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LETTER

On the attribution of the impacts of extreme weather events to anthropogenic climate change

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Abstract

Investigations into the role of anthropogenic climate change in extreme weather events are now starting to extend into analysis of anthropogenic impacts on non-climate (e.g. socio-economic) systems. However, care needs to be taken when making this extension, because methodological choices regarding extreme weather attribution can become crucial when considering the events' impacts. The fraction of attributable risk (FAR) method, useful in extreme weather attribution research, has a very specific interpretation concerning a class of events, and there is potential to misinterpret results from weather event analyses as being applicable to specific events and their impact outcomes. Using two case studies of meteorological extremes and their impacts, we argue that FAR is not generally appropriate when estimating the magnitude of the anthropogenic signal behind a specific impact. Attribution assessments on impacts should always be carried out in addition to assessment of the associated meteorological event, since it cannot be assumed that the anthropogenic signal behind the weather is equivalent to the signal behind the impact because of lags and nonlinearities in the processes through which the impact system reacts to weather. Whilst there are situations where employing FAR to understand the climate change signal behind a class of impacts is useful (e.g. 'system breaking' events), more useful results will generally be produced if attribution questions on specific impacts are reframed to focus on changes in the impact return value and magnitude across large samples of factual and counterfactual climate model and impact simulations. We advocate for constant interdisciplinary collaboration as essential for effective and robust impact attribution assessments.

1. Introduction

Extreme event attribution (EEA) is a climate science field where the influence of physical drivers is isolated for specific extreme events. Commonly, the driver of interest is anthropogenic climate change, considering the influence on the frequency or magnitude of observed extremes. Since its conception (Allen 2003), there has been a wealth of attribution studies assessing how anthropogenic climate change has altered notable and high-impact events (e.g. Peterson *et al* 2012, Herring *et al* 2020). Although exact methodological approaches vary, many studies rely on climate models providing simulations of factual and counterfactual climates, in other words, simulations where observed anthropogenic climate forcings are included, and simulations where these forcings are omitted. Large sample sizes are essential, achieved by fully-coupled multi-model ensembles (Lewis and Karoly 2013), multi-member ensembles of single or multiple models where initial conditions and or/physics differ slightly (e.g. Pall *et al* 2011, Massey *et al* 2015, Perkins and Gibson 2015, Guillod *et al* 2017, Hope *et al* 2018, Stone *et al* 2019), or a combination of these. Moreover, there are multiple techniques to undertake event attribution assessments, such as the fraction of attributable risk (FAR) probability framework (Allen 2003, Stott *et al* 2004, Stone and Allen 2005); the story-line approach (e.g. Hoerling *et al* 2013, Trenberth *et al* 2016, Shepherd 2016, Zappa and Shepherd 2017, Patricola and Wehner 2018, Wehner *et al* 2019, Reed *et al* 2020); a comparison of model ensembles with different forcings and/or physics (e.g. Hope *et al* 2018); and statistical estimations of shifts in extreme return levels (e.g. Eden *et al* 2018). While FAR is commonly used in EEA assessments, any method must accurately reflect the attribution question being asked, which should be clear in the initial study design (Otto *et al* 2012, Stone *et al* 2021).

Recent research is focusing on what we term 'impacts attribution', an extension of EEA to specific impacts within non-climate systems. Examples of impacts attribution assessments undertaken include human mortality during heatwaves (Mitchell *et al* 2016), the sustainability of fisheries (Litzow *et al* 2021), coral bleaching during marine heatwaves (Lewis and Mallela 2018), incurred financial damages from hurricanes (Frame *et al* 2020a, Wehner and Sampson 2021) and financial damages from flooding and landslides associated with extreme rainfall events, and drought (Frame *et al* 2020b). Some impact attribution studies have relied on FAR (see section 2.1) to determine the anthropogenic signal behind a specific extreme event, and its impacts. However, the interpretation of results has been inconsistent with their application of FAR. FAR measures the change in frequency of a class of events, and an impact is a specific outcome of a singular event (Harrington 2017); FAR-based impact attribution studies have interpreted results as applicable to the outcome rather than the class (e.g. Mitchell *et al* 2016, Frame *et al* 2020a, 2020b). We demonstrate this distinction for two examples of impacts caused by extreme events to show that the issue is systemic and does not pertain to just one type of extreme event/impact combination.

2. Fraction of attributable risk (FAR) and case studies

2.1. The fraction of attributable risk (FAR) method

FAR is an attribution diagnostic obtained by comparing frequencies of a class of events in factual and counterfactual simulated climates, where the class is defined by a fixed magnitude threshold, commonly a recently observed weather extreme (e.g. Stott *et al* 2004). Some recent studies have attempted to extend the FAR methodology to attributing changes in impacts to anthropogenic influence (Mitchell *et al* 2016, Frame *et al* 2020a, 2020b). Whilst this paper outlines caution in this extension, the method is powerful for attribution studies in general, including classes of impacts (see section 4.2).

Computed FAR values correspond to the change in likelihood of events due to the causal factor (e.g. anthropogenic climate change) with the same or greater (or lesser, depending on the type of extreme) magnitude of that threshold, and not the individual threshold itself. To understand how anthropogenic climate change influences extreme events, the method compares the frequency of events greater than or equal to a threshold in the factual (which includes historical anthropogenic forcing) and counterfactual (anthropogenic forcing is omitted or removed) climate model simulations:

$$\mathrm{FAR} = 1 - \left(\frac{P_{\mathrm{cfact}}}{P_{\mathrm{fact}}}\right) = 1 - 1/\mathrm{RR}$$

where P_{cfact} is the event frequency in the counterfactual simulations and P_{fact} is the event frequency in the factual model simulations. The risk ratio (RR), also known as probability ratio, is regularly reported in attribution assessments, and is related to FAR as follows:

$$\mathrm{RR} = \frac{P_{\mathrm{fact}}}{P_{\mathrm{cfact}}} \text{ or } \mathrm{RR} = 1/\left(1 - \mathrm{FAR}\right).$$

RR is often used in communicating attribution statements due to its ease of interpretation compared with FAR (note that RR still applies to a class of events). The RR allows statements such as 'the probability of a class of events occurring is RR times what it would have been without anthropogenic influence on the climate' whereas FAR addresses the responsibility of a causal factor for the occurrence of a class of events. For instance, a FAR of 0.9 means that 90% of events in the defined class that have occurred can be attributed to the forcing (Stone and Allen 2005). This interpretation assumes that events can be allocated into a group that would have occurred regardless of forcing, or a group that occurred only because of the intervention, but this allocation can only be determined statistically (Hansen *et al* 2014). The chaotic climate system does not satisfy this assumption, but the interpretation is still considered useful in understanding anthropogenic influence provided it is not taken too literally. We focus on FAR and not RR in this study, since FAR has been computed in recent impact attribution studies (e.g. Mitchell *et al* 2016, Frame *et al* 2020a).

We employ FAR to determine how anthropogenic climate change has altered the likelihood of the class of extreme events in each case study discussed in section 2.2. We also replicate how FAR has been used to estimate the anthropogenic signal behind corresponding impacts (Mitchell *et al* 2016, Frame *et al*

2020a). This demonstrates how FAR estimates may vary both across different extreme events and the impacts; and what it really means when FAR analysis is performed on the estimated impacts of extremes.

2.2. Case studies

In addition to investigating different types of extremes and their impacts, our case studies were chosen to fulfil multiple criteria:

- availability of existing climate model data that adequately simulates the type of extreme event of interest.
- documented relationships between the type of extreme event and the severity of an impact, and:
- availability of a functional formulation relating climate variations underpinning the type of extreme event to an impact (we refer to these as transfer functions).

Our first case study is the hottest day during the 2006 UK summer, a record-breaking summer at the time (Prior and Beswick 2007), and the impacts of the high temperatures on human mortality. The second is the New Zealand extreme rainfall event that occurred on the 4 April 2017, causing wide-spread property damages to the North Island (www.icnz.org.nz/natural-disasters/cost-of-natural-disasters/, accessed 12 June 2020). We briefly describe each below, with methodological details given in the supplementary material.

We rely on transfer functions between weather and impacts previously defined in the literature to estimate impacts of the causal extreme event, with the assumptions that they are fit for purpose in estimating the relative impact from the causal event, and that the impact is altered only by anthropogenic climate change influencing the causal event (i.e. the impact is not altered by other influences such as effective adaptation or mitigation, or that climate change directly alters the transfer function). Note that it is not within scope to evaluate the utility of previously defined transfer functions and how their assumptions or characteristics may impact the resulting attribution assessments. For example, our second case study focuses only on publicly funded insurance payouts for residential property damage (see section 2.2.2 and supplementary material), ignoring the much larger private insurance liability for asset damages as well as downstream economic costs.

2.2.1. UK heat in 2006 and associated mortality

The UK summer of 2006 was unusually warm (Prior and Beswick 2007). July 2006 in the UK was the hottest on record at the time, and a large heatwave covering much of continental Europe and the UK persisted through July. This resulted in large increases in excess temperature-related mortality across the season. In terms of our illustrative attribution assessment, we define our event as the single day with the highest heat-related mortality for London, UK. This was the 26 July, with ∼60 deaths attributable to heat. The observed mean temperature was 26.6 °C, and the transfer function used to estimate mortality is the distributed lag non-linear model (Gasparrini *et al* 2015), based on daily mean temperature. The daily all-cause mortality totals and mean temperature are used for the specific event (section 2.3) and FAR (section 2.1) attribution assessments. Figure 1 summarises the associated methods, which are explained in detail in the supplementary material.

2.2.2. New Zealand extreme rainfall in 2017 and Earthquake Commission (EQC) financial damages

In early April 2017, ex-Tropical Cyclone Debbie made landfall on the North Island of New Zealand. Significant rainfall was recorded between 3 and 7 April 2017, but the peak in terms of both 1-day amounts and the spatial area affected was on 4 April. Thus, we define the meteorological event as the area-averaged 1-d rainfall total for the North Island on the 4 April 2017, which also equated to the highest daily rainfall event in the 18 year record that we examine. A transfer function to estimate excess insurance payouts covered by New Zealand's public insurer, the EQC has been previously defined (Pastor-Paz *et al* 2020). The corresponding excess payout by the EQC for the 4 April 2017 was estimated at NZ$7.39 M using the Pastor-Paz *et al* (2020) methodology fitted to observational data (Tait *et al* 2006; see supplementary material). Specific event (section 2.3) and FAR (section 2.1) attribution assessments were conducted using this financial damage estimate, and the 1-in-18 year area-averaged daily rainfall event from the corresponding model (66.89 mm d^{-1}). Figure 2 summarises the associated methods, which are explained in detail in the supplementary material. It should be noted that the EQC payouts will not reflect the overall economic consequences of the event, or even the insured losses. Most of the damages associated with EQC payouts arises from landslips, whereas most of the overall insured losses from the event (NZ$91 M) were associated with property flooding This complicates direct comparison with studies of insured losses (e.g. Frame *et al* 2020a). As noted in Frame *et al* (2020a), the full economic consequences of extreme weather events extend well beyond insured losses; data availability prevent an analysis of the full economic impacts of this event at this time.

2.3. Alternative approaches for impacts attribution

If we are asking how climate change has influenced the impacts of a specific extreme event we should not in general be assessing how the frequency of a *class* of events has changed between counterfactual and factual conditions. Rather, we should be assessing how the of a specific impact has changed, between factual and counterfactual conditions. For example,

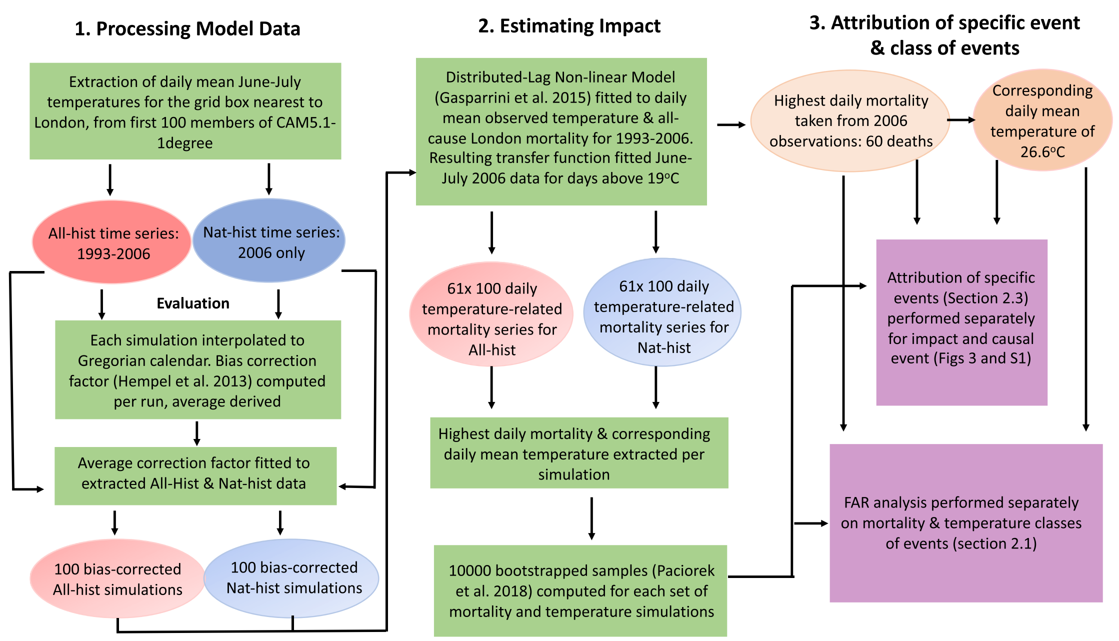

Figure 1. Flow chart outlining steps in performing attribution on the 2006 UK maximum daily mortality and the corresponding daily mean temperature. The process is broken down into three main steps: (1) processing model data; (2) estimating impact; (3) attribution of specific event and class of events. Squares indicate analyses and ovals indicate key data produced. Data from factual model simulations are red; data from counterfactual model simulations are blue; and observed data is orange. General processing is indicated in green (more detail given in the supplementary material), and attribution analysis in purple (sections 2.1 and 2.3).

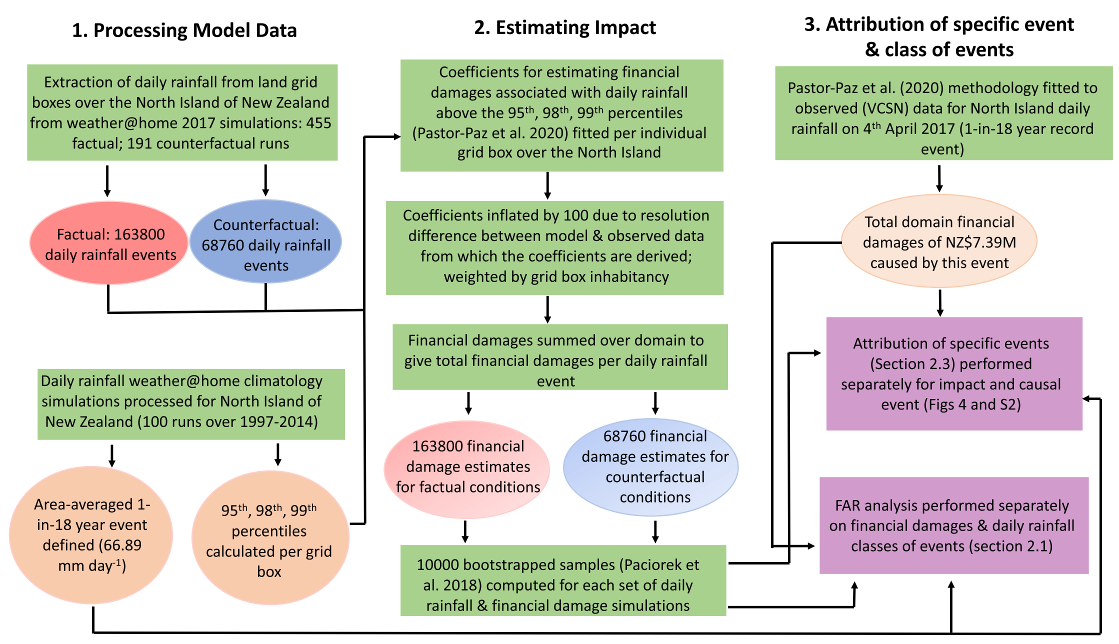

Figure 2. Flow chart outlining steps in performing attribution on the New Zealand North Island highest daily rainfall event (1-in-18 years) and the associated financial damages insured by the EQC (see supplementary material). The process is broken down into three main steps: (1) processing model data; (2) estimating impact; (3) attribution of specific event and class of events. Squares indicate analyses and ovals indicate key data produced. Data from factual model simulations are red; data from counterfactual model simulations are blue; and observed data is orange. General processing is indicated in green (more detail given in the supplementary material), and attribution analysis in purple (sections 2.1 and 2.3).

suppose a heatwave-induced mortality total of 200 people has a return period of 50 years under factual conditions. Under counterfactual conditions, the 1-in-50 year heatwave-caused mortality is 100 people. Thus, the influence of anthropogenic climate change on the impact of this specific event has resulted in 100 extra deaths, which in this case is a doubling of the magnitude of the impact. The FAR and/or RR methods would be appropriate if a mortality of at least 200 people stressed a related system. Concluding

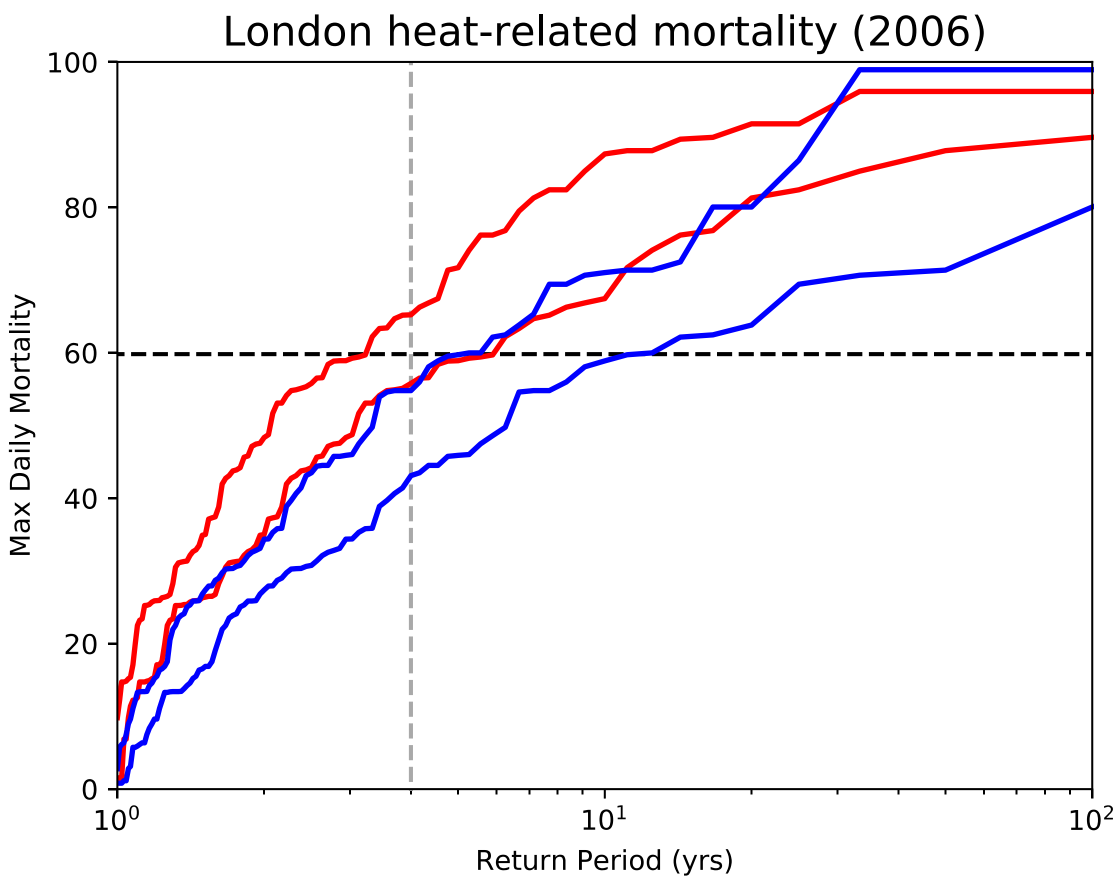

Figure 3. Return periods of the maximum daily heat-related mortality during June and July, for London. The estimated 'observed' heat-related mortality during the heatwave is shown by the black dashed line, which corresponds to 60 excess deaths on the 26 July 2006. For the model results, excess mortality is computed using the same method as per the observations (see supplementary material), but estimated from each bias corrected ensemble member taken from the CAM5.1–1 degree climate model (100 members each for the factual and counterfactual simulations). The lower and higher solid red (blue) lines respectively represent the 5th and 95th confidence intervals of the return periods for the factual (counterfactual) simulations with the dashed lines of lighter shade indicating the median of the respective experiment. The dashed grey line is indicative of a 1-in-10 year return period. Bias correction is done according to the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) method (Hemple *et al* 2013). Confidence intervals and the median are computed using the percentile bootstrap method (Paciorek *et al* 2018), performed 10 000 times.

that the frequency of a heat-induced mortality rate of at least 200 deaths has increased can provide useful knowledge for adaptation to impacts of extremes, particularly when resources such as public health infrastructure may be put under extreme stress or even collapse when this daily mortality rate occurs and/or is exceeded. However, the relevance of this form of attribution statement is specifically tied to the risk of system stress or failure which may not be relevant in many cases where such a threshold cannot be defined. This is not the same attribution information as for the specific impact of 200 deaths.

3. Results

3.1. 2006 UK heat

Figure 3 shows return periods estimated from model simulations of the highest daily heat-related June/July mortality in London. The observed mortality on the 26 July 2006 (60 deaths) is indicated by the dashed horizontal line. Figure 3 shows that the daily heat-related mortality total has increased under factual climate conditions (red), compared to counterfactual conditions (blue). A traditional FAR analysis yields a range of 0.37–0.5. These results describe the anthropogenic signal behind the frequency of a heat-related mortality impact that causes *at least*—not only—60 deaths over a single day during June–July in London. Additionally, a FAR assessment on the corresponding extreme heat has a different signal, between 0.46 and 0.67. This means that 46%–67% of days with London temperatures that exceed 26.6 °C (i.e. that resulted in the mortality total of at least 60) are due to anthropogenic climate change (see figure S1 (available online at stacks.iop.org/ERL/17/024009/mmedia) in supplementary material for corresponding return periods). The attributable change in the meteorological event is greater than that of the impact, highlighting that the relationship between the causal event and the impact can be non-linear.

The currently common impact attribution question concerns the excess deaths attributable to anthropogenic climate change. According to figure 3, the

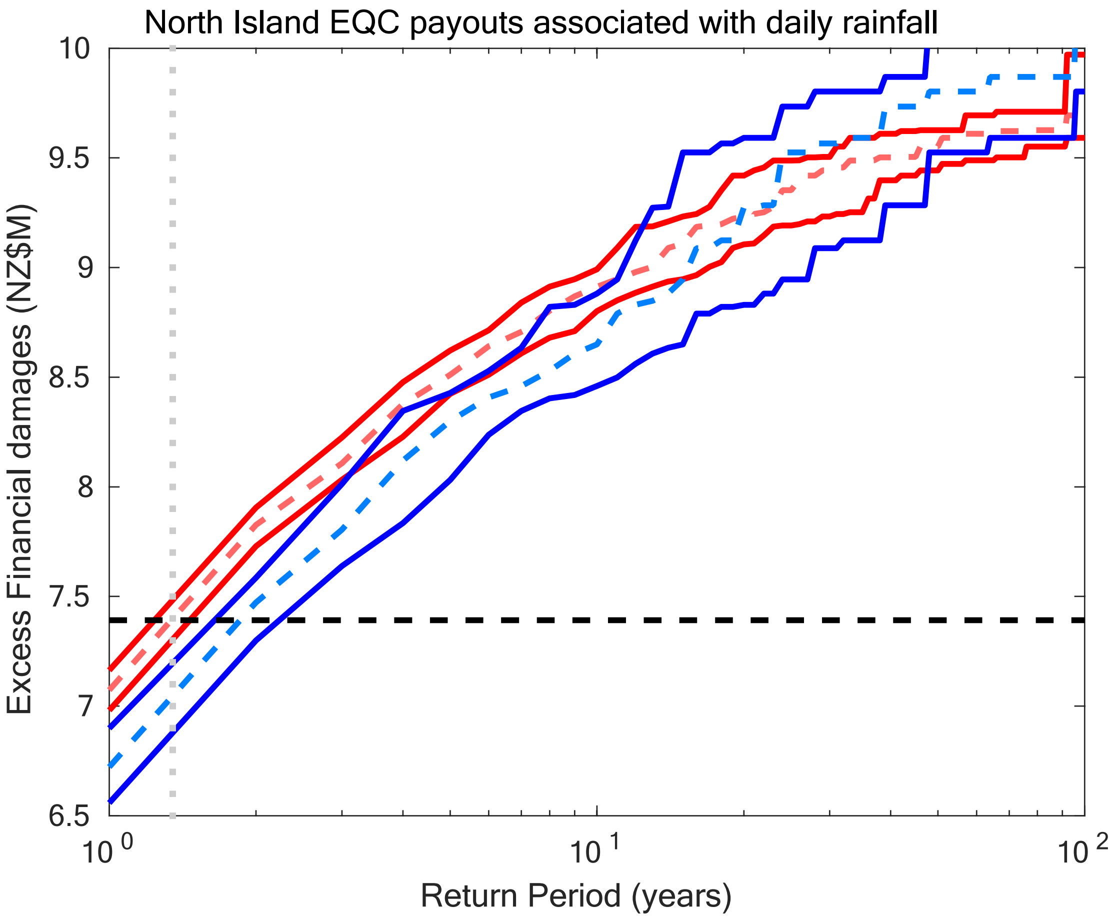

Figure 4. Return periods of the EQC payouts on the North Island during daily rainfall events. The estimated 'observed' excess financial damages of NZ$7.39 M is shown by the black dashed line, which occurred on the 4 April 2017. For the model results, financial damages were computed using the same method as per Pastor-Paz *et al* (2020; please see supplementary material), but fitted to each separate factual (455 members) and counterfactual (191 members) simulation across each year (December 2016–November 2017) from the weather@home ensemble. The lower and higher solid red (blue) lines respectively represent the 5th and 95th confidence intervals of the return periods for the factual (counterfactual) simulations with the dashed lines of lighter shade indicating the median of the respective experiment. The grey dashed line represents the return period of the estimated observed EQC payouts (an event of NZ$7.39 M occurs every 1.35 years on average in the factual simulations). Confidence intervals and the median are calculated using percentile bootstrap method (Paciorek *et al* 2018), performed 10 000 times.

average return period of a heat-related mortality event of 60 people in the factual experiments is once every 4 years, and in the counterfactual the mortality associated with a 1-in-4 year event is 50 deaths. Thus, anthropogenic climate change has increased the number of deaths associated with a 1-in-4 year event in London by ten deaths, with a 5th–95th percentile range of 1–19 deaths. To summarise, when interested in an event class question, 37%–50% of deaths are attributable to anthropogenic climate change when the mortality rate is at least 60, but if we are interested in the event itself, 17% (10 deaths out of 60) are attributable to the anthropogenic influence on the climate.

3.2. 2017 New Zealand North Island rainfall event

Figure 4 shows return periods of EQC payouts (see supplementary material). The estimated payouts on the 4 April 2017 (NZ$7.39 M, indicated by the dashed horizontal line), does not appear to be rare. We compute return periods of payouts worth NZ$7.39 M of about every 1.35 years in the factual world, and about every 1.7–2.3 years in the counterfactual world; and a FAR measure of 0.16–0.41. When concerned about the actual impact, the median figure associated with an event occurring every 1.35 years in the counterfactual simulations is NZ$6.9 M (5th–95th percentile NZ$6.75 M–$7.14 M), compared to the factual median figure of NZ$7.39 M (NZ$7.35 M–$7.49 M). This indicates that NZ$490 000—or 7% (4.6%–8%)—of the cumulative financial impact across the North Island estimated in the factual simulations is attributable to human influence.

The above FAR for the class of rainfall-related EQC payouts is different from the FAR for the class of corresponding daily rainfall, which spans 0.01–0.89. That is, anthropogenic forcing has contributed between none and almost 90% to the frequency of events at least as intense as the 1-in-18 year daily area-averaged rainfall (see section 2.2.2 and supplementary material). The large range indicates that the degree of the anthropogenic signal is uncertain (at least according to the model set-up used). Moreover, the shift in return periods is more considerable—yet variable—for the specific rainfall event compared to the corresponding financial damages, ranging from 16 to 31 years in the counterfactual world, to 21–66 years under factual conditions (see figure S2 in the supplementary material). The uncertain FAR estimates and considerable overlap of rainfall return periods beyond 5 years is likely a result of sampling uncertainty further in the tail of the distribution, especially in the counterfactual simulations (see figure S2).

The anthropogenic effect on the financial risk differs strongly from the effect on the associated meteorological hazard, especially when considering a specific event. This is likely due to a combination of factors, including the spatial extent and intensity of rainfall over inhabited versus non-inhabited regions, and the spatial heterogeneity of the transfer function (see supplementary material). For example, an exceptional amount of rain may have fallen over areas with little residential property, and whilst contributing to the overall extremity of the rainfall event, would not have contributed to the excess financial outcome. This underpins why we strongly recommend that the causal event and the associated impacts be treated separately in terms of estimating the anthropogenic influence.

4. Discussion

Extending weather event attribution to impacts is very new, yet gaining in popularity (e.g. Mitchell *et al* 2016, Schaller *et al* 2016, Kay *et al* 2018, Otto *et al* 2020, Mitchell 2021, Vicedo-Cabrera *et al* 2021). Whilst isolating the climate change signal behind impacts caused by weather extremes can be attractive to many working in impacts-related fields, results are relevant only if the methodologies employed suit the specific question being asked. This paper has demonstrated a subtle, yet important issue surrounding the attribution of impacts of extreme weather events to anthropogenic climate change. Via two separate illustrative case studies we have demonstrated that this issue is non-negligible and applies to multiple types of weather extremes and impact outcomes.

4.1. Considerations when undertaking attribution assessments on impacts

First, we once again make clear that the FAR (and associated RR) framework assesses the change signal on a *class* of events. FAR reflects the change in frequency of an event *at least as big as* the chosen threshold, due to anthropogenic influence on the climate. When a FAR assessment is undertaken, the calculated FAR/RR values pertain to the exceedance of the threshold defined by the observed event, and not specifically the threshold itself (Harrington 2017). Care should be taken to use FAR only in appropriate circumstances.

Secondly, it is strongly recommended that any attribution assessment concerning the impacts of a meteorological event be carried out in full, i.e. in addition to the causal meteorological event. As especially demonstrated by the New Zealand rainfall case study, it should not be assumed that the relationship between an extreme event and its impact is linear and that the anthropogenic signal from the extreme event seamlessly transfers to the corresponding impact. The more non-linear the impact response is to the meteorological event, the more important it is to separate the attribution assessments (Sutton 2019). This non-linearity is likely due to a number of factors, including the inhomogeneous spatial pattern of the meteorological event. Because impacts do not usually scale linearly with meteorological hazards, it will in general not be sufficient simply to equate the fractional attributable risk (FAR) as the fractional attributable impact (Mitchell *et al* 2016, Frame *et al* 2020a).

Thirdly, main assumption of our study is that the only path to altering the impact of an extreme event is via anthropogenic climate change influencing the event itself. In fact, there are very likely other influences on some impacts caused by an extreme event, including whether the corresponding transfer function and its relationship to the causal event is affected by climate change, the adoption of mitigation practises that may negate the potential magnitude of the impact (for example, effective public health warnings, or insurance companies rising their financial thresholds such that less damage is paid out), or even random factors such as the loss of life during floods being at least partially influenced by the unfortunate situation of being in the wrong place at the wrong time. There are also other impacts that are more fixed and therefore so would transfer function that ties the impact to an extreme event, such as damage to existing structures from events including wildfire, floods and landslides. Whilst outside the scope of our study to comprehensively assess this issue, we strongly encourage all authors of impacts attribution assessments to critically evaluate how influences on the impact and/or corresponding transfer function may increase or decrease the uncertainty of their results. Indeed, to more fully understand the complex nature of impacts attribution, there is a need to specifically address this issue with targeted, future research.

Despite these considerations, one can still estimate the anthropogenic signal behind the impacts of a specific extreme event. Indeed, this can and should be done with the same tools (such as extensive factual and counterfactual process-based model simulations) that are used in FAR assessments. As demonstrated with figures 3 and 4, impact attribution can be framed as the change in the waiting time of an impact with a specific magnitude, and/or the change in the magnitude of an impact with the same return period across factual and counterfactual physical climate model simulations.

4.2. Can FAR be useful for attributing impacts to climate change?

There are situations where FAR can be useful for impacts attribution, if we are interested in the signal behind the frequency of a *class* of impacts, and not in a singular event. This measure could be appropriate when concerned about the 'breaking' of a system related to a specific impact. For example, heat-related mortality at or above a certain total or rate could throw public health infrastructure into disarray, similar to what many countries have attempted to avoid during the COVID-19 pandemic. With this framing, FAR is appropriate to determine changes in the frequency of this class of impacts due to climate change, such that the corresponding pressure on related systems is quantified.

Therefore, appropriate question framing is essential during the initial design of an attribution study (Otto *et al* 2012). For example, a question on a specific event might be:

'How has the magnitude of an impact that occurs every Y years changed under anthropogenic influence on the climate?'

or:

'How has the waiting time for an impact of a specific magnitude altered under anthropogenic influence on the climate?'

versus a FAR-based question:

'How much of the frequency of a class of impacts is due to anthropogenic emissions'?

Such questions need to be defined early and kept constant through the study so that the appropriate methods and communication tools are employed (Stone *et al* 2021). Moreover, it is important to consult with relevant stakeholders who may help determine the exact framing of analysis, and understand how the characteristics of impact transfer functions may affect the resulting impact attribution assessment.

5. Conclusions

This paper has discussed a subtle yet important methodological consideration in attributing the impacts of an extreme weather event to climate change. We achieved this by investigating two separate extreme event case studies that induced different impacts. We highlight that for impacts attribution to be relevant, FAR should not necessarily be employed for calculating the anthropogenic climate change signal behind the specific impacts of a specific event. However, FAR can be useful in quantifying the change in risk of a whole class of (usually related) events. We suggest two ways to reframe impacts attribution such that the focus is on a specific event in terms of changes in return period or magnitude. Moreover, any impacts-related attribution—whether on a specific event impact or a class of impacts—should be performed on the impact estimated from the transfer function, and not assumed to be seamlessly related to the anthropogenic signal of the meteorological event.

There is substantial interest in determining the anthropogenic climate change signal behind the impacts caused by extreme weather events. This is an opportunity for the research community, but also brings new methodological questions as we try to grapple with the emergence of extremes that are, in some cases, outpacing our attempts to understand their emergence. However, we must ensure that analyses adhere to the purpose of the underpinning method/s employed, as well as considering any data and methodological limitations in both climate science and the corresponding impact/s sectors. Constant and comprehensive interdisciplinary collaboration, along with clear and well-thought-out project design and methods, will be essential for the robustness of future impacts attribution assessments.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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