and global food and fuel price rises triggered by the conflict in Ukraine (UN News 2022).

Early warnings can help to alleviate the impacts of drought. For instance, in 2017, an effective humanitarian response was put in place early due to a successful forecast of drought conditions (Harrison 2019; Funk et al. 2019). However, in 2011 in Somalia, despite their timeliness and quality, early warnings were not sufficient to mitigate the widespread famine. In part, this was because the response was hampered by conflict and restrictions placed upon aid by the 'Al-Shabaab' militant group, and partly because the warning system did not capture the magnitude of the potential crisis due to factors beyond the failed rains, among other reasons (Hillbruner and Moloney 2012).

To conclude, attribution shows that the anthropogenic signal on drought is mostly much smaller than natural variability; the severe impacts of drought are driven largely by high exposure and vulnerability to this variability. In informing the public about ongoing events, accurate messaging would encapsulate this complexity by highlighting the many factors contributing to disasters in the region and the negligible role of climate change today, while (limited) evidence points to a growing role of climate change from mid-century in the already-drier subregions.

Furthermore, while any anthropogenically-driven change in drought hazards would certainly result in a large absolute increase in impacts, any measures taken to reduce the impacts should first focus on reducing vulnerability and exposure. This should be the main takeaway for the purpose of adapting to climate extremes in the region. Finally, we cannot derive any statement about loss and damage due

to climate change with any confidence. Moving forwards, attribution studies in this region should aim to understand the key changing drivers of drought, use several event definitions, and project future changes in the anthropogenic forcing component to identify when climate change may begin to play a major role.

4.3.4 Summary of results

Region/Hazard Case Study		**Derived changes**		**Future changes (across RCPs, by 2100)**	**Vulnerability and exposure context**	**More studies needed for identified use cases?**
		Probability Ratio	Magnitude (ΔM)			
UK Heatwave (2006 example)	1-day	≥ 2.9	N/A	ΔM > GWL*	Heatwave plan in place, iterated in 2012. Elderly most affected.	No
	10-day	≥ 3.2	N/A	ΔM > GWL*		
	90-day	1 < PR << 84	N/A	ΔM > GWL*		
Tropical Storms in Puerto Rico	Rainfall	1 ≤ PR ≤ 12	7% ≤ ΔM < 38%	ΔM ≥ 10-15%	High poverty rates. Resilience planned for storms < category 4 only. Historical underfunding of health services.	No
	Intensity	≈ 1	≈ 0	6.0 ≤ ΔM ≤ 13.8 kt (knots)		
	Storm surge	> 1	>> SLR**	ΔM >> SLR**		
Drought in East Africa		Variable	Variable	Average affected area +16-54% (Greater Horn of Africa)	Very high poverty rates. Rapidly increasing population. Widespread political instability. Low resilience to food price shocks and high reliance on agriculture.	Yes (based on user needs)

*Table 4.2: A summary of the derived attribution results for the three case studies. The relevant contextual information is highly summarised here and readers are directed to the individual case studies for further detail and accompanying references. *GWL = Global Warming Level, **SLR = Sea Level Rise.*

4.4. Discussion and conclusions

4.4.1 Further Considerations

Throughout the above case studies, the limitations of applying evidence across events largely arise due to the similarities of the event characteristics and the strength of the evidence itself. However, there are two cases in which even a robust pre-existing body of attribution evidence may require additional caution when deriving new statements or, equivalently, cases in which a new study would add great value. First, as the anthropogenic forcing increases, attribution statements will become outdated. This is partly addressed through the analysis in section 2.1.2, in which the relative anthropogenic forcing at the time of occurrence is a key factor. However, as a broader comment on the body of available evidence, it would be useful for the community to provide an updated study in the region at global warming level milestones such as 1.5 ^{o}C and 2 ^{o}C; while scientifically arbitrary, these provide a useful trajectory of change in risk.

Second, in the event of completely unprecedented events, past estimates may be considered too different for comparison. Nonetheless, they provide a lower bound estimate where the physical characteristics of the two events are comparable. Additionally, in many cases past events provide examples of 'near-misses' of far worse events (Woo 2019; Clarke et al. 2021a); for instance, if some of the physical processes are similar but some non-linear interaction of compounding phenomena resulted in the unprecedented impacts, and/or a key threshold is passed relating to operating capacity of some system, then a partial attribution may still be plausible. This could also be allayed by an effort of the community towards multivariate and impact-focused attribution of compound events (Zscheischler and Lehner 2022).

4.4.2 Conclusions

Using the case studies above and consideration of the wider literature, I derive general answers to the first question posed: Under what conditions is it possible to draw useful information about a given

event from past attribution studies? The answers take the form of three categories within the region-hazard matrix in which broadly similar conditions apply: (i) I am confident of using past studies for most purposes; (ii) a new study may be required depending on the question(s) being asked; (iii) more studies are urgently needed. I refrain from proposing strict thresholds of evidence to define each category. In particular, any answer to this question inherently contains an element of expert judgement, and therefore a bias towards the expert's own knowledge and interpretations. Similarly, the evidence required by two different end users could be completely different even for the same purpose. Here, to explain this categorisation of events, I simply set out the conditions that create greater confidence in the derived statements and the evidence it is based on; namely, the event attribution literature and the regional attribution of similar hazards undertaken by the IPCC. Despite these efforts, subjectivity inevitably underlies our own conclusions, and is a cautionary note for applying this method to new events.

In the first category, which includes heatwaves in the UK and tropical storms in the North Atlantic basin, we can confidently estimate quantitative statements about the change in likelihood and magnitude for a new event. There is greater confidence in this process when there are several studies for similar hazards in a region, when studies use multiple models and event definitions, when they come to similar conclusions, and the studied events share similar synoptic characteristics. Nonetheless, even a single study is useful, especially where multiple event definitions are employed, because (probabilistic) event attribution studies distributions of events, and because analysis of other trends or patterns in extremes can also be used to assess any derived result. Conducting this process for a new event can be used to inform the public about the probable influence of climate change without a new study.

Furthermore, derived attribution results can be extended for other uses, such as informing adaptation and adding a further line of evidence towards inferring climate-related loss and damage. First, future risks can be inferred when attribution studies provide estimates of changing likelihoods across

multiple emissions pathways, and/or by combining present day attribution studies with physical reasoning and projections, such as changes in extremes statistics. Second, contextualising any derived results using knowledge of the impacts of past events, and changes in vulnerability and exposure in the affected region, highlights the key drivers of impacts and thus opportunities for effective responsive action. Finally, climate-related loss and damage can be inferred through understanding the relationship between the particular magnitude of the event and the impacts.

The hazards for which this is most likely applicable are extreme heat and cold worldwide; extreme precipitation in northern Europe and central North America; tropical storm rainfall and storm surges in the North Atlantic; agricultural and other largely temperature-driven drought in western North America and Europe; and fire weather in Australia and western North America. Within the overall matrix of hazards by region, those listed above correspond to the level of evidence and consistency in signal of the case studies set out here. Both this and the statements below are based on evidence synthesised within AR6 of the IPCC and a recent topical review (Clarke et al. 2022).

The second category contains cases in which new attribution studies may be required depending heavily on the question being asked, such as for all forms of drought in East Africa. This is the case when there are a range of studies, but it is not possible to derive an attribution statement for a new event because of mixed or inconclusive statements from these existing studies, or there are a limited number of studies. This may be due to a range of factors including: data limitations, high complexity of the hazard (e.g. drought), heavy dependence on event definition, non-climatic factors driving impacts, and high natural intra-regional and temporal variability. In this case, a bespoke study is required for the purpose of informing people of any quantitative influence of climate change in a specific location. That is also the only way to infer whether and how much loss and damage may be considered climate-related.

However, it is still often possible to derive useful information for adaptation purposes. This is an emergent property of having produced several attribution studies for a hazard in one region, because

they inherently raise the question: 'what is driving the risk?', and shed light on the relative significance of climate change as a driver. For instance, results are largely inconclusive for the climate change influence in East Africa and even those studies showing a positive influence are very minor; any event in the immediate future is very likely to be similar. Knowing a likely order of magnitude change, combined with knowledge of the actual impacts and how non-climate drivers are changing, it becomes clearer where interventions will be most effective. Further, even if attribution studies show little signal in the present day, they can also look forwards in time to assess when climate change may play a major role in such events (Philip et al. 2019), or at the very least may suggest insightful ways of investigating this.

This set of conditions, in which the need for an attribution study is most heavily dependent on the question being asked, is most likely to include extreme precipitation in much of the world including most of Asia, Europe and North America, southern Africa, eastern Australia and New Zealand; as well as for tropical storm rainfall in the western Pacific; storm surges in South East Asia; all forms of drought in East Africa, China, South America, South Africa and central North America; and fire weather in southern China (Clarke et al. 2022).

The third and final category includes hazard-region combinations in which more attribution studies that follow modern best practices are urgently needed (van Oldenborgh et al. 2021) to answer any queries about anthropogenic influence. As pointed out in the introduction, identifying this category is an equivalent answer to the question posed in this chapter, and in general consists of those areas in which there are either no attribution studies, or the few that exist are largely inconclusive and the correspond regional trends in extremes are weak. This includes extreme precipitation in most of Africa and South and Central America; tropical storms for most basins in the Indian and Pacific oceans; storm surges, drought and wildfires worldwide, especially South America, Asia and Africa (Clarke et al. 2022).

Using the methodology explored in this chapter, it is possible to utilise the information we have more effectively to devote more time and resources to understudied regions (i.e. those in category 3), rather

than producing studies that are unlikely to add much further information because the answer is already fairly well understood. Further, attribution coverage could also be improved by standardising the recording of extreme events and their impacts, to ensure that attention is focused on the greatest sources of impacts around the world.

Further work on this approach would develop quantitative statements alongside derived statements to further validate the methodology. In particular, groups undertaking regular studies could implement an 'expert elicited estimate' protocol in which attribution statements are simultaneously derived and quantitatively analysed. This would help to refine the process (and the region-hazard matrix developed here) and explore unforeseen caveats. Ultimately, it may facilitate a system in which established groups can answer urgent stakeholder questions with comparatively little work, and release statements such as: "using expert elicitation bringing together multiple lines of evidence, the [event in question] has been increased/decreased in likelihood by at least X due to anthropogenic climate change".

Chapter 5 - The role of anthropogenic climate change in extreme heat and rainfall in Pakistan in 2022 and beyond: a forensic attribution risk analysis

5.1. Introduction

5.1.1 Extreme events of 2022

In 2022, Pakistan experienced multiple severe extremes. In spring, a persistent dry heatwave led to widespread loss of crops and in late summer extreme monsoon rainfall led to devastating flooding. In August, the southern provinces Sindh and Balochistan received 826% and 690% of the usual rainfall for the month, respectively. The most intense 5-day period of rainfall across the two regions (figure 5.1b) represented a roughly 1-in-100 year event (Otto et al. 2023) in today's climate. Meanwhile, the entire nation of Pakistan received 343% of its usual August rainfall (PMD 2022). The subsequent flooding was especially impactful. 33 million people were directly affected by the inundation, with over 8 million displaced and forced to seek shelter in temporary accommodation (Ministry of Planning et al. 2022). Direct damages totalled over US$ 14.9 billion, economic damages exceeded US$ 15.2 billion, and over 1700 people died (Ministry of Planning et al. 2022). Over 750000 livestock were killed and around US$ 2.3 billion in crops were lost, affecting millions of livelihoods (NDMA 2022). The impacts were further compounded by the aftermath of Covid-19 and the disruption to global food and fuel prices by the war in Ukraine and loss of crops due to extreme heat earlier in the year. Water- and vector-borne diseases created an extended health crisis (Bhamani 2022). Between 8.4 and 9.1 million people were projected to be pushed below the poverty line as a result of multiple compounding impacts (Ministry of Planning et al. 2022).

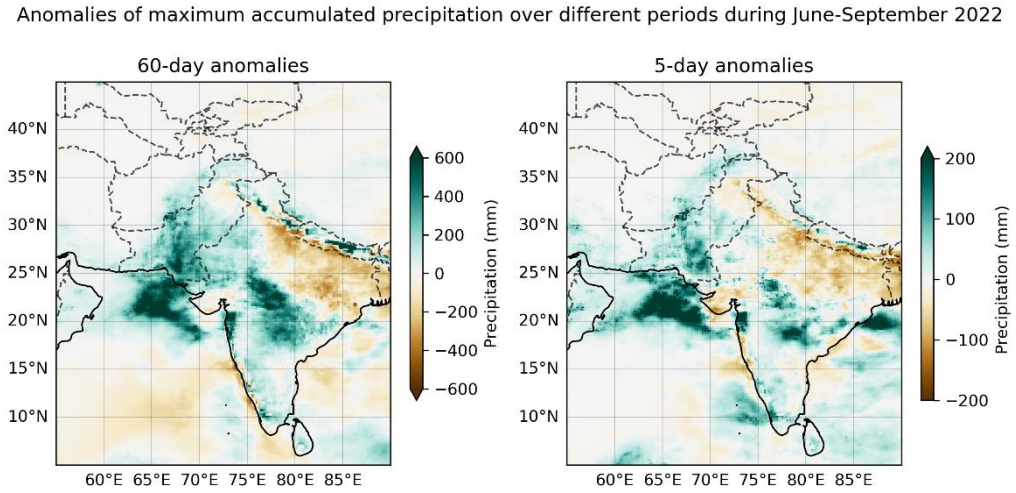


Figure 5.1: Anomalies of accumulated precipitation during the June-September monsoon season in 2022 from the MSWEP dataset. Anomalies are calculated for the wettest 60-day (left) and 5-day (right) period versus the mean of the same statistic over the 1980-2010 period for each grid point.

Extreme weather risk consists of the confluence of the probability of some meteorological hazard, the exposure of a society or system to this hazard, and the vulnerability of those exposed. Pakistan is prone to several meteorological hazards. For example, the nation frequently experiences extreme heat and drought conditions, such as observed in late spring and early summer of 2022. It is also located on the far western edge of the South Asian summer monsoon, making it prone to infrequent and highly variable yet sometimes extreme rainfall, as occurred in summer 2022. Climate change most likely played a role in amplifying both the spring-early summer dry heatwave and summer extreme rainfall (Zachariah et al. 2022a; Otto et al. 2023). Pakistan also has a large and rapidly growing population, leading to significant levels of exposure that continue to increase. Finally, many communities in Pakistan are extremely vulnerable to these hazards, with high endemic poverty rates and limited resources devoted to hazard management (Ajani and van der Geest 2021). As such, Pakistan faces a high baseline risk from climate-related extremes with several of the key components of risk on increasing trajectories. These risks may be further amplified by negative feedback cycles such as between rates of poverty, health and communities' disaster resilience (Fahad and Wang 2020).

Crucially, the drivers of extreme weather risks and possibilities to alleviate them are also chronically understudied in Pakistan, as in much of the Global South. This is due to both a lack of historical observational data of extreme weather events and their impacts (Clarke et al. 2022), as well as a broader global inequality and (even starker) inequity in the focus of research, including catastrophe risk modelling and extreme event attribution (Otto et al. 2020b).

As a devastating manifestation of the climate-related risks faced by Pakistan, the flooding in 2022 provides both a warning and an opportunity to address this deficit and explicitly assess changing drivers of risk. A similarly destructive flood occurred in 2010, which presented a similar opportunity that was not fully taken; though disaster management policies were enacted in the wake of the floods, implementation has been hampered by a range of factors (Ahmed 2013). Consequently, this now underscores the need for both understanding and action.

5.1.2 Background

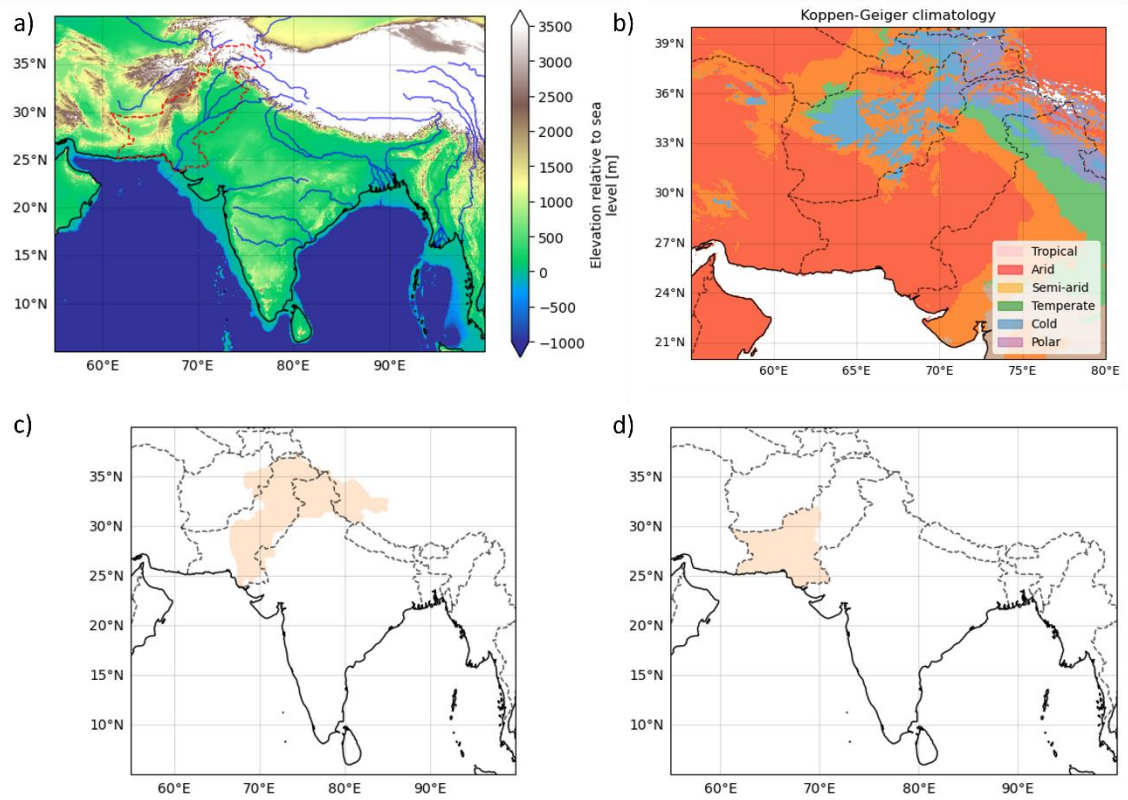
Preliminary evidence on changing risks of such events already exists from a range of sources. In the wake of the flooding, anecdotal testimony and expert speculation suggested that glacial melting driven by the anthropogenically-amplified heatwave (Zachariah et al. 2022a) earlier in the year may have contributed to high river levels. The role of glaciers as a contributor to flood hazards, through both glacial lake outbursts and seasonal melting, is important to consider in a warming world (Shah et al. 2020). However, Nanditha et al. (Nanditha et al. 2023) showed that the flooding was almost entirely driven by pulses of extreme rainfall on top of wet antecedent soils. This further suggests that considering the event as a combination of both short extreme bursts and a longer seasonal extreme is important.

According to working group 1 of the sixth assessment report of the IPCC, extreme rainfall events in the wider South Asian region have increased significantly, with a 'low confidence' attribution of this signal to anthropogenic climate change, which is the same pattern across much of Asia (Seneviratne et al., 2021). For a specific event, the influence of climate change manifests through both

thermodynamic and dynamical effects. Thermodynamically, the Clausius-Clapeyron relation suggests a systematic increase in the atmospheric water vapour content of 6-7% per K of warming; with approximately 0.7 ^{o}C of warming in the region since 1900 (Krishnan et al. 2021), rainfall extremes that do occur are likely more intense as a result. However, complex monsoon dynamics dominated this event. First, the monsoon was likely amplified by the early summer heatwave, creating a strong 'thermal low' drawing moisture onto land regions (Saeed et al. 2011; Bollasina and Nigam 2011; Waqar Bhatti 2022) and resulting in convergence of moisture flux due to the interaction of warm southerlies with extratropical northerlies over Pakistan (Hong et al., 2023) However, the direct influence of this effect on rainfall and the anthropogenic influence upon it have not been quantified. Furthermore, in both this event and in 2010, the co-occurrence of La Nina conditions and a weak high-altitude jet stream led to extreme South Asian monsoonal extent, reaching deep into Pakistan, and other simultaneous extremes across the Northern Hemisphere (Di Capua et al. 2021). Evidence suggests that such co-occurrences are becoming more likely with climate change (Rogers et al. 2022). In summary, a range of factors qualitatively suggest an anthropogenically-fuelled increase in extreme rainfall intensity.

To begin to test this connection more rigorously, the international consortium World Weather Attribution used an extreme event attribution framework in the wake of the event (Otto et al. 2023). Within this framework, an extreme event is defined through one or more spatiotemporal footprint(s) each with a corresponding intensity in some meteorological variable(s), ideally chosen to closely reflect the impacts of the event (Philip et al. 2020; van Oldenborgh et al. 2021). To test the influence of anthropogenic emissions, thousands of years of synthetic weather are simulated by climate models, both with and without the presence of anthropogenic forcing, or with historical transient forcing. The relative rates and intensities of the events in question are calculated, either between the factual and counterfactual scenarios or over the historical period. This is then compared to changes in similarly-defined events predicted by historical observations and across climate models that simulate changes

in historical atmospheric conditions. Within this method it is critical that models are assessed for their ability to accurately represent the extremes of interest, and it is preferable that several models are



used to explore inter-model spread (Li and Otto 2022).

Figure 5.2: Overview of the study region. Panel (a) shows the topography and major rivers of the Indian subcontinent with Pakistan highlighted in red. Panel (b) shows the major climatological regions according to their Koppen-Geiger classifications across Pakistan and its surroundings. Panels (c) and (d) show the two regions studied by World Weather Attribution and in part of this chapter, highlighted in orange – the Indus river basin (c), and the provinces of Balochistan and Sindh (d).

Two studies were undertaken for the similarly-extreme rainfall and flooding in 2010. One study used only a single model, which failed the model evaluation process; it was found to be unable to forecast heavy rainfall events and represent the statistics of rainfall in the region (Christidis et al. 2013b). The second detected an anthropogenic signal for enhanced discharge in the Indus river basin (Hirabayashi

et al. 2013). However, no model evaluation was undertaken for the Indus river basin due to a lack of discharge observations, and thus there is low confidence in these conclusions.

In September 2022, the rapid study undertaken by World Weather Attribution tested the influence of anthropogenic forcing on the extreme rainfall over two spatiotemporal domains: 5-day accumulated rainfall over the Balochistan and Sindh regions, which are largely low-lying and arid, and 60-day accumulated rainfall over the wider Indus Basin, which includes several climatologies and ranges from sea level to Himalayan mountainous regions (figure 5.2). The choice of event definition is in line with the earlier implication drawn from Nanditha et al. (Nanditha et al. 2023) that both short- and longer-term extremes are relevant to this flooding. This study found that the extreme monsoon precipitation was found to have most likely increased in intensity due to current anthropogenic warming of 1.2 ^{o}C. However, a clear quantitative signal only emerged for the 5-day event definition over Balochistan and Sindh by 2 ^{o}C of global warming, while the 60-day event remained quantitatively uncertain due to the high variability of rainfall over the Indus basin (Otto et al. 2023). A limitation of the conclusions from this study is that it treats the rainfall extremes separately, and therefore does not test the degree to which such events are likely to co-occur and thus compound one another.

5.1.3 Events studied and research goals

This chapter seeks to address many of the unanswered questions remaining from these past studies, both to test and improve the robustness of their conclusions, and to further explore the drivers of risk across multiple dimensions. The analysis is conducted in several stages. In section 5.2, the extreme heat and rainfall events of 2022 are investigated in detail across several observational and reanalysis datasets. The events of 2010 are compared and contrasted, and large scale drivers of climate variability and change are considered, to provide insight into the drivers of similar extremes.

Building on the exploratory analysis, in section 5.3 a multi-method multi-model attribution study of heat and rainfall hazards in Pakistan is presented. This analysis utilises the same two rainfall event definitions as World Weather Attribution, as described above, plus the anomalous May temperatures

over Pakistan, first investigating the connection between these to identify the role of the thermal low. Both reanalysis datasets and the wider CMIP6 ensemble are then used to estimate attributable signals on each event. This is calculated both for the present-day event and across two future scenarios, consisting of shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs): 'business-as-usual' (SSP2 - RCP4.5; hereafter SSP245) and 'high-emission' (SSP5 - RCP8.5; hereafter SSP585), as described in the CMIP6 models (Eyring et al. 2016). In doing so, I test how the anthropogenic signal varies across several key dimensions, including different extreme event definitions, different types of models and ensembles used, and its trajectory over time for plausible policy pathways. I also consider the co-occurrence of both 5- and 60-day extremes above the 2022 event thresholds within a single year, within a compound events framework. This addresses the importance of both short- and longer-term rainfall effects in this flooding, in line with the findings of Nanditha et al. (Nanditha et al. 2023), and thus implicitly provides a first order approximation of the effect of high antecedent soil moisture. This analysis leads to an array of co-occurring changes in the various and compounding drivers of the multiple hazards across different development and emissions pathways, along with their uncertainties, followed by an analysis of the changing exposure and vulnerability context.

Finally, in section 5.4, I discuss the appropriate interpretation of these results and their caveats, and place them into a wider context. This involves discussions of the implications for the current loss and damage conversation and for disaster risk reduction and climate change adaptation in Pakistan.To summarise, this chapter builds on recent work, using additional datasets and presenting multiple new approaches in attribution, to present an increasingly comprehensive analysis of changing drivers of risk for flooding in Pakistan.

5.2. Investigation of extreme spring heat and summer rainfall in Pakistan

5.2.1 Observational data

In this study, four gridded observational and reanalysis products are employed to explore extremes in Pakistan. The data are as follows:

- The European Centre for Medium-Range Weather Forecasts, or the ERA5 reanalysis product begins in the year 1950 (Hersbach et al. 2020b). We use precipitation data from this product at a spatial resolution of 0.5° × 0.5°.
- The Multi-Source Weighted-Ensemble Precipitation (MSWEP) and Multi-Source Weather (MSWX) datasets, both v2.8 (updated from Beck et al. (2019). These products combine gauge-, satellite-, and reanalysis-based data for reliable precipitation estimates, at 3-hourly intervals from 1979 to near real-time, and at 0.1° spatial resolution globally. The two products are designed to be fully compatible. Here, we use precipitation from MSWEP and maximum temperatures from MSWX.
- CHIRPS: Observational daily precipitation dataset developed by the UC Santa Barbara Climate Hazards Group (Climate Hazards Group InfraRed Precipitation with Station data) (Funk et al. 2015a). Daily data are available at 0.05° resolution from 1981-present. The product incorporates satellite imagery with in-situ station data
- GPCC Full Data Daily Product Version 2022 of daily global land-surface precipitation totals based on precipitation data provided by national meteorological and hydrological services, regional and global data collections as well as WMO GTS-data (Ziese 2022). It is provided at a regular latitude/longitude grid with a spatial resolution of 1.0 x 1.0 degree and covers the time period from January 1982 to November 2023.

In addition, three other datasets are used to provide values for three indicators of large scale climatic change and variability. These are global mean surface temperatures, the state of the El Nino Southern Oscillation (ENSO), and the Indian Ocean Dipole (IOD), represented by:

- The (low-pass filtered) 4-year smoothed GMST, where GMST is taken from the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Science (GISS) surface temperature analysis (GISTEMP) (Hansen et al. 2010b; Lenssen et al. 2019).
- The detrended Niño3.4 index - this is the Niño3.4 index (average SST over 5° S–5° N, 120°–170° W) minus the SST between 20° S–20° N to adjust the index for climate change, as proposed in Van Oldenborgh et al. (2021).
- The Dipole Mode index (DMI) is used to quantify the state of the IOD and is calculated as the difference between the western and southeastern tropical Indian Ocean indices (WTIO and SETIO), based on the Hadley centre's Sea Ice and Sea Surface Tempertures (HadISST1) dataset (Rayner, N., Parker, D. E., Folland, C. K., Horton, E. B., Alexander, L. V., & Rowell 2003b).

5.2.2 Extremes in Pakistan in 2010 and 2022

While the events of 2022 are the focus of the attribution study later in this chapter, the very similar events of 2010 – a hot spring followed by extremely wet summer – provides a crucial comparison case study to analyse drivers of similar extremes.

Over Pakistan and northwestern India, the spring of 2022 was hotter than 2010, both in duration of the heat anomaly and the peak magnitude (figure 5.3). However, in both years the heat anomaly peaked in late March and was sustained until the start of June. Throughout May, absolute daily maximum temperatures continued to rise further and remained above the climatological mean. This extended hot period drove rapid drying and then heating of the land surface, leading to ideal conditions for a thermal low to form which has been suggested to lead to greater moisture flux convergence over Pakistan (Hong et al.) Figure 5.4 shows the heat anomalies in May in 2010 and 2022 versus the 1980-2010 climatology of May temperatures. Over most of Pakistan the two years are

similar, but in 2022 the heat anomalies were stronger overall and particularly over the northern regions. In contrast, in 2010 the heat was stronger over northwestern India while the north of Pakistan was comparatively cool. This is to be expected given the continuing rise in global temperatures and heat events, and if the 2010 event had occurred today it would likely have been comparable to 2022 in magnitude.

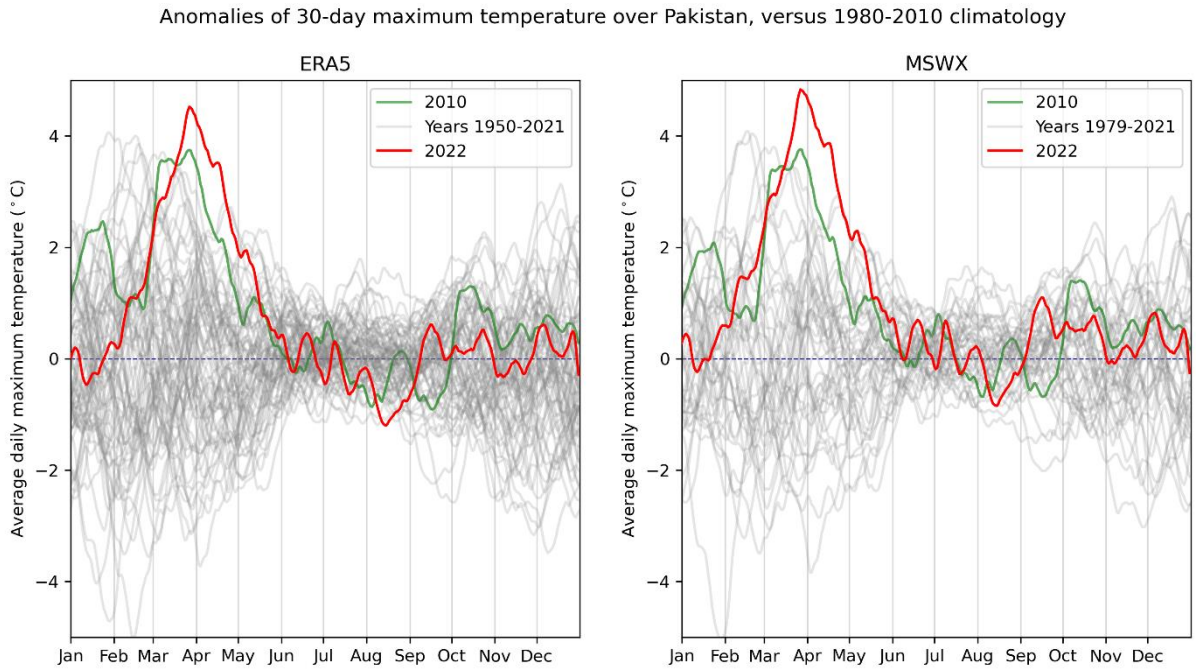


Figure 5.3: Running 30-day mean of daily maximum temperature anomalies each year over Pakistan (bounded by 60-78 °E and 20-40 °N, also shown in figure 5.4) in two observational and reanalysis datasets. 2022 is shown in red, 2010 in green, the 1980-2010 climatology of daily maximum temperature is highlighted with the blue dashed line at 0, and all other years available (specified in the legend for each dataset) are in grey.

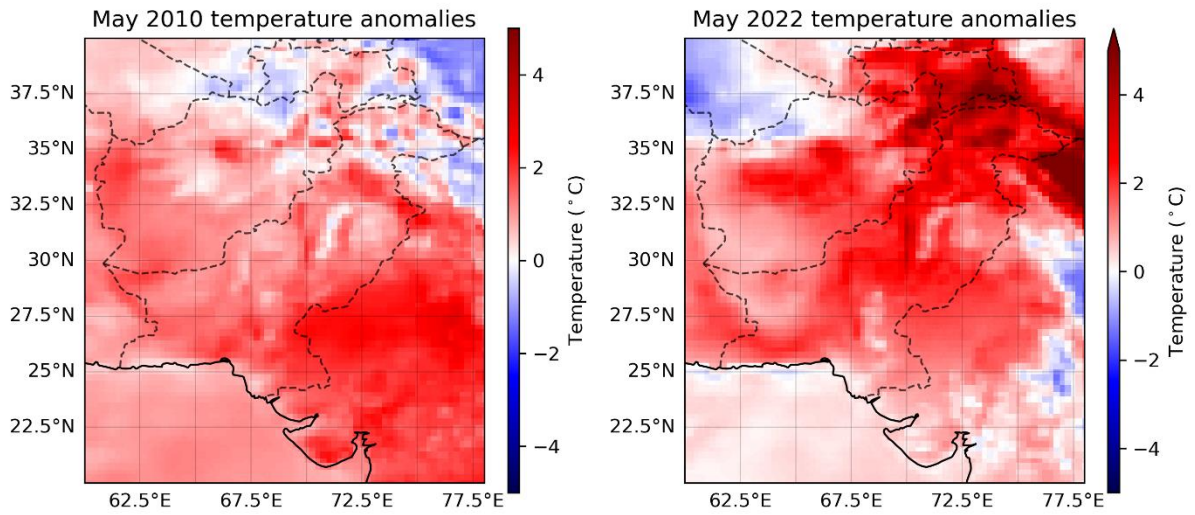


Figure 5.4: Anomalies in mean daily maximum temperature in May 2010 and 2022 versus the May average from 1980-2010. Data from MSWX.

The rainfall extremes for both years show some similarities but also greater discrepancies. Overall, most datasets agree that more rainfall fell in 2022 in June-September both in the Indus basin and in Balochistan and Sindh (henceforth BS) (figures 5.5-5.9). In particular, over the Indus basin the rainfall totals were very similar in the two years, though July was the heavier rainfall month in 2022 and August in 2010 (figure 5.5). Total accumulations for the basin are remarkably similar and, after a dry June, rose consistently across the two months and ranked among the wettest monsoon seasons of all years on record (figure 5.7).

In the BS region there is a much greater discrepancy, highlighting the key differences between the two seasons. Figure 5.6 shows how unprecedented the months of July and August 2022 were for these regions. Visualising the season as a whole highlights this very clearly, with the overall spatial pattern of decreased monsoon rainfall in the east of India and much greater to the west, which extends to southern Pakistan to a much greater degree in 2022 (figure 5.9). Additionally, figure 5.8 shows that the rainfall accumulation occurred as several multi-day pulses of extreme rainfall, suggesting that the 5-day extreme studied by World Weather Attribution was appropriate.

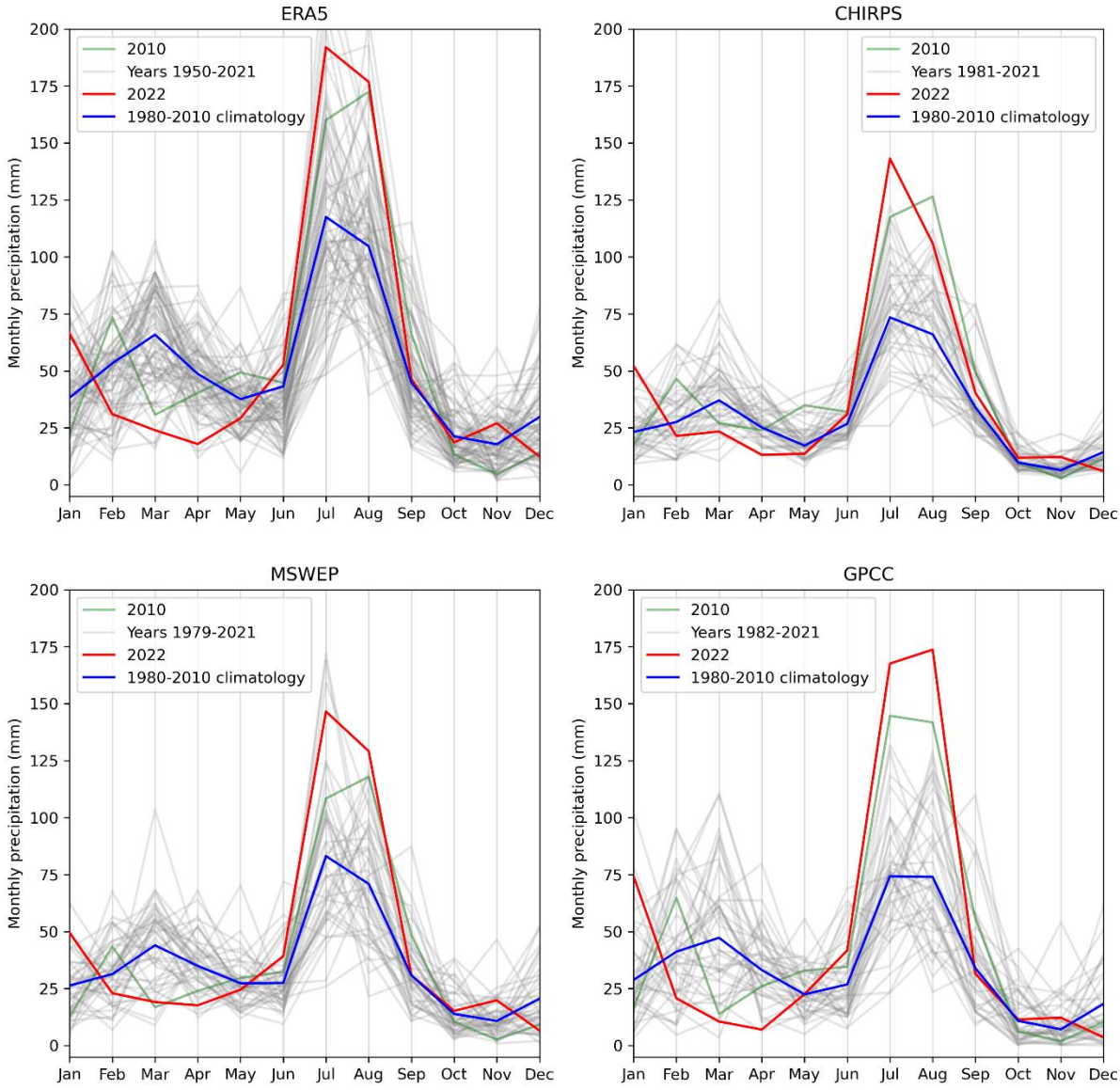


Figure 5.5: Total monthly precipitation over the Indus basin each year in four observational and reanalysis datasets. 2022 is shown in red, 2010 in green, the 1980-2010 climatology is shown in blue, and all other years available (specified in the legend) are in grey.

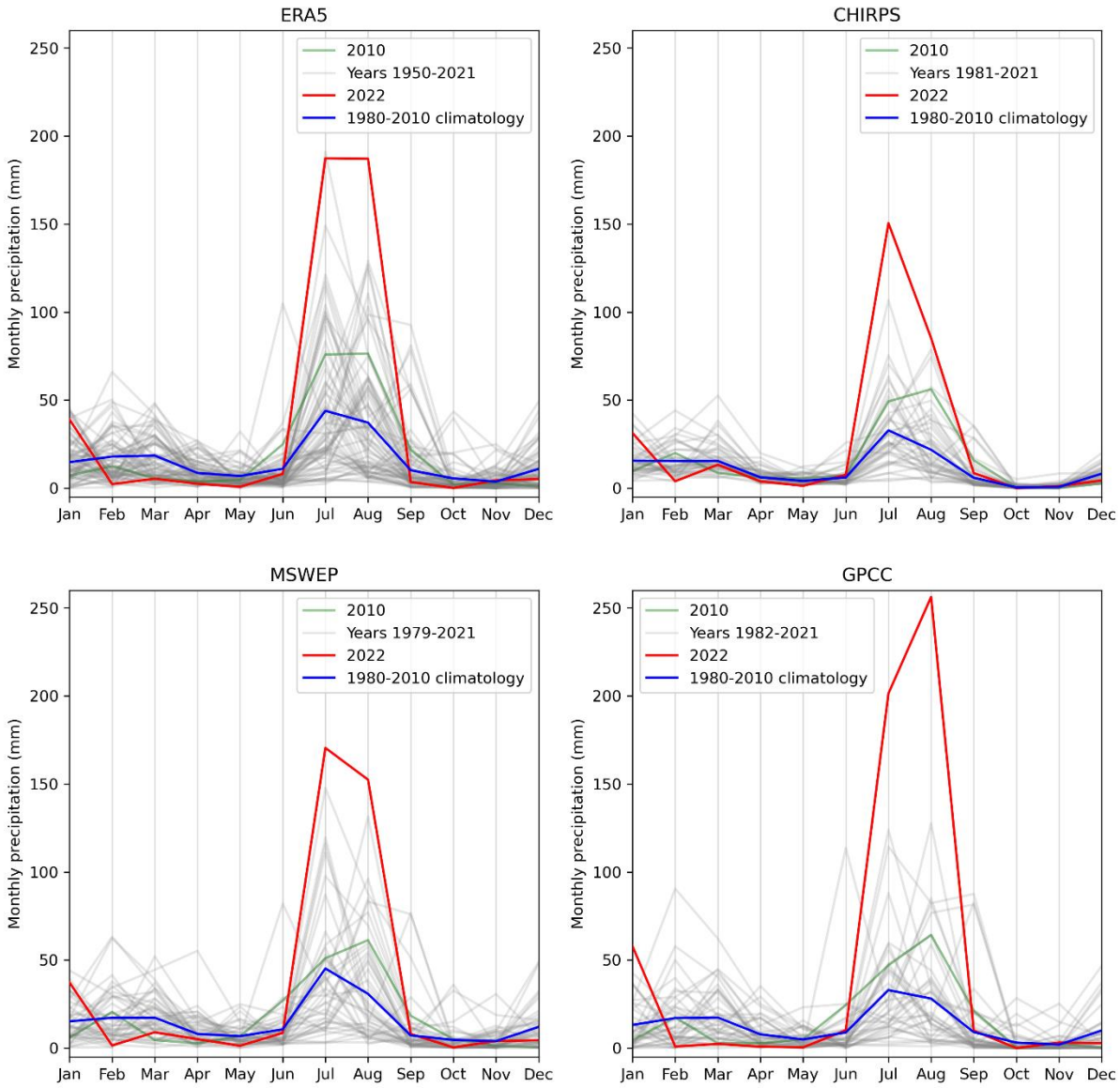


Figure 5.6: Total monthly precipitation over the Balochistan and Sindh provinces each year in four observational and reanalysis datasets. 2022 is shown in red, 2010 in green, the 1980-2010 climatology is shown in blue, and all other years available (specified in the legend) are in grey.

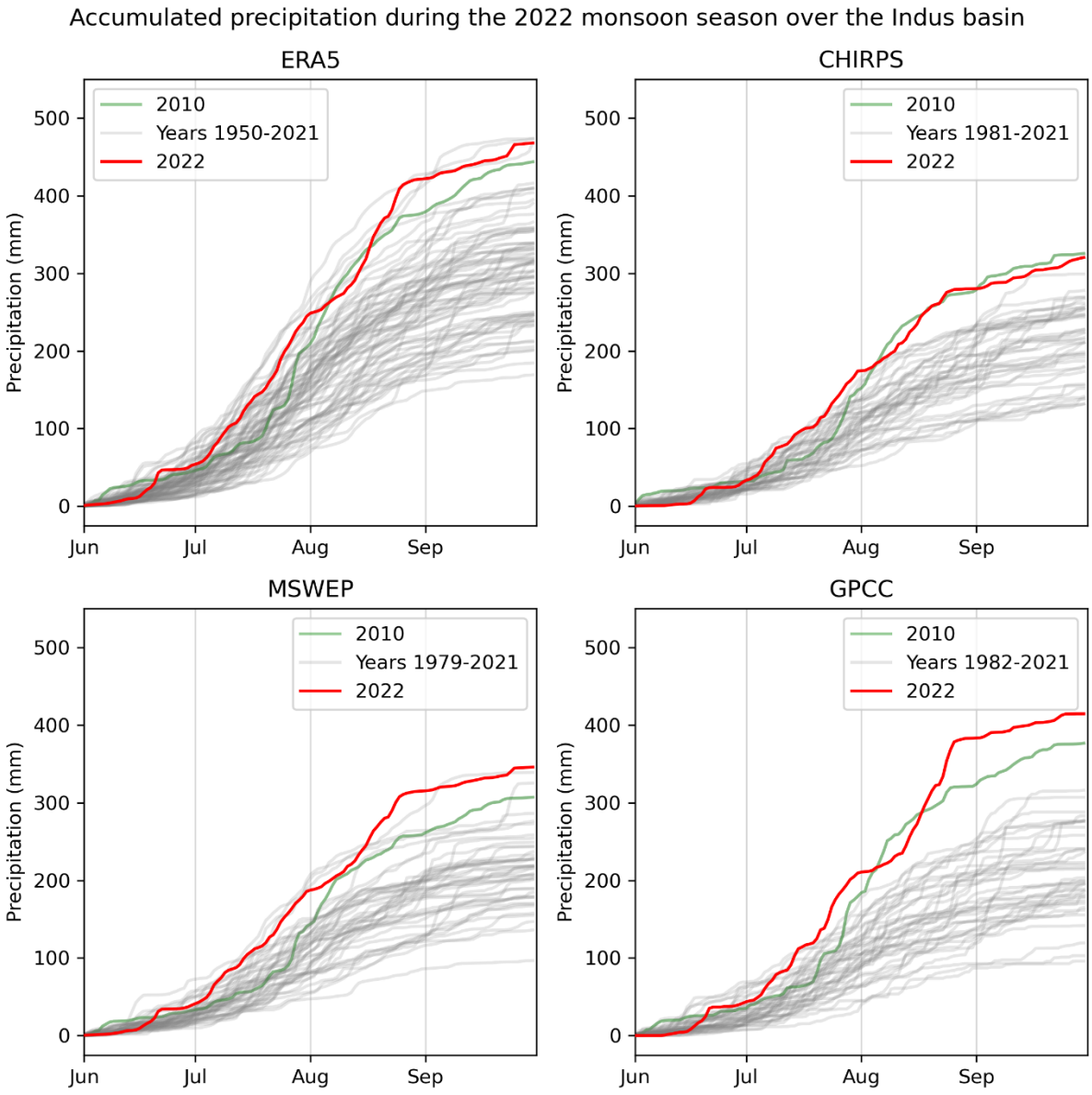


Figure 5.7: Cumulative precipitation over the Indus basin each year in four observational and reanalysis datasets. 2022 is shown in red, 2010 in green, and all other years available (specified in the legend) are in grey.

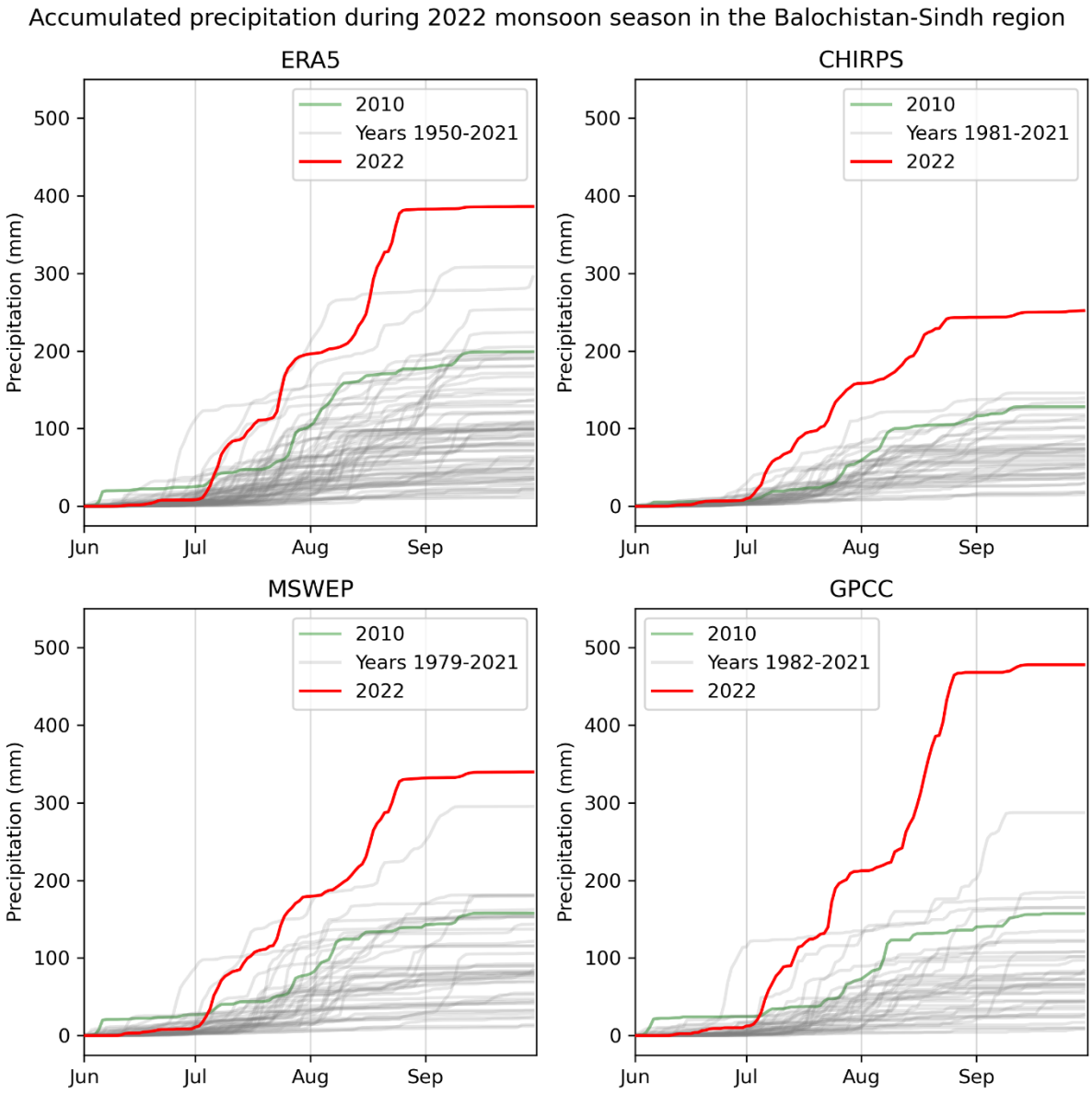


Figure 5.8: Cumulative precipitation over Balochistan and Sindh each year in four observational and reanalysis datasets. 2022 is shown in red, 2010 in green, and all other years available (specified in the legend) are in grey.

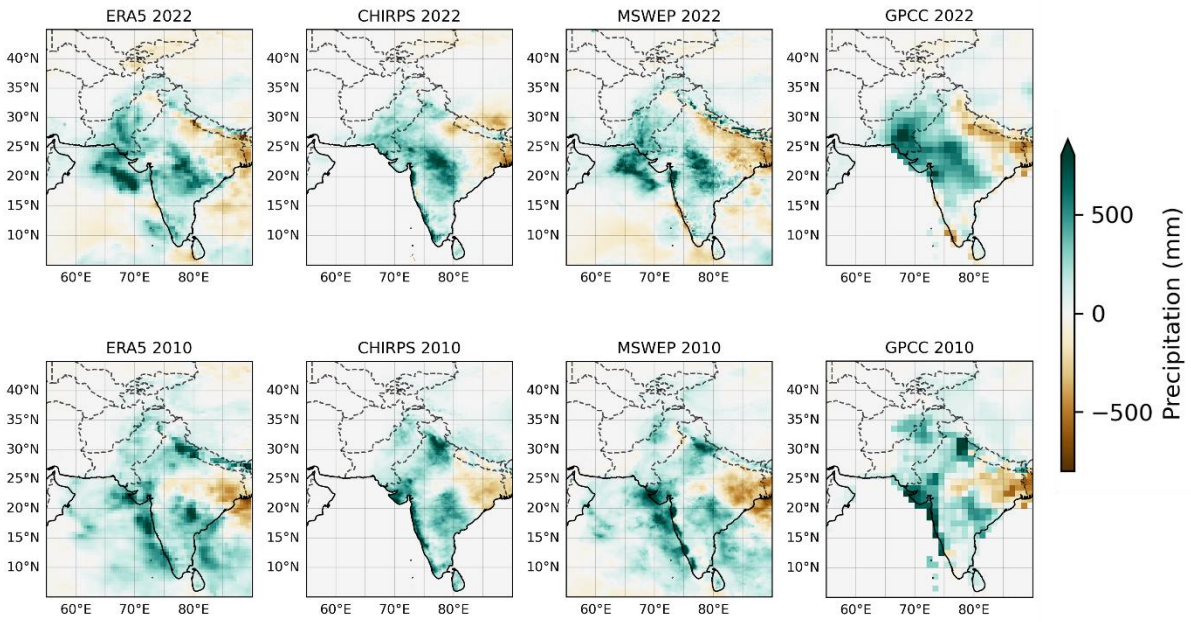


Figure 5.9: Total monsoon season (June-September) accumulated precipitation anomalies in 2022 (top) and 2010 (bottom) versus the 1980-2010 monsoon season climatology, across four observational and reanalysis datasets.

Figures 5.10 and 5.11 show the synoptic conditions leading to the events of 2010 and 2022. In both years, high pressure and hot air masses dominated over Pakistan throughout March and April. In June, cooler air moved in and settled over Pakistan throughout the monsoon season, showing the (expected) advection of moisture from the Arabian sea onto land during the monsoon season. However, the this cool influx is much stronger in 2022, particularly over southern Pakistan. This is likely due to the specific patterns of pressure and surface heat anomalies in each year. In May in 2010, high pressure was present over the northern regions of Pakistan with low pressure over much of the Indian subcontinent, whereas in May 2022 this pattern was reversed, which is mirrored in the atmospheric temperatures (figures 5.10 & 5.11). This may have led to the differences in the spatial pattern of surface heat anomalies displayed in figure 5.4 and thus also represent a stronger thermal low effect in 2022. This in turn likely led to a much stronger advection of moisture from the Arabian sea that is evidenced by other studies of the event, and which go on to suggest that a convergence of moisture flux from both the tropics and extratropics led to the exceptional rainfall in 2022 (Hong et al., 2023).

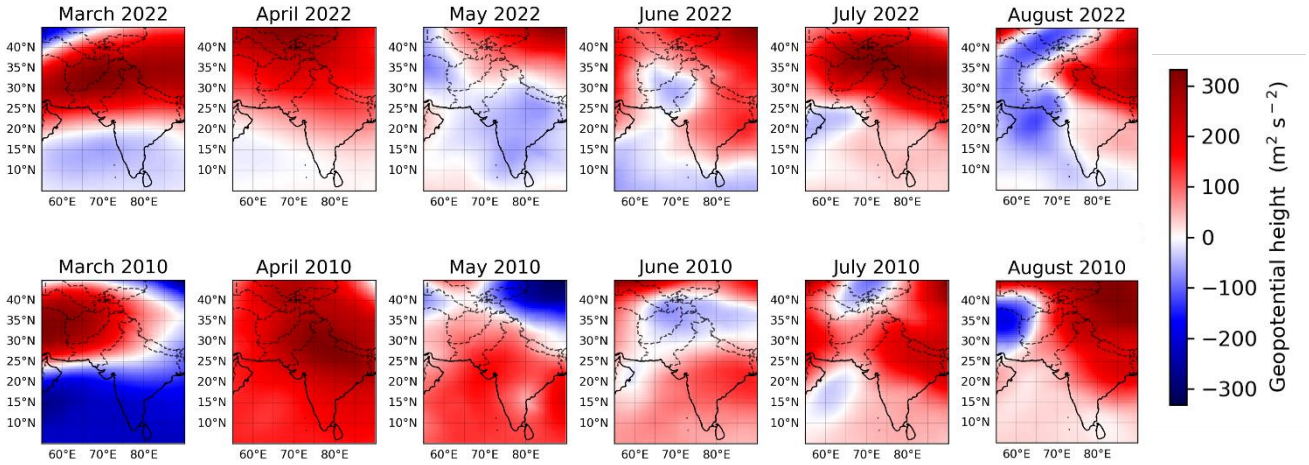


Figure 5.10: Geopotential height (500 hPa) anomalies for each month from March-August in 2010 and 2022, from ERA5 reanalysis (versus the 1980-2010 climatology for each month). Red highlights areas of anomalously high pressure, while blue shows low pressure regions.

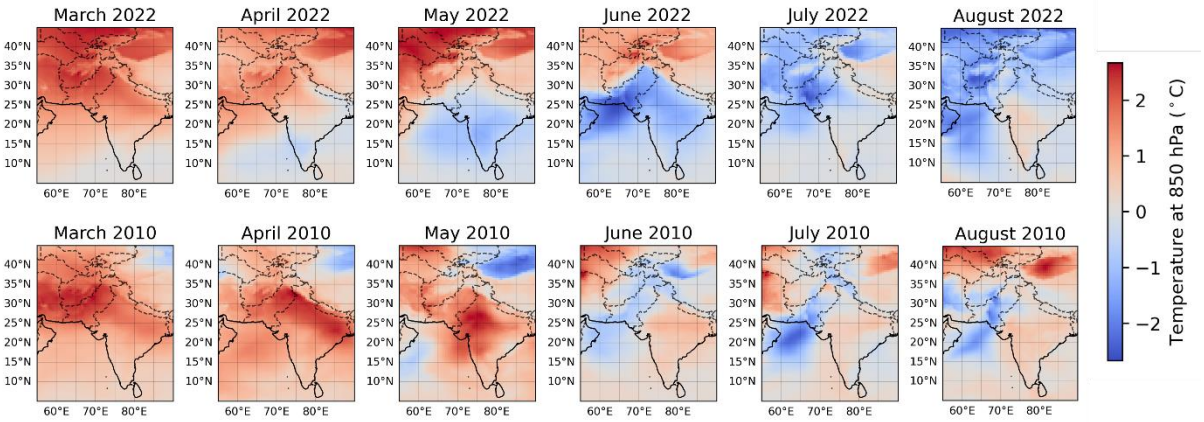


Figure 5.11: Anomalies in the atmospheric temperature at 850 hPa for each month from March-August in 2010 and 2022, from ERA5 reanalysis (versus the 1980-2010 climatology for each month). Red highlights areas of anomalously warm air, while blue shows cool regions.

5.2.3 Drivers of extremes

Numerous meteorological and climatological factors are hypothesised to have influenced the extremes observed in 2010 and 2022, including anthropogenic warming, the anomalously hot dry spring leading to a strengthened thermal low, the negative phase of the Indian Ocean Dipole, and the La Nina phase of ENSO (Nanditha et al., 2023; Otto et al., 2023; Hong et al., 2023). To assess potential connnections between these factors and the extremes in question, the correlations and joint distributions between them, as well as between the extremes themselves, are evaluated (table 5.1, figures 5.12 & 5.13).

Extreme variable	**Pearson correlation coefficient between variables**					
	Nino3.4 rel (May)	IOD (April)	March-April temperature anomaly	May temperature anomaly	Indus basin rainfall	Balochistan-Sindh rainfall
May temperature anomaly	-0.348	0.184	0.433	1	0.353	0.197
Indus basin rainfall	-0.230	-0.035	0.068	0.353	1	0.709
Balochistan-Sindh rainfall	-0.151	-0.182	0.088	0.197	0.709	1

Table 5.1: Pearson correlation coefficients between factors potentially affecting extremes in Pakistan. Blue shows a negative correlation and orange shows a positive correlation. Darker colours show where the correlation is significant at the 5% level ($p<0.05$).

The correlation analysis highlights several key points. First, the negative correlation with 'Nino3.4 rel' reinforces that La Nina events in late spring significantly influence both hot spring and wet late summer monsoons as characterised in these particular event definitions. Second, the IOD in isolation does not have a major influence on the extremes evaluated here. Third, high temperatures in March-April over Pakistan have very little bearing on the extent of late summer monsoon rainfall, whereas when there is a substantial heat anomaly in May, Indus basin rainfall is much more likely to be elevated. Finally, there is a strong correlation between multi-month rainfall in the Indus basin and

multi-day rainfall in the BS region. In part this is unsurprising due to the spatial crossover of the two regions, but given the very different temporal scales this correlation confirms that factors driving flood hazards, from heavy total-season monsoon rainfall to short-term heavy rainfall in the lower Indus basin, are similar and thus compound the risk of extremes.

This is analysis aims to provide a basis for further (attribution) research. It is important to note that the correlations are limited to considering each factor in isolation, while events are ultimately caused by the co-occurrence of such conditions. Further work on the compounding dynamics at play are needed to provide greater insight for improved modelling and seasonal prediction.

Moving forwards, the strongest correlations are observed between the compounding rainfall events, May temperatures and La Nina conditions, as well as the May temperatures and Indus basin rainfall. The joint and marginal distributions of these are further displayed in figures 5.12 and 5.13. In figure 5.12, the stronger relationship between May temperatures and Indus basin rainfall than BS rainfall is clear. In both, there is also moderate clustering of events with the ENSO phase at the May before (or during) occurrence. Figure 5.13 shows the strong correlation between the rainfall events, which shows clustering in events with similar May temperature anomalies, largely due to its influence on Indus basin rainfall (shifting along the x axis).

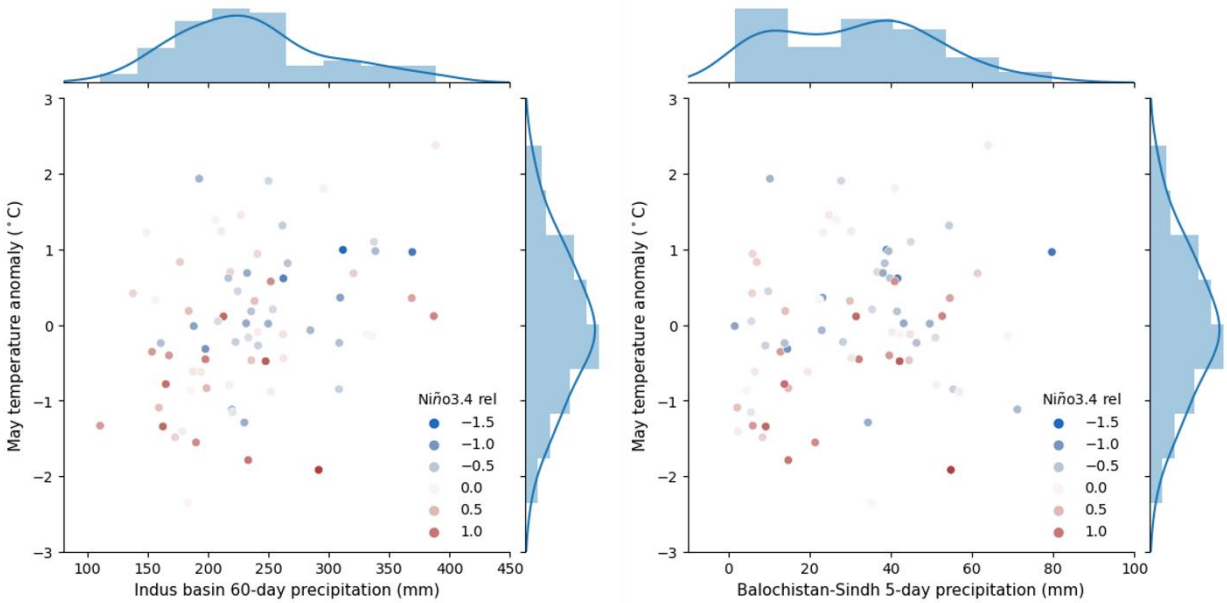


Figure 5.12: Joint distributions of May temperature anomalies and 60-day Indus basin rainfall (left) and 5-day Balochistan-Sindh rainfall (right) for years 1950-2023 in ERA5. The points are coloured by the value of Nino3.4 rel in May of the same year, with blue points representing cool (La Nina) phases and red representing warm (El Nino) phases. The marginal distributions and histograms are shown for each variable.

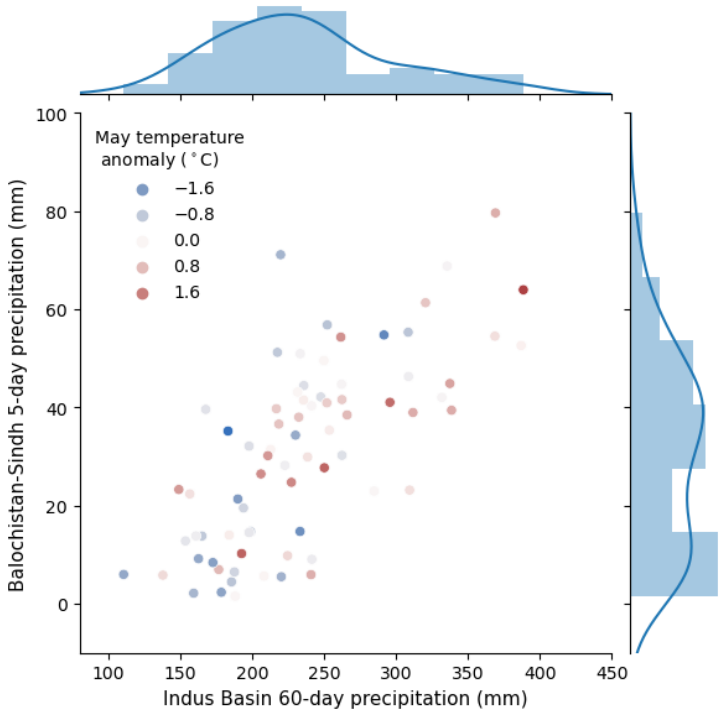


Figure 5.13: Joint distributions of 60-day Indus basin rainfall and 5-day Balochistan-Sindh rainfall for years 1950-2023 in ERA5. The points are coloured by the May temperature anomalies for the same

year, with blue points representing cool and red representing warm conditions. The marginal distributions and histograms are shown for each variable.

From this and previous analysis of extremes in Pakistan, it is clear that there are a range of potentially linked factors at play and multiple possible influences of anthropogenic climate change. Extreme event attribution offers a way of exploring the anthropogenic influence on these factors in isolation and, given their potential dependencies, a way of disentangling these influences. This is highly relevant to management of future risks for sectors and regions affected by multiple compounding and potentially causally linked hazards. As such, in the following section, the anthropogenic influence is assessed for each rainfall event definition (60-days over the Indus basin and 5-days over BS), the co-occurrence of these two events, and the anomalously warm May. This is estimated both for the time of occurrence relative to preindustrial forcing and at expected levels of warming in 2050 across two shared socioeconomic pathways. The influence of anthropogenic warming on monsoon season rainfall extreme is further probed through its influence on the May temperature directly.

5.3. Extreme event attribution

5.3.1 Data and methods

As previously noted, Otto et al. (2023) tested the influence of anthropogenic forcing on the extreme rainfall over two spatiotemporal domains: June-September (JJAS) maxima of the 5-day average daily precipitation over the BS region, and 60-day average daily precipitation over the wider Indus Basin. The data and methods used by that study are as follows. To establish the observed event magnitude, three gridded observational datasets were used. These included ERA5 (Hersbach et al. 2020a) reanalysis from 1950-, as well as gridded observational datasets, CPC (the 'Global Unified Gauge-Based Analysis of Daily Precipitation data', provided by the NOAA PSL) and GPM-IMERG (the Integrated Multi-satellitE Retrievals for GPM algorithm, used to estimate precipitation from GPM satellite data) (Bolvin et al. 2020).

To calculate the return period of the 2022 event, the study used the well-established event attribution protocol detailed in Philip et al. (2020) in which a statistical model is fit to the data, which is assumed to vary with GMST. In this case the time series data are block maxima – the largest observations of precipitation drawn from seasonal samples – so the most appropriate fit is to a Generalised Extreme Value (GEV) distribution. As such, the cumulative distribution function is given by

$$P(x) = exp\left\{-\left(1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right)^{-\frac{1}{\xi}}\right\} \quad (5.1),$$

where μ is the location parameter, σ is the scale parameter, and ξ is the shape parameter. In order to reduce the number of fit parameters, the shape and dispersion parameters (the latter the ratio between the scale and location parameters) are assumed to be constant, which has been shown to be robust. The location and scale parameters depend on the covariate GMST, T', in an exponential relation modulated by fit parameters α, μ_0 and σ_0, and are thus given by

$$\mu = \mu_0 exp\left(\frac{\alpha T'}{\mu_0}\right), \sigma = \sigma_0 exp\left(\frac{\alpha T'}{\mu_0}\right). \quad (5.2)$$

Finally, to find the return period of the event in the present-day, the probability of exceeding the observed magnitude at the covariate level of occurrence is calculated and inverted to give a return period. Across the multiple observational and reanalysis datasets it was found that both events corresponded to an approximately 1-in-100-year return period event (with a lower bound of 85 years). This is then compared with the return period of an event with the same magnitude at a different covariate level: in this case a GMST of -1.2 ^{o}C, to calculate a probability ratio. Equivalently, the change in intensity of an event with the same return period (1 in 100 years) at the comparison covariate level is estimated.

For the model-based attribution analysis, both the CORDEX and HighResMIP models were first tested for their ability to accurately simulate events (as described in 'CMIP6 scenarios' below) such as that observed in the Indus basin and BS region, from which 17 and 11 out of 24 CORDEX models and 0 and 4 out of 6 HighResMIP models were subsequently used, respectively.

Here, I expand on this study in several ways. First, I undertake a study of the May temperature anomalies in a region over Pakistan bounded by 20-40 ^{o}N, 60-78 ^{o}E using the ERA5 and MSWX datasets. This uses the same attribution framework as laid out above but using a normal distribution to model the May average temperatures (as they are not block maxima – see the marginal distribution in fig 5.12), and with a modified assumption that the extreme in question shifts with GMST rather than scales, the standard and physically-based assumption for temperature changes (Philip et al., 2020). Second, I employ the same rainfall spatiotemporal event definitions as Otto et al. (2023), as set out above. However, I refine the estimates of present day return period using higher resolution observational and reanalyss datasets (MSWX, CHIRPS and GPCC – ERA5 is used in both studies, see section 5.2.1). The study is then expanded further as detailed below.

CMIP6 scenarios

To further explore the anthropogenic influence on rainfall and heat extremes, I use a set of model ensembles from CMIP6 to estimate attributable signals on each, both for the present and across two future integrated climate-socioeconomic development scenarios, SSPs 245 and 585 (as described in section 1). The results from observational and model analysis are then synthesised into individual attribution statements. Results are reported for the year 2050, with the covariate GMST in each case set at its mean value in 2050 across all datasets for that scenario; for SSP585 this is a further 1.07 ^{o}C above present day, and for SSP245 it is 0.71 ^{o}C (for a total warming of ~2.3 ^{o}C and ~1.9 ^{o}C, respectively).

Before conducting any model analysis, the models are evaluated for their ability to simulate the local climatology and statistics of events similar to the one observed. In line with Otto et al. (2023), I apply three tests. First, I check that two key parameters of the generalised extreme value (GEV) distribution, the dispersion and the shape parameter, fall within the combined uncertainty ranges of the same distribution fit to the observational data, ERA5, MSWEP/MSWX, CHIRPS and GPCC (section 5.2.1). Second, that the model produces a realistic spatial pattern of annual rainfall over the Indian subcontinent with respect to observational data. Third, that the model produces a seasonal cycle in the monthly average rainfall that peaks between the months of July and September and is similar to observational data. The figures and tables setting out model evaluation are shown in appendix B. These correspond to the models used for the SSP585 future analysis, but a smaller subset of these models were used for SSP245 due to data availability, so the same model evaluation applies.

The role of amplified May temperatures

The role of anthropogenically amplified May temperatures on rainfall extremes is also explored here, thus quantifying the direct effect of anthropogenic climate change through a causal physical mechanism. This is conducted using the ERA5 and MSWX datasets for which physically consistent temperatures and precipitation data are available. To do so, a statistical model is fitted to the rainfall time series' with average May daily maximum temperature as covariate. Then, the estimated

attributable shift in May temperatures for each dataset is used to estimate return periods of rainfall with and without the influence of anthropogenic climate change on this region.

Compound rainfall attribution

The univariate analysis of rainfall involves two event definitions (5-day accumulated rainfall in BS region and 60-days over the Indus basin), including both shorter and longer-term extremes, to ensure that the study is as relevant as possible to the flooding itself (Nanditha et al. 2023). Ultimately, however, it was the simultaneous occurrence of both; an intense pulse of rainfall over a few days on top of ground that was already saturated as a result of the longer-term rainfall, that led to the flooding and hence such severe impacts. As a result, I also extended the analysis to attribute the simultaneous occurrence of both extremes. Attribution of compound events is an area of active research, motivated by recent events in which compounding phenomena led to extreme impacts, such as the Northwest Pacific dry heatwave in 2021 or the simultaneous Northern Hemisphere heat events of summer 2018. Recent work highlights that the joint distribution between two climate variables depends on their respective marginal distributions and their degree of correlation, implying that the attribution signal for a given compound event also depends on both of these factors (Zscheischler and Lehner 2022).

The two rainfall extremes in this study are very highly correlated phenomena, due to using the same meteorological variable and overlapping spatially, and thus we might expect an amplified anthropogenic signal given sufficient data (Zscheischler and Lehner 2022). Nonetheless, this does not nullify the need for such an evaluation. On the contrary, it only highlights the need to understand hazards in greater detail; there is nothing sacred about the univariate approach, and to attribute only part of the meteorological event may cause us to underestimate the risk. In addition, no two events are ever truly independent in a chaotic but integrated climate system.

As a result, I apply a slightly modified version of the framework of Zscheischler & Lehner (Zscheischler and Lehner 2022), using the rainfall maxima for the two event definitions within each year as the initial bivariate distribution. An event is considered to occur if and only if extreme events in both regions

happen in a given year; there is no other temporal dependence such as the relative time of occurrence within the year, or that they must overlap. While this means that the sequence of events in 2022 is not necessarily followed in detected events, it also increases the sample size and makes fewer assumptions about what actually leads to flooding in the region. Then, rather than requiring a fixed threshold to be exceeded in both regions, I normalise and combine the data in each region to create a univariate index as detailed below.

For the observational data, I 'normalised' the time series by dividing all values by the value for 2022, such that all values did not necessarily fall between 0 and 1 but took values on the same relative scale, with the year 2022 represented by a value of 1 in each region. Then, I summed the normalised values for the two regions in each year. This created a univariate index in which the 2022 event (in observations) had a value of 2 and within which the two events were equally weighted. This equal weighting is important to capture the fact that both shorter and longer duration rainfall extremes with very different absolute magnitudes contribute to flooding. For the model analysis of compound rainfall, a slight modification was required. I first limited the pool of models to those that passed evaluation (see Appendix B – tables B.1-B.4). Then, all time series' were divided by the value of events with the same observed return period as the event in question (as there is no reference '2022' value in the simulated datasets). Across both compound observational and model time series, I then followed the same attribution analysis process as above, applying extreme value theory directly to this new dataset. Using this method, the interpretation of results requires care.

A shift in magnitude in this index corresponds (roughly, because they could occur at the same time in which case it's possible that at least some of the same rainfall is counted twice, and not in equal proportion) to an overall percentage change in the simultaneous occurrence of both events; so, a 5% decrease in the Indus basin but a 10% increase in the BS region would return a (net) 5% increase in the index. Similarly, the probability ratio is the change in the chance of both events exceeding this combined index (so an increase in one could offset a decrease in the other and still be counted as

above the threshold). While somewhat abstracted from the 2022 event, I believe this is still appropriate from an impacts perspective because both events were so extreme that even if one decreased slightly, a larger increase in the other would still result in significant impacts. It also increases the pool of events compared to limiting both indices to simultaneously exceeding the 2022 values, which is useful in the absence of very large ensembles, and again makes physical sense due to the extreme nature of the 2022 event's impact.

5.3.2 Observational analysis

May temperatures

Both observational datasets show clear trends in the likelihood and intensity of May temperatures similar to those observed in 2022. Such temperatures are fairly common in the present climate with a return period of approximately 4 years (table 5.2). However, datasets disagree on the return period in the preindustrial world, with estimates of 1 in ~10 (ERA5) and 1 in ~100 years (MSWX). This is likely due to the difference in temporal length of the datasets, with ERA5 stretching back to 1950 and MSWX beginning in 1979. The result of this is that ERA5 also includes more of the pre-2000s period in which high concentrations of aerosols in South Asia resulted in local cooling, while a larger fraction of the period of MSWX is that in which global greenhouse gas forcing began to dominate in the region and aerosols began to be reduced (van Oldenborgh et al. 2018).These localised trends are not accounted for in the statistical model, which only treats GMST as a covariate. The earlier cooling may therefore dampen the change in May temperatures due to GMST and confidence is higher for the statistically significant result from MSWX, suggesting that hot May conditions like in 2022 have become around 30 times more likely (van Oldenborgh et al. 2018), in agreement with March-April analysis for the same year (Zachariah et al. 2022b).

Dataset	**2022 event magnitude (°C)**	**Return period in 2022 (yrs)**	**Return period at -1.2 °C (yrs)**	**Probability ratio (95% C.I.)**	**Magnitude change (°C)**
ERA5	30.07	4.19	9.72	2.32 (0.73 - 8.70)	0.53 (-0.18 – 1.24)
MSWX	30.95	3.12	97.74	31.31 (2.92 - 1603.4)	1.87 (0.62 – 3.18)

Table 5.2: Observed magnitude of mean of daily maximum temperatures in the region over Pakistan (20-40 °N, 60-78 °E), its return period in the current and preindustrial climates, and the estimated probability ratio and magnitude change of such extremes. Blue highlighting shows increasing trends in frequency and intensity, with darker colours for statistical significance at the 95% level.

Heavy monsoon rainfall

Indus Basin 60-day precipitation

In the Indus basin, the overall return period of such an event in the present climate is estimated at 1 in 50 years, lower than the estimate of 1 in 100 years used by WWA, due to the different higher-resolution observational datasets used. Modelling the effect of warming since preindustrial times, the ERA5 shows a decreasing trend with ACC while all other datasets show increases (table 5.3). This may be due in part to the local cooling effect of aerosols offsetting the rise in GMST discussed above. However, synthesising all estimates gives a strong increase in likelihood of around a factor of 30 and an increase in intensity of 11.5%. The relatively short length of the time series' results in large sampling uncertainties across all estimates.

Dataset	2022 event magnitude (mm)	Return period in 2022 (yrs)	Return period at -1.2 °C (yrs)	Probability ratio (95% C.I.)	Magnitude change (%, 95% C.I.)
ERA5	369.00	60.84	27.20	0.45 (0.09-inf)	-7.50 (-27.96 - +14.92)
MSWEP	276.70	73.42	277.06	3.77 (0.003-inf)	7.83 (-29.87 - +43.87)
CHIRPS	254.56	23.86	inf	Inf (25.26-inf)	34.03 (-4.14 - +105.40)
GPCC	341.81	45.17	2017.7	44.67 (0.35-inf)	45.04 (-29.26 - +181.27)
Synthesis				29.5 (1.54-939)	11.5 (-5.79 - +31.3)

Table 5.3: Summary of observational changes in Indus basin 60-day rainfall extremes due to the influence of ACC with 95% confidence intervals. Blue highlighting shows increasing trends in frequency and intensity and orange shows decreases, with darker colours for statistical significance at the 95% level.

Balochistan-Sindh 5-day precipitation

There is also variation between both the estimated return periods and trends in BS events (table 5.4). The return periods have a mean of approximately 1 in 40 years, but placing slightly more emphasis on the longest time series (ERA5), the return period is also taken as 1 in 50 years going forwards. The trend variation is likely due to a combination of factors. First, as mentioned above, short time series lead to large sampling uncertainties. Second, the BS region has very large variation in the index selected due to its nature as an arid region; in some years this index is close to 0 (figures 5.12 & 5.13). Nonetheless, the synthesis also shows a likely overall increase in both likelihood and intensity.

Dataset	2022 event magnitude (mm)	Return period in 2022 (yrs)	Return period at -1.2 ◦C (yrs)	Probability ratio (95% C.I.)	Magnitude change (%) (95% C.I.)
ERA5	79.64	98.02	240.32	2.45 (0.001-inf)	7.47 (-35.16 - 55.05)
MSWEP	57.88	13.06	8.74	0.67 (0.002-1345.3)	-10.77 (-68.94 - +108.04)
CHIRPS	41.58	8.80	3x10^9	$3.8x10^8$ (8.59-inf)	108.61 (15.16 - 264.91)
GPCC	91.42	41.58	366.43	8.81 (0.02-inf)	61.30 (-54.73 - +385.01)
Synthesis				19.5 (0.82 – 540)	34.0 (-15.1 - +97.0)

Table 5.4: Summary of observational changes in Balochistan-Sindh 5-day rainfall extremes due to the influence of ACC with 95% confidence intervals. Blue highlighting shows increasing trends in frequency and intensity and orange shows decreases.

Compound precipitation

The trend in compound events is dependent on both the results for the other indices and their correlation. In the current climate, the datasets give a wide range of estimates for return period. The

mean of these estimates is 1 in 60 years, but placing slightly more emphasis on the longest time series (ERA5) as above, the return period is taken as 1 in 75 years going forwards.

Trends in this index show the widest variation between datasets, due to the combined effects on the individual events described above and the additional challenge of capturing their correlation (table 5.5). When synthesised, the relatively weak decreases shown in ERA5 and MSWEP are outweighed by the strong increases in CHIRPS and GPCC, resulting in the conclusion that compound events have significantly increased in likelihood by a factor of 17 and (not significantly) in net intensity by around 22% (substantially above Clausius-Clapeyron scaling, which would lead to 8.4% in a 1.2 ^{o}C warmer world). The uncertainties are very large, spanning two orders of magnitude in probability ratio, as a result of the wide variation in observations. Consequently these results have low confidence and further analysis using models is required to refine this estimate.

Dataset	2022 event magnitude (mm)	Return period in 2022	Return period at -1.2 ◦C	Probability ratio (95% C.I.)	Magnitude change (%) (95% C.I.)
ERA5	2.0	127.06	73.46	0.58 (0.0006-inf)	-4.75 (-33.84 - +28.09)
MSWEP	2.0	25.43	22.51	0.89 (0.003-inf)	-1.77 (-46.77 - +74.15)
CHIRPS	2.0	29.34	inf	Inf (72000-inf)	54.95 (10.84 - 131.41)
GPCC	2.0	54.28	961.61	17.72 (0.07-inf)	52.76 (-23.54 - +252.99)
Synthesis				17.4 (1.26-723)	22.0 (-6.14 - +61.8)

Table 5.5: Summary of observational changes in compound rainfall extremes due to the influence of ACC with 95% confidence intervals. Blue highlighting shows increasing trends in frequency and intensity and orange shows decreases, with darker colours for statistical significance at the 95% level.

Precipitation extremes conditioned on May temperatures

The influence of anthropogenic influence on the various rainfall extremes through enhancing Pakistan May temperatures is shown here (table 5.6). The two datasets with both precipitation and temperature data were estimated to have increased in intensity by 0.53 ^{o}C (ERA5) and 1.87 ^{o}C (MSWX) (table 5.2). The effect of these shifts is to increase extreme monsoon precipitation, hypothesised to be due to the enhanced thermal low. In table 5.6 the changes for each hazard are synthesised. In the Indus basin these changes are statistically significant with an estimated probability ratio of more than 5, and a weaker non-significant increase of 15% in likelihood in the BS region. Consequently, the likelihood of a compound event has increased by 70% and net intensity has increased by 7%. These estimates are all lower than those for the overall influence of GMST, which accounts for other potential interactions between warming and rainfall extremes. The uncertainties are also lower, particularly for the Indus basin, suggesting a robust connection between the phenomena of amplified May temperatures leading and enhanced monsoon precipitation in the Indus basin.

Event definition	Probability ratio	Confidence intervals (95%)	Change in intensity (%)	Confidence intervals (95%)
Indus Basin 60-day	5.15	1.23 - 133	9.32	1.86 - 20.5
Balochistan - Sindh 5-day	1.15	0.484 - 8.16	1.21	-13.8 - 45.0
Compound event	1.70	0.70 - 8.70	7.10	-3.50 - 28.0

Table 5.6: Synthesis of observational changes in each rainfall extreme due to the influence of ACC on May temperatures. Blue highlighting shows increasing trends in frequency and intensity, with darker colour for statistical significance at the 95% level.

5.3.3 Model analysis and multi-hazard synthesis

By combining the observational trend analysis with a set of CMIP6 model runs, the overall anthropogenic influences on the extremes in Pakistan in 2022 are estimated (table 5.7). In general, for all events as they happened in the present day across all regions, the model simulations show a likely increase in the probability of the event occurring and an increase in the intensity of comparably rare events. The results for rainfall events from this analysis generally agree with and strengthen the results of Otto et al. (Otto et al. 2023) (table 5.7). Statistically significant changes are detected in the May temperatures, the Indus basin rainfall and the compound rainfall, both in present with respect to preindustrial, and across both scenarios by 2050 with respect to present levels of warming. In the BS region, overall increases are also predicted across future scenarios but these changes are less clear in the models and observations available, possibly due to very high variability in the region.

Event		**Change from preindustrial to 2022 (95% C.I.)**	**Change from 2022 – 2050 across different SSPs**	
			SSP245 (95% C.I.)	SSP585 (95% C.I.)
May temperature anomaly	Magnitude change (°C)	1.19 (0.99 – 1.39)	0.86 (0.77 – 0.94)	1.13 (1.04 – 1.22)
	Probability Ratio	6.99 (5.17 – 10.4)	2.18 (2.08 – 2.30)	2.39 (2.28 – 2.51)
Indus Basin T60x	Magnitude change (%)	12.2 (5.53 – 19.0)	8.03 (5.81 – 9.96)	8.95 (6.99 – 10.7)
	Probability Ratio	6.66 (2.02 – 24.3)	1.71 (1.32 – 2.11)	2.20 (1.79 – 3.33)
Balochistan-Sindh T5x	Magnitude change (%)	11.0 (-7.98 – 30.4)	0.56 (-9.29 – 7.65)	2.20 (-8.03 – 8.53)
	Probability Ratio	2.41 (0.86 – 6.89)	0.91 (0.63 – 1.14)	1.01 (0.79 – 1.18)
Compound event	Magnitude change (%)	12.3 (2.60 – 23.4)	10.9 (7.26 – 14.2)	9.21 (6.21 – 11.9)
	Probability ratio	3.63 (1.55 – 13.0)	1.62 (1.12 – 2.05)	1.68 (1.35 – 2.24)

Table 5.7: Synthesis of extreme heat and rainfall attribution for the May temperatures, the two rainfall event definitions and the compound occurrence of both, along with sampling uncertainties. The colours denote the strength of the attribution statement: orange indicates a possible decrease (in intensity or probability) but with the change not being statistically significant, light blue indicates a possible increase but overall no change, darker blue indicates a significant increase.

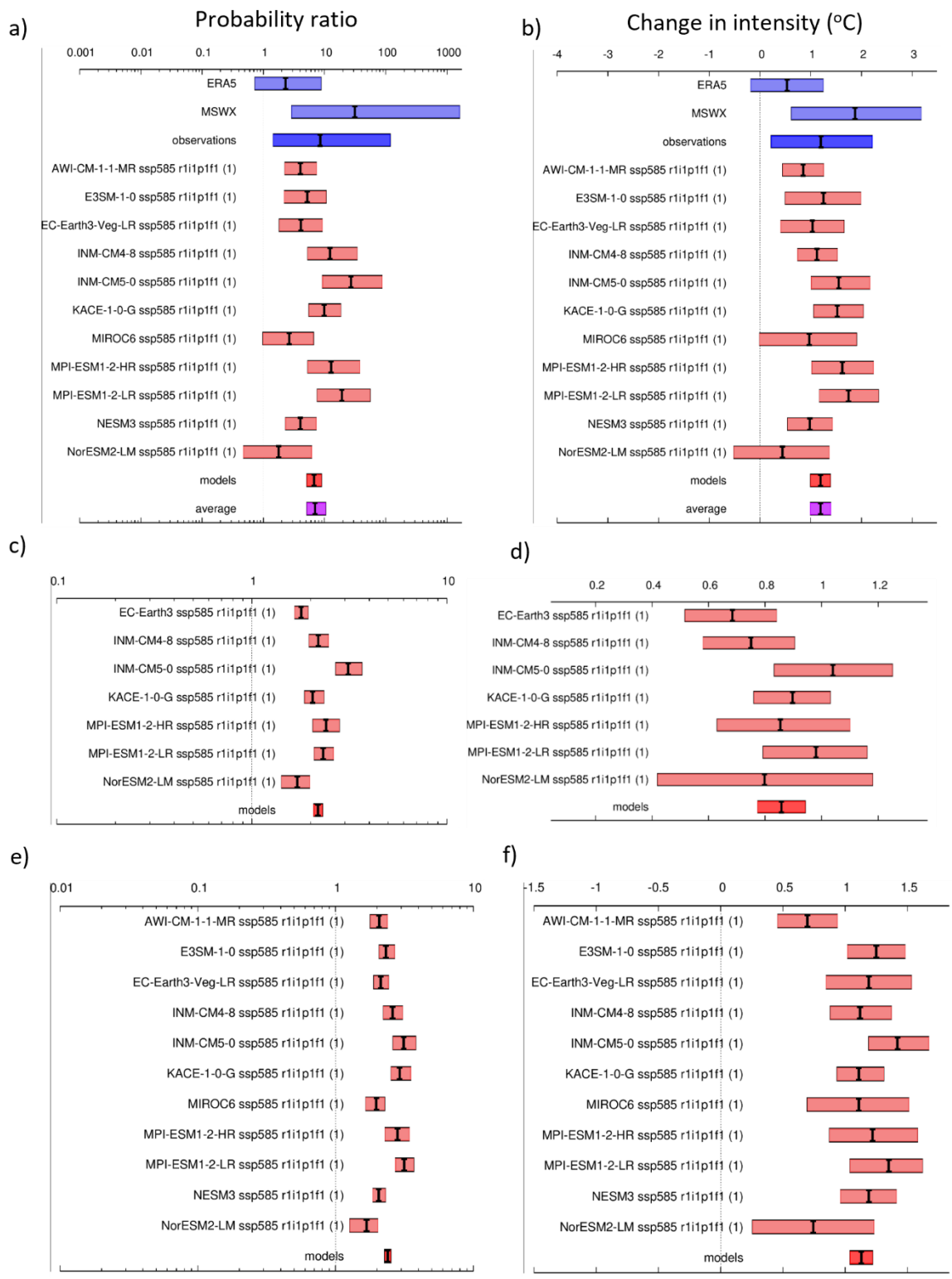


Figure 5.14: Synthesis of observational and model analysis of May daily maximum temperatures in the region over Pakistan, showing probability ratios (left) and change in intensity (right) due to anthropogenic climate change. a) and b) show changes from past to present day, c) and d) show changes from present day to 2050 in the SSP245 scenario, and e) and f) are the same for the SSP585 scenario.

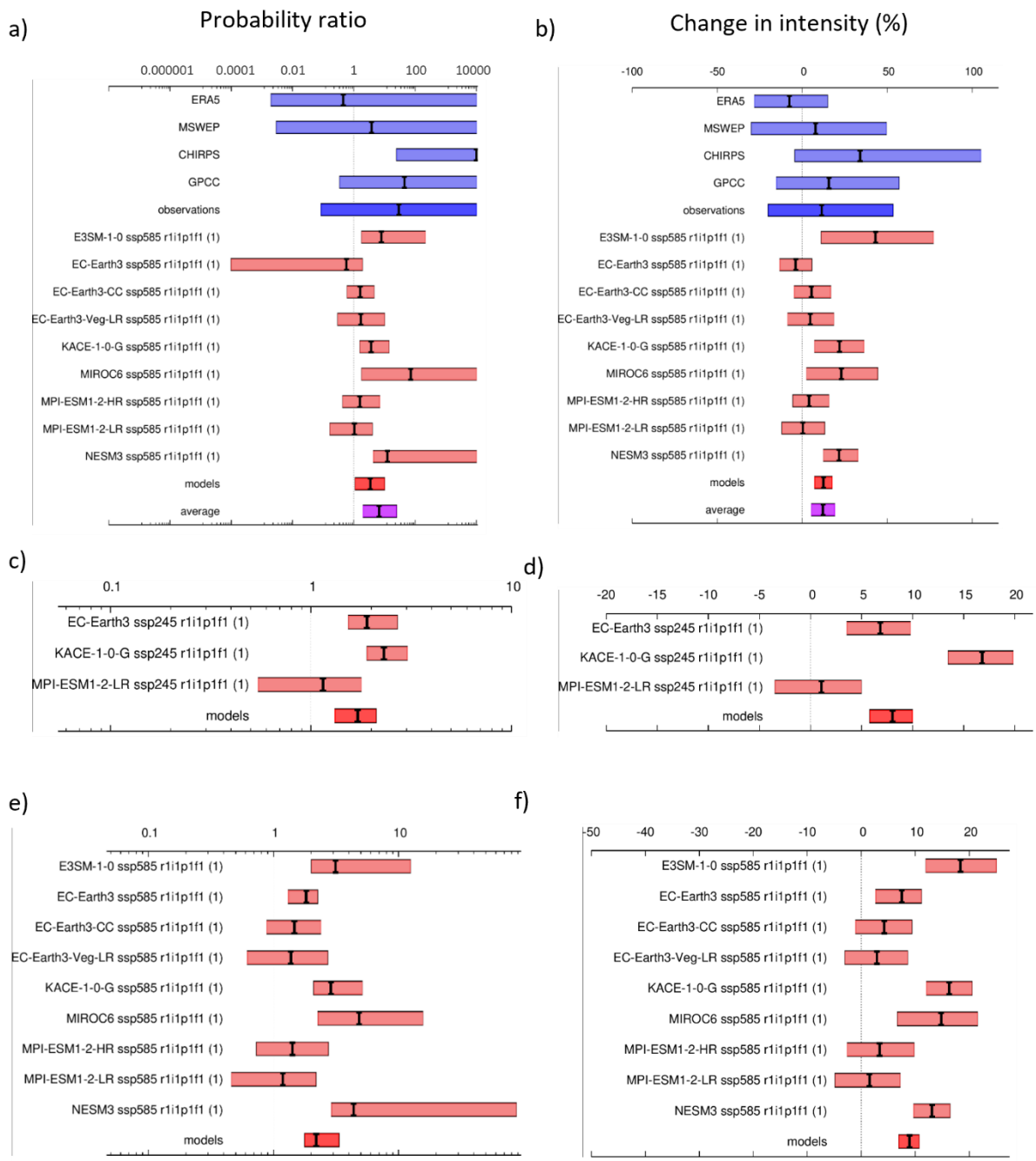


Figure 5.15: Synthesis of observational and model analysis of Indus basin 60-day JJAS precipitation, showing probability ratios (left) and change in intensity (right) due to anthropogenic climate change. a) and b) show changes from past to present day, c) and d) show changes from present day to 2050 in the SSP245 scenario, and e) and f) are the same for the SSP585 scenario.

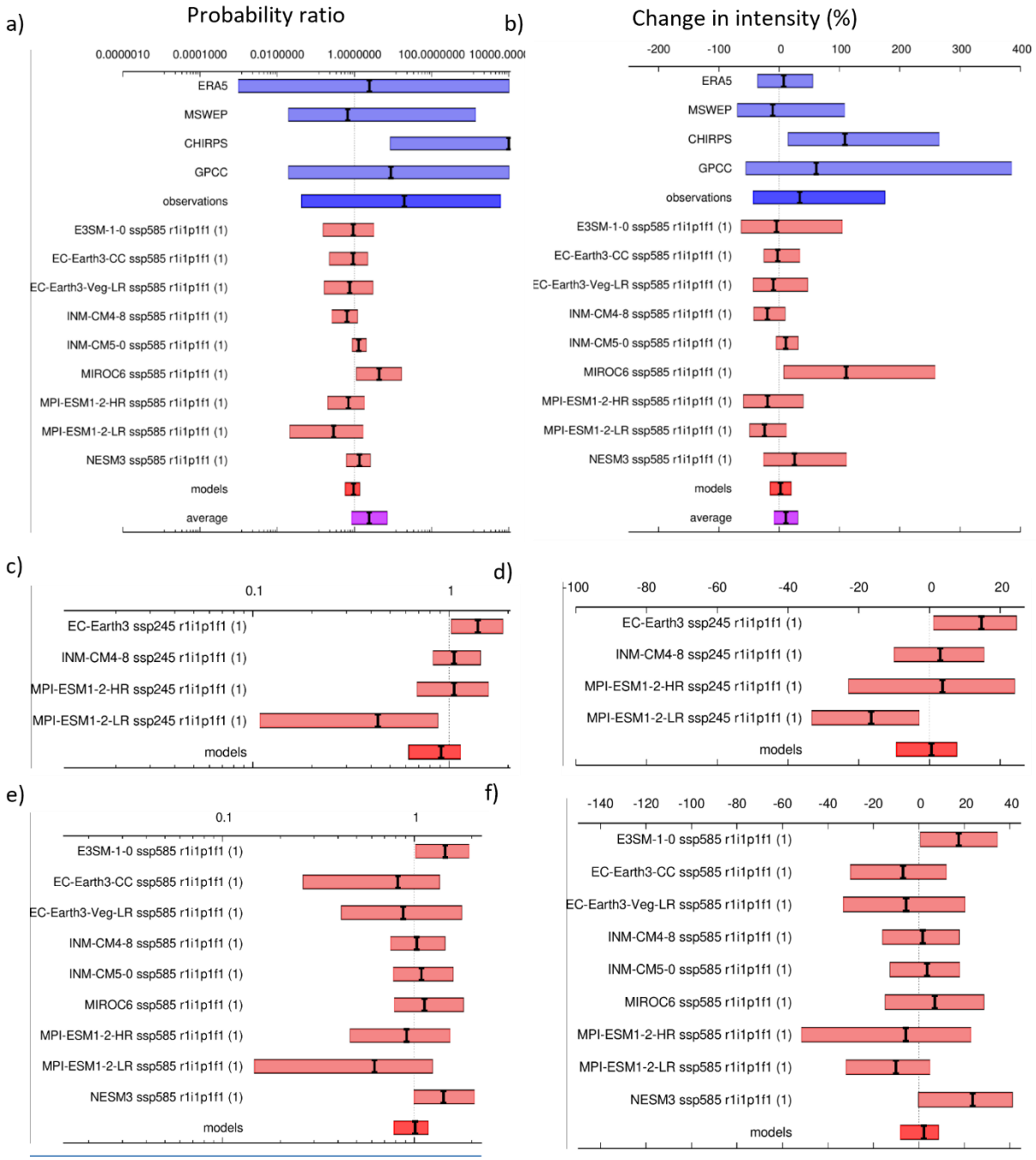


Figure 5.16: Synthesis of observational and model analysis of BS region 5-day JJAS precipitation, showing probability ratios (left) and change in intensity (right) due to anthropogenic climate change. a) and b) show changes from past to present day, c) and d) show changes from present day to 2050 in the SSP245 scenario, and e) and f) are the same for the SSP585 scenario.

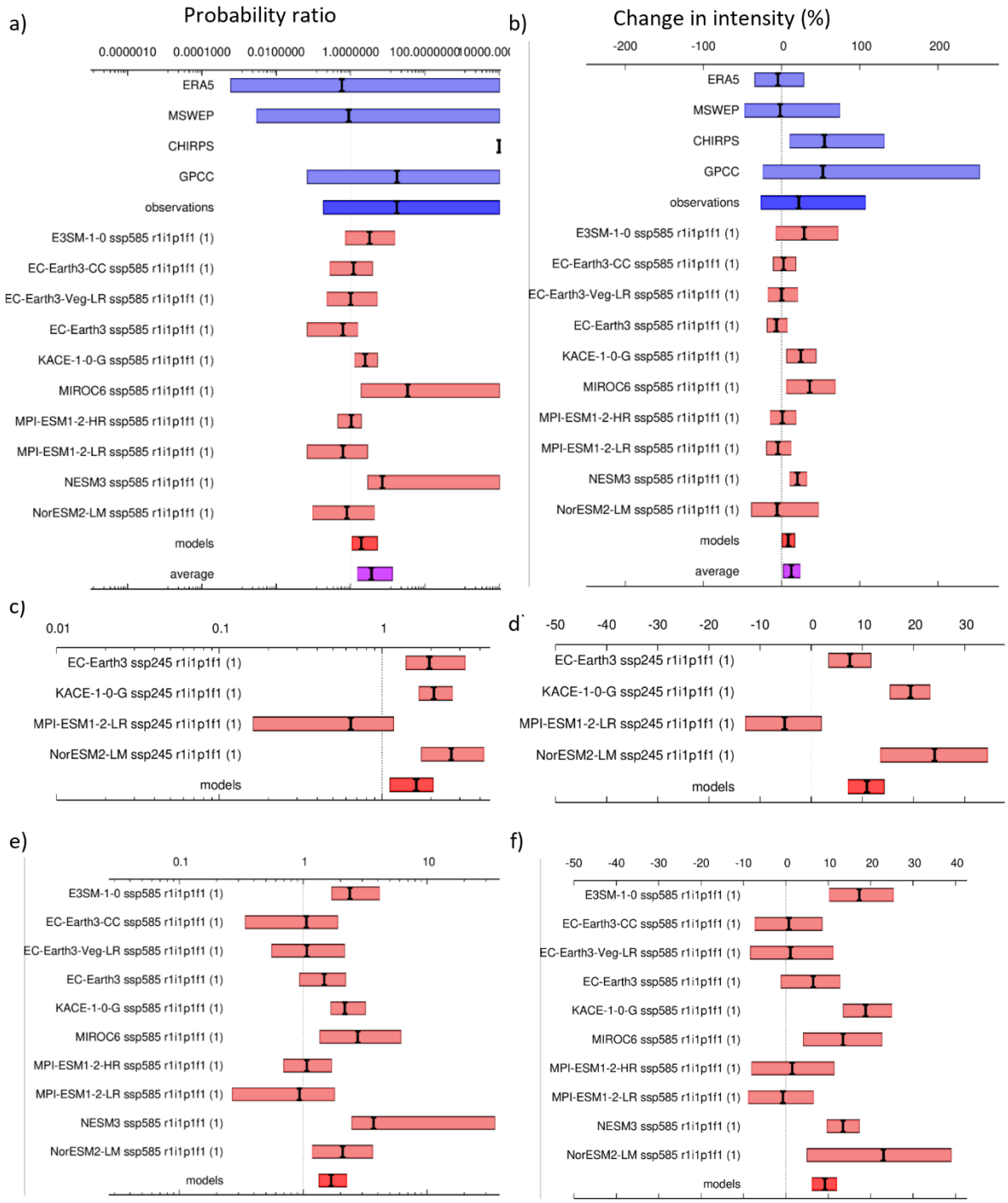


Figure 5.17: Synthesis of observational and model analysis of compound precipitation, showing probability ratios (left) and change in intensity (right) due to anthropogenic climate change. a) and b) show changes from past to present day, c) and d) show changes from present day to 2050 in the SSP245 scenario, and e) and f) are the same for the SSP585 scenario.

An increase in May temperatures is expected in a warming world, but it is useful to quantify the changes at present and across various scenarios, especially in light of its postulated connection with rainfall extremes in the Indus basin. The likelihood of May temperatures like 2022 has increased 7-fold since preindustrial times, and a further doubling at least is expected by 2050, with variation in likelihood of approximately ~20% dependent on the scenario (Figure 5.14, table 5.7). The change in intensity of 1 in 4 year events will increase roughly the same as the overall GMST increase.

At present, all rainfall extremes studied here are shown to have increased in intensity by around 11-12% (Figures 5.15-5.17, table 5.7). Probability ratios suggest a doubling in likelihood of BS region 5-day extremes, around 7-fold increase in the Indus basin 60-day extremes, and 3-4 for simultaneous events that lead to such devastating flooding. Future estimates across the Indus basin and in compound events are expected to increase by a further 8-11%, with the chance of such events likely to double again by 2050, though this depends on the emissions pathway. In the Indus basin, the SSP585 scenario results in an increase of 120% in likelihood and 9% in intensity, compared to a 70% increase in likelihood and 8% in intensity for SSP245. For compound events, the two emissions scenarios are very similar, suggesting that even lower emissions pathways are required to mitigate further risk of dangerous rainfall extremes.

5.3.4 Exposure and vulnerability

The analysis above provides an attribution of the changing heat and rainfall hazards. In order to link to changes in risk, it is crucial to account for the myriad factors that translate these extremes into impacts. The actual impacts of such hazards are heavily modulated by the people, assets and systems in their path (exposure) and their degree of susceptibility to such hazards (vulnerability).

Pakistan is a lower middle-income nation with the fifth highest population in the world and a highly spatially and temporally variable climate. As a nation, it is therefore extremely exposed and vulnerable to the impacts of climate change (Eckstein et al. 2021). This became abundantly clear through the sheer number of people affected by the flooding in 2022 at over 33 million (or almost 1 person in 200 on the planet).

Pakistan has undergone rapid population growth across the entire nation in the past ~70 years but especially in the southern provinces of Balochistan and Sindh, those most affected by the flooding. These population changes provide us with a very crude but nonetheless illustrative estimate of the changes in exposure due to population increase (Table 4). The clear implication is that even if there was no signal from climate change in present day extremes, the level of risk in the region is increasing rapidly. This directly affects the exposure of assets, the level of disaster response required in terms of evacuations, shelter and supplies, and the overall degree of risk of humanitarian crises on a larger scale.

Region	**Population (millions)**		**Exposure change factor**
	1951	2017	
Balochistan	1.17	12.34	10.55
Sindh	6.05	47.85	7.91
Pakistan	33.74	207.68	6.16

Table 5.8: Census data from 1951 up to 2017 for the regions of Balochistan and Sindh, and the entire nation of Pakistan.

Vulnerability is the third key determinant of risk and amplifies or mitigates impacts when people are exposed to some hazard, depending on an array of socioeconomic, cultural and institutional factors. Foremost, poverty is high in Pakistan. While the nation has experienced rapid economic growth in recent decades, GDP per capita remains low on the world stage, ranking at around 138 out of 192 countries (World Bank). Most crucially, around 38% of the population lived in multidimensional poverty as of 2018, a measure incorporating purchasing power and access to education and infrastructure, with around 5% still in extreme poverty (living on $2.15 per day or less) and 85% living on less than $6.85 per day (World Bank).

Vulnerability to both extreme heat and floods in Pakistan is further exacerbated by the predominance of the agricultural sector, which forms the primary source of income for ~37% of the population and one of the nation's main exports, providing nearly a quarter of national GDP (World Bank). Furthermore, the extremely hot and dry spring that preceded the wet summer was also amplified by anthropogenic climate change and had a substantial impact (losses of ~6%) on the wheat crop, and the agricultural sector more broadly as outdoor workers were most exposed to the heat (Zachariah et al. 2022a). The sector is also undergoing a rapid transition to livestock farming, which represents a significant and multi-year investment at the scale of individuals (Jamshed et al. 2018). They are also especially vulnerable to flooding and in the recent flooding 750000 livestock were killed (PMD 2022).

Insurance is often a key mechanism for mitigating the impact of disasters when they happen. While it does not avoid short-term losses, it softens the blow of losses, reduces the need for public emergency assistance and ensures that some assets can be regained rapidly, which in turn reduces cascading impacts including mental and physical health and long-term economic downturns on a broader scale (Kousky 2019; French and Kousky 2023). The data is sparse but parts of Pakistan have been shown to have extremely low insurance penetration (Ullah et al. 2021) and a negligible fraction (~1/200th) of the direct damages from the 2022 flooding were reported as 'insured' by international disaster database EMDAT (EMDAT 2019).

Factors that are external to the specific event and nation can also affect vulnerability, such as other compounding events and the state of interconnected global trade networks. For instance, in 2022, Pakistan was experiencing the repercussions of internal political turbulence, which dominated media headlines and likely lead to sluggishness in both disaster preparation and response by the authorities (Salikuddin and Siddiqui 2022; Bhutta et al. 2022). The ongoing partisanship and instability is likely to reduce the chance of forms of governance needed to build long-term climate resilience, for example through reform of water management systems (Pande 2022; Bhutta et al. 2022). The ongoing economic crisis has been deepened by both political turbulence and the flood impacts, slowing growth and increasing the nation's reliance upon IMF loans that come with austerity measures, thus further impacting the population (Salikuddin and Siddiqui 2022).

External to the nation, the loss of wheat in the dry heat also coincided with the invasion of Ukraine, which led to both a global shortfall in wheat from that breadbasket, and economic sanctions on Russia that sent global fuel prices soaring, which in turn compounded agricultural challenges in Pakistan further (Osendarp et al.; Jagtap et al. 2022; Ben Hassen and El Bilali 2022; Arndt et al. 2023). The food and fuel price volatility both contributed to the multidimensional impacts experienced in the wake of the flooding (Harvey et al. 2022), still ongoing months after the event (ReliefWeb 2023).

All of these factors point to increasing risk due to increases in vulnerability and exposure. In the face of extremely high levels of vulnerability and exposure, any change due to the hazard causes large changes in impacts. Reducing future risks in the region therefore requires focusing on all contributing drivers. However, it is also critical to underline that this event has already occurred and it likely would have been far less impactful in the absence of greenhouse gas emissions. Thus, regardless of the implications for future risks, loss and damage due to multiple compounding extremes amplified by anthropogenic emissions have occurred in Pakistan.

5.4. Discussion and conclusions

In this chapter I integrate multiple attribution analyses of the extreme heat and rainfall in Pakistan to understand the compounding drivers of risk, using the 2022 event as a case study that signals a clear and present risk. To do so, the events of 2022 and the analogue event of 2010 are explored. This shows a clear role for the thermal low in amplifying the rainfall extremes and that heat in late spring is crucial for this to develop. It also justifies the study of both short- and seasonal-scale rainfall extremes for assessing changes in flood risk.

I then build upon previous attribution studies of the rainfall (Nanditha et al. 2023; Otto et al. 2023) by using a range of high resolution observational and reanalysis datasets and the CMIP6 ensemble across three spatiotemporal events: one for extreme May heat over Pakistan, and two that together characterise the extremes that led to flooding. These are used to attribute changes in these extremes in the present day and three plausible future scenarios.

The direct effect of the anthropogenic influence on the May heat and the effect of this shift upon the subsequent high rainfall is also estimated, using this as a proxy for the thermal low that plays an important role in the monsoon. This is only undertaken using observational analysis but suggests a strong causal connection. In particular, extreme seasonal rainfall over the Indus basin is amplified by hotter May temperatures, with a roughly 5-fold increase in likelihood of events like 2022 due to the effect of anthropogenic warming on this mechanism to date. This is a novel multi-step hazard attribution, allowing us to test the anthropogenic influence on extremes that compounded not only through their impacts but also their causality.

The attribution analysis broadly ratifies and build upon prior studies. In particular, it indicates that climate change has most likely increased extreme May heat and both rainfall hazards in the present day and that this will increase with further warming. In all present day and future scenarios for the May heat and Indus basin rainfall, the results are statistically significant, suggesting increases in

intensity of May temperature extremes roughly in line with GMST and rainfall increases on the order of 10% (or equivalently, increases in likelihood by a factor of 7 and 6 times, respectively). For rainfall extremes in the BS region it is challenging to quantify this change in all scenarios due to the large uncertainties inherent in model simulations of the region, high variability and the small sample sizes available, though the best estimate intensity change is slightly above Clausius-Clapeyron scaling.

In addition, a novel compound attribution framework is developed by constructing a univariate index from a normalised combination of both rainfall events. This analysis shows that such extremes have also become significantly more likely and intense, by a factor of 3.6 and 12%, respectively. They will also continue to increase in all warming scenarios, but the magnitude of these changes are not monotonic across scenarios, suggesting that even moderate warming results in severe impacts. This in turn underlines the value in mitigating as much warming as possible to the population of Pakistan.It would be helpful to conduct similar analysis for lower emissions scenarios.

These hazard changes have occurred alongside other drivers of risk, such as population (table 5.8). As a result, for extreme heat affecting the population of Pakistan the joint increase in hazard and exposure is a factor of ~42 (combining the 7-fold hazard likelihood and 6-fold population increase), while for compound flooding affecting BS it is ~30 (combining the 3.6-fold hazard likelihood and ~8-9-fold population increase), representing a substantially elevated risk of impacts upon people assuming constant vulnerability. More broadly, coupled with changes in population and the context of other events, the attribution analysis shows that climate change was a one of several key drivers of the impacts; it provided a likely increase in an already highly at-risk society under duress due to internal and global events. It therefore provides a warning about changing risk going forwards, underlines the importance of disaster risk management in Pakistan to reduce vulnerability to similar extremes, and can contribute evidence to global stocktakes of the ongoing loss and damage due to anthropogenic climate change.

To facilitate these efforts and further scientific understanding, additional work is required on a variety of fronts. For instance, undertaking a direct analysis of flood risk would be informative for both risk management and scientific understanding of the mechanisms driving flooding. This could either be undertaken causally, using the rainfall analysis here to drive inundation models, or in parallel, using pre-calculated maps of flood risk to estimate the change in return period of events such as this. It would also be informative to further explore the climatic causal mechanisms leading to this event. For instance, the co-occurrence of states of ENSO and the Indian Ocean Dipole, heat content in the Indian ocean from which the moisture originated, and the configuration of the mid-latitude jet stream. Some but not all of these factors bore a distinctive signature during the 2010 floods (Di Capua et al. 2021). The anthropogenic influence upon and in the presence of such a configuration (Rogers et al. 2022) may then provide greater insight into the overall changes in hazard probability going forwards.

More broadly, it would be informative to study plausible risk scenarios, featuring event similar to 2022 in the context of a variety of internal and external compounding risk factors, such as anthropogenic amplification of the event, outbreaks of disease or pests, geopolitical strife affecting global supply chains, and wealth and population scenarios. This constitutes a conditional (storyline) approach and would help to partition uncertainties in the incredibly complex task of risk prediction and thus inform greater resilience (Hazeleger et al. 2015; Shepherd et al. 2018).

Chapter 6 - Conclusions: A new era for extreme event attribution?

6.1 Aims and findings: Thesis only the beginning

In the global conversation, there is an abundance of evidence surrounding the mitigation of climate change. This contrasts starkly with the evidence available for adaptation and loss and damage purposes. In part, this is because the latter issues have a far more complex causal link to climate change, suffer from heterogeneities in data availability, and generally have a higher dimensionality. However, they are just as pertinent. It is challenging to assess the relative contributions to risk posed by a given lack of mitigation versus a given lack of adaptation, but a substantial level of global warming is already locked in, which means that both are critical. Furthermore, widespread and unequal loss and damage has already been experienced and grows cumulatively. The non-linearity of extreme weather impacts with magnitude, and of the rate of increase of some of the most severe weather thresholds with global warming, reinforces the imperative for adaptation and loss and damage recording.

As set out in section 1.2.2, this thesis is concerned with the overarching and substantial challenge of understanding the risks and impacts of climate change on human systems through its influence on extreme weather around the world. In particular, the thesis aims to do this by using the framework of extreme event attribution and capitalising on the hundreds of studies that already exist, in which the fingerprint of climate change on many past (and thus definitionally plausible) events has been tested and, in many cases, identified and quantified.

To this end, in order to identify the current strengths and gaps in the knowledge, this project began with a very broad review of the relevant literature to assess the degree to which the impacts of recent extreme weather events could be attributed to climate change. This is a complex and multi-faceted challenge, with unique causal processes and attribution capabilities across the different hazards, and unequal recording of impacts and scientific study of extremes in different parts of the world. However,

a substantial body of evidence suggested that climate change was most often increasing the intensity of extreme weather events with devastating impacts. In addition, it suggested that there is a vast diversity in the signal and degrees of causality for different hazards in different regions. This pointed to the imperative for understanding this in far greater detail and in a more equitable way.

As a result, I identified three research areas for improving his understanding: first, record the impacts of extreme weather far more systematically around the world; second, improve the coverage of attribution for more regions around the world, for a more diverse range of hazards, and with a focus on event definitions that are most pertinent to the impacts upon people; third, bring attribution into broader risk analysis to elucidate climate change as one driver of risk among others. Advancing efforts towards each of these formed the three pillars of my research. The aims below do not correspond directly to the recommendations, in part because these are broader challenges for the field, but they each represent (an evaluation of) one practical step towards achieving them.

Aim 1: Documenting past events and their impacts in a systematic manner

To address the first aim, I compiled inventories of recent extreme weather events that occurred from 2000-2019 within the UK and Puerto Rico, alongside their impacts and any attribution statements that exist. I then conducted a meta-analysis of this system, which involved the implications and potential use cases of collecting this data.

Attribution has vast potential calculating loss and damage by linking the global phenomenon of climate change to lived experiences. While the use of the traditional FAR approach is clearly flawed for approximating attributable impacts, it provides a first order estimate when many events are gathered together, as in an inventory. It also gives a more valid estimate of expected costs over hypothetical, extended periods with elevated carbon dioxide levels. Additionally, a growing number of studies provide an attributable magnitude change as well as the traditional probability approach, which is more applicable for causation. This is becoming increasingly pertinent to the international

conversation given the existence of a loss and damage fund since COP27 (Mahase 2022) and the increasing (albeit very slowly) pervasiveness of adaptation discussions in global summits (Leiter 2022).

For risk assessment and adaptation purposes, the information in an inventory was shown to be useful to highlight ongoing vulnerabilities. This was illustrated with a simple attribution study based on the information recorded for a heatwave in the UK in 2018, in which hundreds of people died, most of whom were over 65. Changes in the hazard, both in the present day and in the future, were then combined with projected changes in exposure, both of the general population and the highly vulnerable older population. This showed how these combine to form a non-linear change in both present and future risk without any change in vulnerability. Finally, such information provides an avenue for exploring the risk of extremely rare or even 'unknown unknown' events, by using past events as 'near misses' of similarly plausible but far more impactful disasters.

There is an array of limitations inherent in this approach. First, the comprehensiveness of such a system is constrained ultimately by the existence of the input data (meteorological, impacts and contextual information, and attribution results), which is highly heterogeneous around the world. It is also impossible to guarantee comprehensiveness due to the use of impact thresholds for inclusion, which inevitably eliminates events that still did have an impact, and in particular biases the system against those events that may have crossed such thresholds in the absence of climate change. However, standardising and open-sourcing the process of such data collection is the fairest and most comprehensive system possible, and indicates most clearly where deficits in such recording likely exist. Additionally, the non-linearity of impacts from many extremes means that a threshold-based system should still capture the majority of all impacts. Input data may also be constrained by language barriers around the world. While an inventory would begin primarily in English, gathering data from around the world could be facilitated through providing guidance in a range of languages, and eventually may benefit from input forms tailored to specific nations or regions.

Second, an inventory is a collation of an array of information types, including across multiple fields of science, intended for use by all. It may therefore be prone to misinterpretation, especially regarding the attribution of impacts. While the inventory in its published form does contain an explanation of the event definition, this is likely not easily interpretable by non-experts. As such, I envisage a sliding scale indication of how applicable the event definition is to the actual primary impacts experienced (with this explicitly clarified where it is not immediately obvious which the primary impacts are). This could also be reinforced with a direct 'interpretation' column. This requires expert judgement, ideally added by the attribution researcher(s), and is therefore also prone to a degree of informed subjectivity. However, as a general guide, attribution statements on abstract phenomena (such as event definitions that are selected based on maximising the climate change signal) have the lowest applicability, those selected to relate closely to impacts have medium applicability, and those with causal modelling systems have the highest. This would also be facilitated by a user guide to the inventory and an explanation of exactly how these conclusions are drawn. It would also be facilitated by a robust and regular system for adding information to the inventory. The attribution researcher(s) responsible for results would be best placed to add this information and could do so in the wake of either a rapid or full published study, with results from rapid (non peer-reviewed) studies demarcated using an asterisk or similar.

Third, the impacts of many events are very complex, spatially heterogeneous, and arise from a number of aspects of a given meteorological system coupled to the land surface, hydro-, bio- and cryo-spheres. This leads to both primary and secondary impacts in many cases. I could make a number of changes to improve impact recording in the face of this complexity. For example, by including the secondary impacts (in the same way that secondary hazards are already recorded within EMDAT) separately where they would independently cross the threshold for the inventory, with an option for 'uncertain' to explicitly show that this has not been deciphered in a given case. I could also endeavour to include a map of the impacts of a given type, for instance the hospital admission or mortality rates in a

heatwave, or the inundations due to pluvial and coastal flooding during a hurricane, to facilitate future investigation.

Finally, the use cases mooted in the published paper could be enhanced further by including additional contextual information. In particular, maps of the synoptic conditions leading to the extreme would enable users to quickly determine the baseline causation behind the extreme and compare to other events. This would enable a smoother investigation of unprecedented events, as well as the derivation of attribution results for new events based on past similar cases as suggested in chapter 4. Separately, in the event of some extreme striking the same location repeatedly, it would be informative to record the level of recovery achieved at the time of the subsequent occurrence. Rate of recovery is a measure of resilience, while the level of recovery affects the overall impacts.

By itself, and with the changes suggested above, this inventory system would provide a greater platform for understanding past impacts and costs of climate change, crucial for the loss and damage conversation, as well as ongoing vulnerabilities that will inevitably lead to future risks in the absence of adaptation and mitigation. It also provides much of the contextual information needed to explore plausible risk due to different drivers or even otherwise unprecedented events. It therefore fulfils the first aim and provides a valuable milestone in the first challenge set out in the literature review.

Aim 2: Assess when we need new attribution studies by utilising existing evidence more effectively

This aim fits within the much broader push to improve the coverage of attribution studies for hazards and regions that are currently understudied. I hope that it may do so by directing scientific research to where it could make the most difference in the face of limited resources for conducting studies.

The first part of this study features a discussion on the various use cases for attribution results, concluding what the minimum level of information is in each use case: for the purpose of

communicating climate change, an estimate of the change in magnitude or probability is ideal but a simple change in the sign is still valuable; for adaptation, the same is true but uncertainty estimates and future changes are also valuable, the context of exposure and vulnerability is crucial to include a broader consideration of risk; finally, for estimating loss and damage, a quantitative statement is necessary, with contextual information including exposure, vulnerability and the relationship between magnitude and impacts where possible. This information is crucial for determining when we need a new study based on the process developed in the remainder of the chapter, which shows when we can and cannot attain certain types of information, and to what degree.

This is explored through three case studies of specific hazards within specific regions. I show that for some cases, such as heatwaves in the UK and hurricanes in the North Atlantic, nearly all use cases can be satisfied by studies that already exist (combining attribution and other regional climate information). It is worthy of note that for some cases, such as highly localised extremes and scenarios, more specific risk assessment is likely still required. For other cases, such as drought in East Africa and rainfall in most of the world, it is sometimes possible to derive a new statement depending on the use case. For a final category, including all types of drought and wildfires in most of the world, new attribution studies are urgently needed for all purposes.

This chapter develops a framework to facilitate the production of more results, rather than conclusions that actually produce them. In doing so, it still requires work and resources to derive the results. Furthermore, there is an intrinsic compromise in every such case because deriving rather than directly calculating the new attribution statement sacrifices the addition of new data (other than the raw knowledge that such an event occurred); it will never be as accurate or as precise as doing a new study.

It will also always, for as long as global warming increases, be necessary to eventually conduct new studies for all hazards and regions. To minimise the impact of this, benchmark events could be reassessed at regular intervals (for example, every 0.5 °C of global mean temperature) to sketch out a

trajectory of change. Additionally, phenomena with climate signals that were once projected to emerge at future global warming levels, such as wind speeds from tropical storms, must be reassessed as events occur. Despite this, the system developed here still saves on resources and points towards areas for prioritisation.

In some cases, it is only possible to derive a direction of change, which seems relatively futile. Even in the simplest case of raising awareness of climate risks, this is a minor amount of information. It is also very similar to the kind of information that can come from traditional trend and projection analysis. However, I would argue that it still has value due to the specific nature of a single extreme; climate model analyses are often tied to future changes on a regional scale whereas attribution describes an event in a specific location with specific drivers in the present day.

This chapter does not directly improve the global coverage of attribution studies. However, in as much as this chapter aims to use past studies more effectively to facilitate this, it succeeds. In the course of this, I also inherently highlight the areas in which attribution studies should be directed to maximise both equity and scientific value, which is critical to refining the overarching aim. Additional improvements on global coverage could be made through the other suggestions in the conclusions of the literature review.

Aim 3: Integrate attribution into a broader risk framework for a recent extreme event

In line with the conclusions of chapter 3, very recent impactful extremes (and those longer ago but without clear signs of reductions in vulnerability and/or exposure since) represent an ongoing vulnerability. This is especially the case when attribution analysis shows an increase due to climate change, suggesting an increasing trend in at least one driver. The Pakistan heatwave and floods of 2022 exemplify such a case.

I posit that extreme event attribution across a range of aspects of an event is useful for understanding changing drivers of risk, in a way that is applicable to a wide range of uses. In this chapter, I explore this assertion by studying the case of the Pakistan extreme heat and rainfall of 2022.

Our attribution analysis builds upon previous studies of the event, in particular by using different models (thus helping to ratify conclusions where agreement is reached), studying the extreme heat that preceded and likely amplified the rainfall (quantifying the latter effect), using multiple future scenarios, and studying the compound nature of the flooding. I find likely increases across nearly all scenarios and event definitions of rainfall alongside increases in the late spring heat that constitutes a key driver. In all present day and future scenarios for the May heat and Indus basin and compound rainfall, the results are statistically significant.. By 2050, the changes in extremes are stronger for higher warming scenarios. However, current changes have already combined with rapid increases in population in the region to pose a substantial humanitarian threat.

Considered together, this thesis constitutes an attempt to use what we already have available to understand risks and impacts within a rapidly changing climate system. It shows that a pragmatic approach to using the imperfect information that we already have available is a significant improvement on waiting for an idealised system of global risk assessment. Furthermore, this can aid us in directing the limited resources invested in attribution research to where it is likely to deliver the greatest benefits in an equitable manner.

6.2 Blue and grey skies in attribution: Recommendations and future work

The course of researching this thesis has also provided broader reflections on practices within the field of EEA and its place within the wider field of climate science. At the 20th anniversary of the field, it has moved from largely hypothetical beginnings to its current status as a well matured, modernised and increasingly societally-relevant science. This is evidenced by the vast array of methods that now fall

within the field, the hundreds of studies for events around the world, the inclusion of broader risk information into hazard studies, the numerous discursive studies permeating the conversation, the existence of a peer-reviewed protocol for rapid attribution, and its penetration into news cycles and global climate reports alike.

Clearly, it has already come a long way since its conception (during which time atmospheric CO_2 has increased by approximately 40 ppm). However, the field is now ready for a new step change in its development to become commensurate with the risks posed by increased and increasing greenhouse gases. The natural next stage of this field is part scientific and part operational service. The latter is embodied in calls for operationalisation of a rapid attribution service by national met services. It is also encapsulated within the future changes that are set out in the introduction, and those suggested by the literature review to specifically improve the attribution of impacts.

But the state of the field and ideas within this thesis mean that we can now also answer a broader question that encourages a pragmatic and proactive approach in a changing climate. Namely, when a new extreme event occurs, how should we think about it in a way that provides useful insight for users of such information, is within our means, and maximises equity and scientific value?

The foundation of this going forwards should be a global inventory of extreme events, their impacts, and their attribution. This will ensure that we have the best possible idea of the evidence that already exists as new events occur. It will also provide a valuable and actionable line of evidence for the increasingly pertinent loss and damage conversation, particularly feeding into the distribution of the new climate Loss and Damage fund.

With that established, a coordinated and 'operational' system on a global scale could evolve as follows:

Given an extreme event with major impacts, it is documented by experts (ideally those equipped with local knowledge), within the same inventory system.

Other existing information is then consulted. Based on the demands of an attribution study for an event, it is determined (using the framework set out in chapter 4) whether a new study is required. This could take the form of a formal decision-tree, which should include the following questions:

- Are there existing studies in the region for the same type of hazard?
- Do the causes of the event match or partially match previously attributed events?
    - Was this event unprecedented in magnitude?
    - If so, are there some aspects of this event that match past events?
- What are the dominant questions being asked of an attribution study for the event?
- What other events are under investigation and what is the relative value of a study to prospective users, with a focus on improving equity?

With this information, it is possible to build a recommendation either to conduct a new study or that one is not required, with guidance on how to derive the information of interest without it. In essence, if attributing the event explicitly would add value (relative to other demands on the finite resources of attribution at the time of occurrence), then a study should be undertaken. This should be a consideration even in an ideal operationalised service to prioritise resources for the most impactful and scientifically interesting events.

In the event of a new study, the actual study methods that are appropriate and the level of conditioning depend on the questions being asked, the study timeframe, and the key sources of uncertainty involved. These should follow current good practice, as set out in the published protocol for probabilistic approaches (Philip et al. 2020; van Oldenborgh et al. 2021), but broadened for a compound events framework, and the current leading thinking on storyline framing (Shepherd et al. 2018). While the distinction between probabilistic and storyline approaches is useful for understanding the trade-off offered by conditioning, it is ultimately arbitrary and should be unified into a single EEA framework within which the type and degree of conditioning is simply a tool for tailoring the investigation to optimise utility.

Further to this, a unified system would include explicit acknowledgement of the value-based decisions involved in the level of conditioning used, alongside recommendations of how conditioning is being (and perhaps also could be) used to explore the influence of different drivers of impacts. This system should strive for informativeness above perceptions of reliability, protecting against both type I and type II errors in equal measure. This consideration is particularly when deep uncertainties may undermine the potential for detecting results. Unifying the field along this axis – bringing together methods that are currently considered as largely disparate – could be facilitated by setting out a guide to the types of questions that EEA can answer. Hypothetically, this unification process would be most effective under the auspices of a global committee such as an IPCC task-force or the Transitional Committee for Loss and Damage, bringing together attribution experts globally to inform changes in risk. The outcomes of such an undertaking could then feed directly into the Loss and Damage fund and assessments of risk.

Finally, once an attribution study has been conducted, it can form a valuable input to a variety of applications from within an inventory. In the case of risk assessment and adaptation planning, attribution is well placed to assess the climate change driver of a given risk, comparing it to other individual drivers, alongside a more consolidated approach to overall risk. Again, this would be most useful if managed by a globally-recognised body.

6.3 Pretentious closing remarks

Changes to extreme weather impacts are the tip of the spear that is anthropogenic climate change. Across the world, the probability and intensity of some of the greatest perils faced by societies are changing rapidly. The signature of this unnatural perturbation has been manifesting in events for decades, adding a toll in lives, livelihoods, wealth, and innumerable less tangible assets including health, well being and cultural and historical sites. It is an insidious tax on civilisation's fossil fuel addiction. In much of the popular understanding, the apocryphal stories are of doom and despair, or

of dogmatic denial, both born of fear and ignorance. In our complex reality, changes in risks are not so convenient.

In the dark and multidimensional landscape of risk, extreme event attribution studies are lighthouses elucidating small regions of peril. With enough of them, we can build up a network of understanding to compliment all that we know from other sources. This field is now ready to be viewed in such a way; though the landscape is vast, lighthouses festoon and illuminate it.

Regardless of the inscrutable choices of world leaders in the years to come, extreme event attribution can become an increasingly valuable contribution to the conversation around climate change, forming a fresh and complimentary line of evidence both in how we think about and manage risk, and in assessing the costs of climate change that we are all bearing.

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