Check for
updates

Climate change attribution and the economic costs of extreme weather events: a study on damages from extreme rainfall and drought

David J. Frame[1] · Suzanne M. Rosier[2] · Ilan Noy[3] · Luke J. Harrington[1,4] ·
Trevor Carey-Smith[2] · Sarah N. Sparrow[4,5] · Dáithí A. Stone[2] · Samuel M. Dean[2]

Abstract
An important and under-quantified facet of the risks associated with human-induced climate change emerges through extreme weather. In this paper, we present an initial attempt to quantify recent costs related to extreme weather due to human interference in the climate system, focusing on economic costs arising from droughts and floods in New Zealand during the decade 2007–2017. We calculate these using previously collected information about the damages and losses associated with past floods and droughts, and estimates of the "fraction of attributable risk" that characterizes each event. The estimates we obtain are not comprehensive, and almost certainly represent an underestimate of the full economic costs of climate change, notably chronic costs associated with long-term trends. However, the paper shows the potential for developing a new stream of information that is relevant to a range of stakeholders and research communities, especially those with an interest in the aggregation of the costs of climate change or the identification of specific costs associated with potential liability.

Keywords Climate change · Probabilistic event attribution · Disaster economics · Climate change economics · Climate change adaptation

Highlights
• We calculate a measure of the degree to which human-induced climate change has affected the chance of a number of extreme events in New Zealand, 2007–2017.
• We combine these assessments with existing estimates of economic costs associated with these events to examine what fraction of the costs of these extreme events can be attributed to human influences on the climate.
• We discuss possible uses of and limitations of this approach, and its potential future development.

✉ David J. Frame
david.frame@vuw.ac.nz

Extended author information available on the last page of the article

🙋 Springer

1 Introduction

The idea of using information from probabilistic event attribution (PEA) studies to quantify damages associated with climate change was first proposed by Allen (2003). In its essence, this approach couples the attributable change in the probability/intensity of extreme events (the PEA) with their costs, obtained from other sources, to arrive at quantifications of the attributable cost of these events. PEA researchers can draw on two different, though compatible (Otto et al. 2012), interpretations, which essentially seek to assess how extreme weather is changing in terms of either frequency (how the "return period" of a given intensity of event is changing) or magnitude (how the intensity of an event of given return period is changing).

Surprisingly, PEA studies—that identify the role of anthropogenic climate change in changing the frequency and intensity of specific extreme weather events—have not yet been used in any assessment of attributable weather event–related costs. However, several communities and sectors that are interested in the aggregation of climate change–related events—e.g. insurers, actuaries, national treasuries, and investors in adaptation infrastructure projects—may find the outputs of such attributable economic cost studies of value.

These communities and groups are first likely to be national or supra-national in scale, since these are the scales on which the integration of information about the emergence of climate signals tends to be most relevant. It is with such a group in mind, the New Zealand Treasury, that this project was originally conceived. However, the assessments described here can also be of interested to specific (micro) individuals directly affected by specific extreme events for which one can both quantify the damage inflicted and conduct a PEA assessment.

At the meso-scale (between the aggregate macro and the individual micro), local planners may admittedly be less interested in the sort of calculations being developed here, in part because they are less interested in the aggregation of probabilistic events that did happen, and in part because local contingencies are often assessed by local planners to be the most crucial elements of adaptation. However, those working in the meso-scale may still find information about the speed at which attributable climate change signals emerge, and their respective costs, of importance.

Another use of this approach is to compare the costs calculated here with the estimates of climate change costs obtained from general equilibrium macroeconomic models coupled with climate modelling (the integrated assessment models (IAMs)). Within the climate change economics literature, there has been an on-going debate about the functional form of climate damage functions. In many IAMs, damages are parameterized or characterized as a low-order polynomial function of temperature (Nordhaus 1993; Nordhaus and Boyer 1999; Hope 2006). Other authors are highly critical of these damage functions: Weitzman (2012) described (polynomial) damage functions as "a notoriously weak link in the economics of climate change" on the basis of deep structural uncertainty in their underlying functional form. Another very prominent researcher, (Pindyck 2013) is even more scathing about them, and argues that "IAM-based analyses of climate policy create a perception of knowledge and precision, but that perception is illusory and misleading".

By developing assessments of economic costs that are based on hydrometeorological changes that are attributable to anthropogenic climate change, we can provide a valuable comparison to those maligned damage functions. The costs identified in this paper are not a full assessment of the costs of climate change, but they do begin the process of assembling a "bottom-up" understanding of climate change attributable costs, as distinct from the "top-down" approach adopted using IAMs (Conway et al. 2019). A companion paper (Frame et al.

2020) makes this top-down and bottom-up comparison for the USA, by focusing on a specific event—Hurricane Harvey from 2017. That work argues that the top-down IAM approach appears to dramatically underestimate the risk. The present study focuses on extreme rainfall and droughts, but leaves out many other channels through which the climate, and climate change, affects economic activity. We do not include an assessment of potential economic benefits associated with climate change, though our methodology permits the inclusion of either increased benefits associated with events that have become more likely (e.g. longer growing seasons for some crops) or negative damages (i.e. benefits) associated with damaging events that may have become *less* likely because of climate change. The method, however, is restricted to events that have actually occurred.

Below we present preliminary estimates of the economic costs to New Zealand associated with floods and droughts in the period 2007–2017 that are attributable to anthropogenic climate change. We use two sets of inputs: estimates of economic costs associated with these floods and droughts, and estimates of the "fraction of attributable risk" (FAR) of the weather events, i.e. the fraction of the risk of such events that is attributable to anthropogenic climate change. The estimates we obtain are not comprehensive, and almost certainly represent an underestimate of the economic costs of climate change. We describe the scientific and economic dimensions of the approach, and suggest potential avenues for its future development.

Extreme events, and associated FARs, are expected to change in the coming decades because the climate continues to change in response to on-going emissions of greenhouse gases (and other factors). Changes in FARs should be negligible within the decade-long analysis period of this study. The economic costs are also likely to change, as these depend not only on the hazards (the extreme weather phenomena) but also on exposure of people and assets to that hazard, and their vulnerability. Exposure and vulnerability are also not static, and are likely to change, leading to changes in the economic costs. Changes in exposure and vulnerability may be adaptive responses to experienced or anticipated climate trends, and thus, historical trends in both factors may have differed in the absence of anthropogenic forcing. It is only very recently that anticipated climate trends have started being considered in an adaptation context, and trends have been predominantly towards increasing exposure of property to flooding, so we ignore the possibility of adaptation in this study.

Consequently there is significant uncertainty around the FARs and both types of cost estimates. Insured damages for floods, in particular, almost certainly underestimate the full economic costs as they ignore any loss in economic activity in the aftermath of these events, and do not include the damage to uninsured assets (especially public infrastructure). However, if the users of such cost estimates are only interested in that specific subset of the costs (e.g. insurers) or are interested in the costs in relation to other economic events measured with the same metrics (e.g. some government departments or investors seeking to understand the evolution of climate risks), then the cost estimates may still be informative and useful.

2 Terminology

Our terminology follows the open-ended Intergovernmental Expert Working Group on Indicators and Terminology relating to disaster risk reduction that was established by the United Nations General Assembly in 2017.

A *disaster* is defined as a serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts. *Disaster damage* (or direct damage) occurs during and immediately after the disaster. This is usually measured in physical units (e.g. square metres of housing, kilometres of roads), and describes the total or partial destruction of physical assets, the disruption of basic services and damages to sources of livelihood in the affected area. Disaster damage is "nearly equivalent" to the concept of direct economic loss. Direct economic loss is the monetary value of total or partial destruction of physical assets existing in the affected area. Examples of physical assets that are the basis for calculating direct economic loss include homes, schools, hospitals, commercial and governmental buildings, transport, energy, and telecommunications infrastructures; business assets and industrial plants; and production-related assets such as crops, livestock and machinery. They may also encompass environmental assets and cultural heritage, but these are rarely quantified. Direct economic losses usually happen during the event or within the first few hours after the event and are often assessed soon after the event to estimate recovery costs and insurance payments. In principle, these are tangible and relatively easy to measure. Our estimates for flood costs are based on such measures of direct, and insured, damages. In contrast to damage, *indirect economic loss* is defined as a decline in economic value-added as a consequence of direct economic loss and/or human and environmental damage. Indirect economic loss includes microeconomic impacts (e.g. revenue declines owing to business interruption), meso-economic impacts (e.g. revenue declines owing to impacts on natural assets, interruptions to supply chains or temporary unemployment) and macroeconomic impacts (e.g., price increases, increases in government debt, negative impact on stock market prices and decline in GDP). Indirect losses can occur inside or outside of the hazard area and often are experienced with a time lag. As a result, they may be intangible or difficult to measure.

As we detail below, our estimate for drought costs are focused on economic loss, rather than direct damages (which are the focus of the flood cost estimates). Indirect economic losses can be measured (imprecisely) with several methodologies. One approach is through econometric assessment of past historical data—with diverse methodologies such as difference-in-difference or synthetic control. One estimate for the drought losses (Kamber et al. 2013) uses this approach, by estimating a set of vector autoregressions using past observational data. One drawback of the Kamber et al. (2013) approach is that it does not clearly account for the size of the shock once it passes a certain pre-determined threshold. The other approach is through a model of the economy which is then perturbed with the appropriate shock (whose magnitude is obtained from observational data). Modelling tools vary, from computable general equilibrium to static or dynamic input-output approaches. The Treasury (2013) estimate of the drought impact is based on the former.

In this conceptualization of the economic dynamics following natural hazard shocks, these eventually lead to a potential loss (or gain) in well-being, through diverse channels such as by changing risk awareness or risk tolerance, or leading to other psychological, financial, environmental and social changes with long-term well-being implications (Fig. 1). This last part is very difficult to measure (Noy and duPont 2018), and is outside the scope of the assessment undertaken here.

3 Data and methods

3.1 Events

The fourteen extreme weather events considered in this paper are listed in Tables 1 and 2. These events all occurred in New Zealand during the decade from mid-2007 to mid-2017. The list is restricted to weather events for which a clear link is established between the meteorological event and damages, and for which anthropogenic climate change attribution analyses are available. Note that the attribution analysis was performed on rainfall, not the actual flood magnitude itself. It was pluvial flooding in these events that led to the damage, as is the standard in the small, high-slope catchments in New Zealand, so precipitation intensity should serve as an accurate proxy. For the floods, the event duration that was used to estimate the FAR was chosen to be the longest period over which the rainfall was extreme, since the damages accrue from the full pulse of excess water. Drought durations vary, and last several months.

3.2 Climate modelling experiments

For the flood events, we assume a step-change damage function, where no damage occurs except when precipitation exceeds a specified threshold, with a fixed amount of damage then occurring irrespective of how much the precipitation exceeds that threshold. That threshold is defined as the amount that occurred during each of the identified events. Strictly speaking, we should use delta functions, i.e. the observed amount of damage only occurs for the observed event magnitude (Harrington 2017). However, we adopt the step-change functions because it corresponds to the most common method of calculating FARs and because it affects the FAR estimates calculated in our study by only about 10%. Climate station rainfall observations from NIWA's National Climate Database (NIWA 2017) are used, provided there is at least 40 years of observations available. In most cases, these were continuous 40-year periods and exclusion of locations with one or more missing years made negligible difference to the results. At each observing location impacted by the event, extreme value theory is used to estimate an annual exceedance probability as described below in Section 3.5. The event duration was chosen to be the longest period over which the rainfall was extreme, since the damages accrue across the period over which the rain falls. In a New Zealand context, two points are worth noting: first, catchments are small, so floods are usually pluvial events; second, it is not usually just the most extreme peak that does the damage, but the full event.

The basis for our inferences about extreme precipitation comes from extremely large ensembles of simulations of a regional climate model from the "weather@home" experiment (Massey et al. 2015) for the Australia/New Zealand (ANZ) region (Black et al. 2016). In this
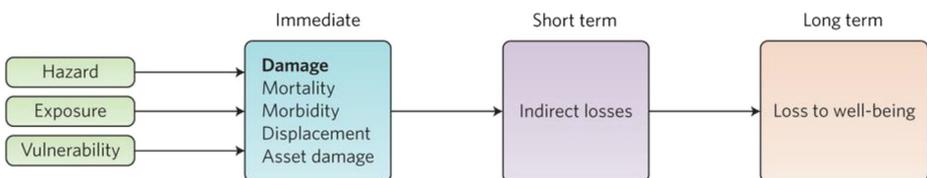

Fig. 1 The dynamic socio-economic consequences of cyclones at different timeframes, showing the progression of losses over time. Source: Noy (2016)

Springer

Table 1 Insured damages associated with flooding events (resulting from extreme rainfall) in New Zealand over the period 2007–2017 for the 12 costliest events where it has been possible to form estimates regarding the FAR of the rainfall event. Estimates of insurance costs for each event are in the column second from right in CPI-adjusted 2017 NZ$. These data were collected from the private insurers operating in New Zealand, so only include the types of assets that are typically insured, and only where insurance was actually purchased. These mostly include residential housing and privately owned commercial property. It does not include publicly owned property (such as council buildings) and infrastructure such as roads. The right-most column contains the insured losses attributable to climate change, i.e. the insurance loss estimate multiplied by the FAR of the event. The insured cost estimates are from the Insurance Council of New Zealand; no uncertainty estimates are available (obtained on 17/05/19). Full economic costs are expected to be far higher. See text for discussion

Year	Date	Location	Climate change FAR	Total cost ($m) best estimate	Cost ($m) attributable to climate change
2017	3–7 Apr	North Island	0.35 ± 0.2	91.46	32.011
2007	10–12 Jul	Upper North Island	0.30 ± 0.2	72.7	21.81
2017	7–12 Mar	Upper North Island	0.40 ± 0.2	61.7	24.68
2013	19–22 Apr	Nelson, Bay of Plenty	0.30 ± 0.2	48.2	14.46
2015	18–21 Jun	Lower North Island	0.10 ± 0.2	42.4	4.24
2016	23–24 Mar	West Coast-Nelson	0.40 ± 0.2	30.9	12.36
2015	2–4 Jun	Otago	0.05 ± 0.2	28.8	1.44
2015	13–15 May	Lower North Island	0.30 ± 0.2	22.4	6.72
2011	29 Jan	Northland, Bay of Plenty	0.30 ± 0.2	21.3	6.39
2014	8–10 Jul	Northland	0.30 ± 0.2	19.3	5.79
2017	13–16 Apr	Mostly North Island	0.35 ± 0.2	17.2	6.02
2007	29 Mar	Far North	0.30 ± 0.2	15.2	4.56
Total attributable extreme rainfall insured damage costs					$140.48

setup, the Met Office HadAM3P model (Pope et al. 2000) is run globally, providing lateral boundary conditions to the regional model HadRM3P (Jones et al. 2004), which covers a domain spanning Australia, New Zealand and much of Indonesia at approximately 50-km resolution (Rosier et al. 2015; Black et al. 2016). The model has been shown to reproduce many large- and medium-scale features of weather and climate with a good degree of accuracy (Black et al. 2016). In particular, model rainfalls are captured well, albeit with some dry bias in the extremes, and associated synoptic conditions, such as atmospheric rivers, are also realistically simulated (Rosier et al. 2015).

For this study, we use very large initial condition ensembles to represent many different realizations of possible weather under varying climate conditions. Two climate forcing ensembles are compared: (1) all forcings (ALL), which includes sea surface temperatures

Table 2 Financial losses associated with the two costliest droughts (in CPI-adjusted 2017 NZ$) that occurred in New Zealand during the period 2007–2017, along with estimated FAR of these events. Estimates of economic costs for each event are in the column second from right, and are based on economic computable general equilibrium modelling done by the New Zealand government, and the right-most column shows the economic losses attributable to climate change, i.e. the economic loss estimate multiplied by the FAR of the event. Note that the quantities are different from those used in estimating the costs associated with floods (insured losses). In this case, for droughts, the losses represent a more comprehensive assessment of impact on the economy. Along with those for floods (Table 1), these cost estimates are also uncertain. See text for discussion

Year	Date	Event	Climate Change FAR	Total cost ($m) best estimate	Cost ($m) attributable to climate change
2007/08	Summer	Drought	0.15 (0.05–0.4)	3237	485
2012/13	Summer	Drought	0.20 (0.15–0.4)	1575	315
Total attributable drought losses					$800

(SSTs) from the "Operational Sea Surface Temperature and Sea Ice Analysis" (Donlon et al. 2012), as well as greenhouse gases, aerosol, ozone, solar, and volcanic forcings; (2) "natural forcings only" (NAT) where the anthropogenic contribution to the forcings has been removed; this produces many realisations of the weather possible in a hypothetical world without anthropogenic influence on climate. Estimates of what SST fields might have looked like in the NAT world were constructed using SST changes ("delta SSTs") taken from different global coupled models from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012), using results from "HistoricalNat" runs subtracted from "Historical" runs. These delta SSTs were then subtracted from the SST fields for the year in question of simulation. To try to span the uncertainty in this estimation, delta SSTs from several different GCMs were used, together with a multi-model mean. The setup is very similar to that described by Schaller et al. (2016). Other forcings such as greenhouse gas concentrations, ozone and aerosols are set to pre-industrial levels, as described in Schaller et al. (2016) and Black et al. (2016). Paired ensembles of "ALL" and "NAT" forced simulations were available for the years 2013, 2014 and 2015.

This basic experiment setup has been used in many pieces of recent climate research, and is a recognised part of the climate change detection and attribution literature; interested readers should see Bindoff et al. (2013), or the recent review article by Stott et al. (2016).

The study's assessments of droughts are based primarily on Harrington et al. (2016), in which the CMIP5 ensemble of models (Taylor et al. 2012) was investigated using self-organising maps (Hewitson and Crane 2002; Gibson et al. 2017) to estimate FAR for such events.

3.3 Costs

Cost estimates used here are for the episodic floods and droughts, and ignore chronic costs resulting from gradual climate trends or trends in nuisance flooding. As we discussed earlier, the cost figures for floods account only for direct insured damages, while the cost estimates for droughts measure the annual indirect loss. The figures for insured damages associated with floods are from the Insurance Council of New Zealand (2017). These flooding costs represent a significant underestimate of the full financial and economic impacts of these rainfall events as they do not include losses in economic activity in the aftermath of the events, nor emergency response costs that prevented damage to insured properties. The estimates of economic losses for the two droughts are from government estimates (Ministry of Agriculture and Fisheries 2009; Treasury 2013).

The cost figures for insured damages from floods are reliably measured, as the ICNZ data include the actual amount of payments made by all the ICNZ member companies (ICNZ membership accounts for maybe 95% of overall commercial insurance available in New Zealand). However, while precise, these figures under-state the total economic impact (including both loss and damage) associated with these events. Even the damages under-represent the full extent of damages from extreme rainfall, as they do not include uninsured damages. Uninsured damage includes damage to transportation, communication and utility networks, which are typically uninsured, public and community-owned buildings which are almost never insured commercially, and those commercial and residential buildings that were not under current insurance cover at the time of the event. This latter category is not very large, as insurance penetration rates in New Zealand are quite high (more than 95% for residential buildings, and 70–75% for commercial ones). In addition, the measure of damage (insured and

uninsured) does not include economic losses, such as lost production because of infrastructure failures, the costs associated with medical and pastoral care of affected communities, and the costs of disaster relief and clean-up.

The costs associated with droughts, in contrast, are estimates obtained from modelling of the indirect economic losses. These will be very sensitive to the modelling assumptions that are used, and to the exact specification of the shock with which the model is perturbed. Two modelled estimates of the cost of the 2013 drought are available, and are fairly similar (0.6 and 0.7% of annual GDP).

As noted, direct damages and indirect losses are not the same (the former is a flow, the latter is a stock measure) and the two are therefore not comparable. In this specific case, the indirect loss, as estimated for droughts, is probably the more comprehensive figure, as the extent of direct damage to assets from drought is fairly minimal. Nonetheless, the drought cost figures are also much more speculative as they are modelled rather than counted. So, in this case, we observe a tradeoff between a more comprehensive estimate (droughts) and a more accurate one (floods).

The absence of accurate assessments of economic costs associated with the extreme events, including both damages and losses, is probably the largest source of uncertainty in this report. In the absence of full and accurate accounting of economic damages and losses associated with extreme rainfall events, we have drawn on insured losses as the most readily available data. Fuller analysis of the economic impact of weather-related disasters that will tally the range of both damages and losses is required for a better understanding of the total impact of extreme weather, in New Zealand and elsewhere. These estimates of complete costs (damages and losses) are not available consistently anywhere else, either, so their collection or estimation should be a priority in furthering the research agenda outlined in this paper.

3.4 Fraction of attributable risk

In estimating the risk of events attributable to anthropogenic climate change we use the "Fraction Attributable Risk" metric, defined as

$$\text{FAR} = 1 - P_0/P_1$$

where P_0 is the probability of an event occurring in the absence of human influence on climate, and P_1 the corresponding probability in a world in which human influence is included. While strictly speaking for this study P_0 and P_1 should be the likelihoods of a certain event magnitude (Harrington 2017), here we use exceedance probabilities because of their established usage in event attribution studies, their better sampling, and their only small bias (about a 10% overestimate for the events in this study). FAR is thus the fraction of the risk that is attributable to human influence (Bindoff et al. 2013). An "event" in this context occurs when a specified threshold is exceeded for some measure of interest, such as cumulative rainfall over a 3-day period. In the rainfall examples in this study, the synoptic conditions for the rainfall events identified within the weather@home/ANZ simulations were found to be consistent with the events that actually occurred, meaning that the simulated event produced the event-above-threshold in a manner physically consistent with observations (Rosier et al. 2015). To calculate extreme rainfall FARs, we follow the practices established in Pall et al. (2011), and, in Australasian contexts, Rosier et al. (2015) and Black et al. (2016). The estimates of FAR in this study are, for the most part, indicative estimates based on the current state of knowledge aimed at providing an approximate order of magnitude estimate of the costs of current climate

change. It is acknowledged that, as a metric, FAR has some limitations. Christiansen (2015) has shown, for example, that as the extreme high end of the distribution is approached, FAR tends towards one for Gaussian-distributed variables but towards zero for heavy-tailed distributions. Our modelled rainfall maxima distributions tend to be heavy-tailed, and the interpretation of what could well be underestimated values of FAR is not straightforward. A different measure of likelihood change, such as the risk ratio, might actually be more interpretable; however, we found FAR to be a useful metric in the context of this study, especially given the high level of uncertainty in many of the estimates used here (in particular, the costs).

While in general extreme precipitation at midlatitudes increases with the thermodynamic contribution from the Clausius-Clapeyron relationship (Pall et al. 2011), recent research (Risser et al. 2019, in prep) has demonstrated that changes in weather patterns associated with extremes can compete with this effect. In some instances, at some locations, the net effect can be a reduction in extreme precipitation (Pfahl et al. 2017). This would imply a FAR < 0, i.e. where the risk of extreme events in some places has been reduced because of human influence. There is nothing in our framework to prevent the inclusion of events which have become less likely as a result of human influence on the climate, i.e. events associated with reduced rather than increased costs (but with the Fraction of Attributable Decrease in Risk measure, (Wolski et al. 2014)). However, because our analysis is based on events that have occurred, we have an expected selection bias against events that have not occurred because they are less likely under anthropogenic forcing (i.e. FAR < 0). We only examine two types of events in this study though, and calculate similar moderate FAR values for all wet events and similar moderate FAR values for both dry events. This suggests that the issue of a selection bias is not important for the types of events considered here. Nevertheless, further work is needed to investigate the importance of this selection bias in New Zealand when considering a more expansive list of event types (cold events in particular). In this paper, we focused on the most damaging rainfall events from an insurance perspective, without prior consideration of whether FARs might be positive or negative, or near zero.

3.5 Floods

We multiply the FAR by the cost estimate to obtain attributable costs. For some of the events considered, we have simulations for the SST patterns that characterize the year in question. Resourcing constraints mean that we only had three full years of simulations on which to draw—the years 2013 to 2015. As a result, we have restricted the analysis to considering only the impact of climate change on events to the 2007–2017 period, on the basis that these three ensembles provide a reasonable starting point for the quantification of FARs in the context of New Zealand's climate (Risser et al. 2017).

Observed rainfall was analysed at stations within the catchment of a flooding event for three event durations: 1 day, 3 days and 5 days (none of the events lasted more than 5 days). All events involved heavy precipitation immediately before the flooding, which is generally the case for flooding events in New Zealand. The rainfall associated with each flooding event is the largest over the recent 14-year period for the relevant area and storm duration. The event probability was estimated for each station after fitting a generalized extreme value (GEV) distribution to each station annual maxima series for the three durations. This was done separately for each season where the annual maxima series was based on rainfall observed within that season. The annual exceedance probability for each event was determined at nearby stations based on the fitted GEV distribution for the relevant season. The event probability was

calculated as the average over the chosen stations and the duration selected as the longest period over which the event was extreme. Finally, we focused the analysis on the most financially significant flooding events over the period July 2007–June 2017, considering only those events with insurance losses in excess of an arbitrary threshold of 15M in NZ$ (CPI-inflation-adjusted to 2017 NZ$).

In assessing the FARs of each event, we first ensured that the modelled FARs validated towards the tail of the distribution—this is to reflect the uncertainty in estimating the rarity of the actual event. We examined FAR maps for extreme precipitation events at each integer threshold across 1–4% annual exceedance probabilities inclusive, for each season. We then determined a FAR value for each event by examining maps of FAR at the location and percentile determined from the observations, for the appropriate season in which the event occurred, and using the map of FAR computed for the appropriate rainfall duration (1, 3 or 5 days). Where we had the explicit year of modelling for an event (i.e. for events in 2013, 2014 or 2015), we used the model ensembles from the year in question to compute FAR; where we did not, we used results from the 3 years of modelling (2013–2015) pooled.

Based on the FARs presented in Table 1, we estimate that major-flood insured costs attributable to anthropogenic influence on climate are currently somewhere in the vicinity of $140M for this decade. This is what anthropogenic climate change cost the insurance sector in these events. This figure of $140M is understated, as it does not include the attributable costs of more minor floods, and these costs will very likely increase over time, given our finding that virtually all rainfall FARs were substantially positive. As stated earlier, nor does it include all the damages and losses associated with these floods that were not insured. Further investigation into additional smaller flooding events, and extension of the analysis framework to include storm damage and flooding associated with cyclones (especially the four tropical cyclone remnants that hit New Zealand in 2017–2018), an accounting of uninsured damages, and estimates of indirect economic losses would almost certainly represent a large net increase over these numbers.

3.6 Droughts

The drought FARs are based primarily on Harrington et al. (2016), in which the CMIP5 ensemble of models (Taylor et al. 2012) was investigated using self-organising maps (Hewitson and Crane 2002; Gibson et al. 2017). Two droughts are considered, one in 2007/2008 and one in 2012/2013. In the case of the latter, estimates of the FAR depend considerably on how the drought is characterized, and this yields a range of plausible FARs, from 40% (using monthly pressure anomalies or the frequency of blocking high pressure systems) to 15% (using precipitation deficits or daily circulation properties). There is a robust anthropogenic increase in the likelihood of observing those SOM nodes which occurred frequently during the 2013 drought. In addition, the SOM approach in Harrington et al. (2016) also represents a method of circumventing difficulties in evaluating anthropogenic changes in drought likelihood, particularly for those locations where precipitation-temperature coupling mechanisms are less significant. Since the overall FAR of the drought will be some (uncertain) combination of the individual FAR components, the choice of a low but plausible FAR of 20% represents a conservative choice.

The 2007/2008 drought occurred on the back of a significant El Niño event. Contributions from El Niño events may not add linearly with contributions from anthropogenic climate change. Without a full study of 2007/2008 conditions, we cannot be sure that the

anthropogenic contribution is similar in the 2007/2008 and 2012/2013 cases, since the relative frequency of different synoptic patterns contributing to the drought may be different in El Niño years compared with neutral years and compared with La Niña years (Risser et al. 2017). Joint effects could well be additive, increasing the FAR, since there are reasons to believe that the frequency of ENSO conditions is increasing as a result of climate change (Wang et al. 2017). In this study, we have chosen a moderate value of 15%, but higher values are highly plausible.

Costs associated with the 2012/2013 drought have been estimated at NZ$1.5 billion by the New Zealand Treasury based on a reduced growth in gross domestic product, compared with a hypothetical year without drought (Treasury 2013). With a FAR of 20%, this yields excess costs of the drought due to anthropogenic climate change of NZ$300M. We note that the two drought events analysed were not the only droughts occurring in any part of New Zealand during this decade (2007–2017). We focus on these two events as these events are the only ones for which there is an available quantification of their economic losses. Other extreme weather or extreme weather–related hazards that might have FAR ≠ 0 associated with them— such as storm (damage from winds and storm surges), hailstorms, wildfires, frosts or tornadoes—were all omitted from the analysis because no peer-reviewed attribution studies have yet been conducted for these events occurring in New Zealand.

While developing a simple estimate of the insured losses from floods and the economic costs of droughts which are associated with climate change, the study is not comprehensive, and represents a significant underestimate of the full range of losses of climate change in New Zealand. At the end of the paper, we describe the prospects for including other hydrometeo-rological events within the framework, as well as secondary systems and cascading impacts.

3.7 Treatment of uncertainties

The economic impact cost estimates and FAR estimates in this report are uncertain, with uncertainties around cost probably being the larger of the two. Uncertainty estimates for FARs are presented in the table. Uncertainties associated with the heavy precipitation FARs, estimated by examining the FAR maps for the appropriate location, season and percentile, were estimated as usually likely to be around ± 0.2. In some cases—notably the Otago flood event, which is the subject of a paper in preparation—this means that the FARs even have some considerable likelihood of being negative, i.e. there is a likelihood that the event in question has become less likely because of climate change, even though the balance of evidence suggests certain aspects within the event (namely the intensity of rainfall) were likely made more severe because of climate change. Uncertainty in the drought FARs was estimated by attempting to combine information from Harrington et al. (2016), who examined various metrics (e.g. high surface pressure, low precipitation) individually. A combination of these influences would likely lead to higher FARs than is implied by each component individually; this in part contributes to the uncertainty estimate (Table 2) being asymmetric. The uncertainties about economic impact costs arise first and foremost because in both cases (droughts and floods), we only have a quantification of a part of the overall impacts (economic losses and insured damages, respectively). In addition, the quantities we do use are estimates of the true quantities, and the estimates of economic losses for droughts in particular are subject to substantial uncertainties around them. In fact, the Reserve Bank of New Zealand estimated that the economic loss of the 2013 drought event could be twice the magnitude we used in our analysis here (Kamber et al. 2013).

An additional uncertainty arises through our use of a rainfall, as against flooding, attribution. The scale of flooding clearly depends on other factors, such as antecedent soil moisture conditions, as well as rainfall. In New Zealand, it does seem a reasonable assumption that rainfall could provide an acceptable proxy for flooding in assessing the attribution results; however, it is acknowledged that we do not currently know the scale of the uncertainty introduced by this approximation. Future work, requiring substantially increased resources, is necessary to investigate this.

4 Discussion

4.1 Future developments

The framework developed in this paper needs further development. On the climate science side, we are planning to incorporate multiple lines of evidence, a broader set of hydrometeorological variables, and, eventually, ecosystem change. On the economic impact side, we are developing datasets, based both on government-produced statistics and on remote sensing data, which should give us a much greater insight into the impacts of weather-related disasters on New Zealand. Further into the future, we are planning to engage with other communities in the areas of ecosystem health, conservation, and especially non-monetised impacts associated with damage to indigenous cultural capital.

One important step is to broaden the science basis on which we make inferences about FARs. The use of multiple lines of evidence, each with its own capabilities and limits, would help us develop a more rounded picture of the physical processes governing changes in climate, and would therefore improve the assessments we are able to produce.

Incorporating more types of events would also make the attribution exercise deeper and more comprehensive. A 2016 study discussed scientific confidence in the ability of climate models to simulate phenomena relevant to extreme events (National Academies of Sciences and Medicine 2016). Nearly always, larger-scale phenomena (such as extreme heat and extreme cold) were better simulated than smaller-scale ones (such as severe convective storms). Incorporation of other important elements of change is more challenging because models cannot yet simulate adequately the appropriate scales or processes, as is the case, for instance, with tropical cyclones and tornadoes. As climate modelling progresses, the range of events amenable to quantification via attribution techniques is expected to increase.

Furthermore, cascading impacts—impacts in which anthropogenic climate change effects are mediated by other systems—present additional challenges for climate change attribution frameworks (Otto et al. 2017; Challinor et al. 2018; Lawrence et al. 2019). One future development that is directly relevant is the integration of climate and hydrological work within an attribution setting (Hidalgo et al. 2009; Kay et al. 2018; Philip et al. 2019). Utilising an integrated hydrological and climate infrastructure to calculate FARs would allow better quantification of flood risk, as well as improvements in our understanding of current and future climate risks.

4.2 Potential uses and limitations of the approach

Our approach is intended to augment rather than replace other streams of information regarding climate change costs. As sketched above, for many adaptation planners, especially

at the local scale, other forms of quantification of impacts may be preferable. There is a rich literature focused on climate change adaptation and practice which emphasizes the roles of policy (Noble et al. 2014) (Mimura et al. 2014), and the centrality of vulnerability, inequalities, and other social factors (Olsson et al. 2014). This literature critiques the tendencies of scientists to over-provide numerically substantive inputs, while failing to address the underlying social contexts in which climate change impacts and adaptation occur (Olsson et al. 2014). In developing the present approach, we are mindful of these concerns, and we emphasise that studies like this can provide a new set of inputs which may have value for some researchers, practitioners and policymakers with interests in the aggregation of climate change cost information.

Our method quantifies the probability of the combined weather-cost/damage events that have occurred in recent years. This context has some consequences. First, it is not a comprehensive assessment of the anthropogenic role in weather-related risk. While in theory we could have included events with decreased probability because of human interference, in practice those events are less likely to occur and thus less likely to be included in our type of event-triggered analysis, producing a selection bias towards increased attributable costs (NAS 2016). A more systematic selection of events could be used that does not depend on event occurrence (Risser et al. 2019), but that would decouple the assessment from experienced costs and damages.

Second, as is well-recognized in the climate change adaptation literature, experienced costs and damages take place in the context of the historical pathway of adaptation actions, whether as proactive approaches to mitigate against anticipated climate change damages or as reactive responses to avoid repeats of experienced damage. These decisions may have differed in a world without human interference in the climate system. Hence, in such a natural world, the same sequence of extreme weather may have induced higher or lower costs and damages than actually occurred. As such, our estimates only include the impacts after adaptation to the changes wrought by climatic change, and therefore do not count the full costs of climate change (which should include these adaptation measures that were already taken and paid for).

Third, our assessment used a very simple model of translating extreme weather to costs and damages: a step function. Though attractively simple, the step function translation also leaves out complexities inherent in that translation. In the case of flooding, potential complexities include antecedent conditions which might be less hazardous under anthropogenic climate change by, for example, being likely drier or having a smaller snowpack (Kay et al. 2011). In the flooding events analysed here, we expect the role of these complexities and antecedent conditions to be reduced, compared with the situation for much larger catchments found in continents, since we are dealing only with short-duration rainfall events with a direct connection to pluvial floods.

Fourth, and related to the point immediately above, the attributable anthropogenic costs we have calculated may bear on responsibility for costs and damages but does not amount to a full assessment of responsibility, since damage results from a confluence of causal factors such as historical policy on property development, building codes, and local and regional land management, as well as maintenance and usage of local and regional drainage systems (in the case of flooding). A full assignment of responsibility would require assessment of the role of such factors and whether that role can be considered reasonable.

Finally, it is perhaps surprising that there have not been more comprehensive attempts to tie PEA techniques to disaster losses in public discussions. One reason may be a general lack of awareness of PEA capabilities among users of climate science information. A frequent, but somewhat mistaken, comment is that we cannot attribute single events to climate change. Yet

for a decade or so the climate research community has been able to say with some confidence how the odds of such events have been changing because of climate change. A few studies have made quantitative attribution statements about damaging impacts of climate change, e.g. on flood risk (Schaller et al. 2016), on numbers of homes flooded (Kay et al. 2018) and on extreme heat-related deaths (Mitchell et al. 2016). Such studies are, however, very few in number compared with those on the attribution of the meteorological events themselves, and do not address disaster losses in financial terms, as done here.

The caution which some commentators have expressed around event attribution's potential roles (Hulme 2014) may also have contributed to its slow uptake, as adaptation researchers and practitioners sometimes subscribe to a vulnerability-centred view in which policymakers have to address extreme events, regardless of whether climate change is a driver (Parker et al. 2017). We think this line of argument is incomplete, however. How much change there has been in extreme events, and how fast they may be expected to change, and what are the costs associated with this change, are all highly relevant issues, even within a vulnerability-led conception of adaptation priorities. PEA can help with these quantifications.

Finally, not all those who need to adapt to a changing climate operate in a vulnerability-led paradigm. Some work more with hazards and some work more with risks. We envisage, and have encountered, significant interest in this type of study among people working in diverse areas such as risk management, insurance, or capital management.

5 Conclusion

The purpose of this pathfinder study was to develop a method for quantifying approximate costs associated with recent (2007–2017) extreme weather–related climate change in New Zealand, especially those related to extreme precipitation (both abundance and dearth). Our results are necessarily approximate and represent an underestimate because (1) limited resources dictated that a simple approach be taken with the modelling that was readily available, and thus the study restricts its attention to the most significant fourteen climate change–related extreme weather events (specifically rainfall and drought) in New Zealand across the chosen decade. (2) We are further limited by data availability, which forces us to use only insured damages—and not uninsured damages nor economic losses—associated with flooding events, and only economic losses—and not damages—when examining droughts. Despite these limitations, the study provides a rough estimate of current climate change attributable costs of floods and droughts, and the methodology could be extended to examine a wider range of other impacts, potentially forming one element of a more comprehensive "bottom-up" understanding of climate-related risks in New Zealand.

The method introduced in this paper is also intended as a preliminary "bottom-up" approach to complement the "top-down" approach of IAMs (Conway et al. 2019). This aspect of the research is further developed in the companion piece on Hurricane Harvey (Frame et al. 2020), where we argue that IAM-based estimates of the costs of anthropogenic climate change ignore a substantial contribution to the actual costs.

Our next steps include generating a comprehensive database of extreme weather and its associated damage; expanding the analysis to different types of damage associated with further types of extreme weather events; and assessing the relative importance and role of the various sources of incompleteness, contingency, and potential biases in our analysis. Additional plans include developing New Zealand's detection and attribution capability, and developing ways to

better assess the economic losses associated with extreme weather events (as per the 2015 Sendai Agreement).

Human influence on the climate has played a role in changing the frequency of extreme weather events in New Zealand. We have attempted to quantify the effects of climate change on the economic costs associated with those events. This approach provides a new "bottom-up" approach to the quantification of economic costs associated with anthropogenic climate change.

Author contributions DJF and Kate Hodgkinson from the New Zealand Treasury suggested and initiated the project. SMR provided the modelling inputs on extreme rainfall events. LJH provided the modelling inputs on droughts. TCS provided observational data. IN led the economic aspects of the paper. SS provided climate modelling computing services. SMR, LJH, DJF, DAS, IN and SMD contributed to methodological points. All authors wrote the paper.

References

Allen M (2003) Liability for climate change. Nature 421(6926):891–892

Bindoff N, Stott P, AchutaRao M, Allen M, Gillett N, Gutzler D, Hansingo K, Hegerl G, Hu Y, Jain S, Mokhov I, Overland J, Perlwitz J, Sebbari R, Zhang X (2013) In: Stocker T, Qin D, Plattner G-K et al (eds) Detection and attribution of climate change: from global to regional. Climate Change 2013 The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, pp 867–952

Black MT, Karoly DJ, Rosier SM, Dean SM, King AD, Massey NR, Sparrow SN, Bowery A, Wallom D, Jones RG, Otto FEL, Allen MR (2016) The weather@home regional climate modelling project for Australia and New Zealand. Geosci Model Dev 9(9):3161–3176

Challinor AJ, Adger WN, Benton TG, Conway D, Joshi M, Frame D (2018) Transmission of climate risks across sectors and borders. Philos Trans R Soc A Math Phys Eng Sci 376(2121):20170301

Christiansen B (2015) The role of the selection problem and non-Gaussianity in attribution of single events to climate change. J Clim 28(24):9873–9891

Conway D, Nicholls RJ, Brown S, Tebboth MGL, Adger WN, Ahmad B, Biemans H, Crick F, Lutz AF, De Campos RS, Said M, Singh C, Zaroug MAH, Ludi E, New M, Wester P (2019) The need for bottom-up assessments of climate risks and adaptation in climate-sensitive regions. Nat Clim Chang 9(7):503–511

Donlon CJ, Martin M, Stark J, Roberts-Jones J, Fiedler E, Wimmer W (2012) The Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) system. Remote Sens Environ 116(Supplement C):140–158

Frame DJ, Wehner MF, Noy I, Rosier SM (2020) The economic costs of Hurricane Harvey attributable to climate change. Clim Chang. https://doi.org/10.1007/s10584-020-02692-8

Gibson PB, Perkins-Kirkpatrick SE, Uotila P, Pepler AS, Alexander LV (2017) On the use of self-organizing maps for studying climate extremes. J Geophys Res Atmos 122(7):3891–3903

Harrington LJ (2017) Investigating differences between event-as-class and probability density-based attribution statements with emerging climate change. Clim Chang 141(4):641–654

Harrington LJ, Gibson PB, Dean SM, Mitchell D, Rosier SM, Frame DJ (2016) Investigating event-specific drought attribution using self-organizing maps. J Geophys Res Atmos 121(21):12,766–712,780

Hewitson BC, Crane RG (2002) Self-organizing maps: applications to synoptic climatology. Clim Res 22(1):13–26

Hidalgo HG, Das T, Dettinger MD, Cayan DR, Pierce DW, Barnett TP, Bala G, Mirin A, Wood AW, Bonfils C, Santer BD, Nozawa T (2009) Detection and attribution of streamflow timing changes to climate change in the Western United States. J Clim 22(13):3838–3855

Hope C (2006) The marginal impact of CO2 from PAGE2002: an integrated assessment model incorporating the IPCC's five reasons for concern. Integr Assess J 6(1):19–56

Hulme M (2014) Attributing weather extremes to 'climate change': a review. Prog Phys Geogr: Earth Environ 38(4):499–511

Insurance Council of New Zealand (2017) Cost of disaster events in New Zealand. from http://www.icnz.org.nz/statistics-data/cost-of-disaster-events-in-new-zealand/

Jones R, Hassell D, Hudson D, Wilson S, Jenkins G, Mitchell J (2004) Geenerating high resolution climate change scenarios using PRECIS. M. O. H. Centre, Exeter, U.K., p 40

Kamber G, McDonald C, Price G (2013) Drying out: investigating the economic effects of drought in New Zealand. Reserve Bank Analytical Notes. Reserve Bank of New Zealand. AN2013: 2:31

Kay AL, Crooks SM, Pall P, Stone DA (2011) Attribution of Autumn/Winter 2000 flood risk in England to anthropogenic climate change: a catchment-based study. J Hydrol 406(1):97–112

Kay AL, Booth N, Lamb R, Raven E, Schaller N, Sparrow S (2018) Flood event attribution and damage estimation using national-scale grid-based modelling: winter 2013/2014 in Great Britain. Int J Climatol 38(14):5205–5219

Lawrence J, Haasnoot M, McKim L, Atapattu D, Campbell G, Stroombergen A (2019) In: Marchau VAWJ, Walker WE, Bloemen PJTM, Popper SW (eds) Dynamic adaptive policy pathways (DAPP): from theory to practice. Decision making under deep uncertainty: from theory to practice. Springer International Publishing, Cham, pp 187–199

Massey N, Jones R, Otto FEL, Aina T, Wilson S, Murphy JM, Hassell D, Yamazaki YH, Allen MR (2015) weather@home—development and validation of a very large ensemble modelling system for probabilistic event attribution. Q J R Meteorol Soc 141(690):1528–1545

Mimura N, Pulwarty RS, Duc DM, Elshinnawy I, Redsteer MH, Huang HQ, Nkem JN, Rodriguez RAS (2014) In: Field CB, Barros VR, Dokken DJ et al (eds) Adaptation planning and implementation. Climate Change 2014: impacts, adaptation, and vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, U. K.

Ministry of Agriculture and Fisheries (2009) Regional and national impacts of the 2007–2008 drought. M. o. A. a. Fisheries, Wellington, N. Z

Mitchell D, Heaviside C, Vardoulakis S, Huntingford C, Masato G, Guillod BP, Frumhoff P, Bowery A, Wallom D, Allen M (2016) Attributing human mortality during extreme heat waves to anthropogenic climate change. Environ Res Lett 11(7):074006

National Academies of Sciences, E. and Medicine (2016). Attribution of extreme weather events in the context of climate change. Washington, DC, The National Academies Press

NIWA (2017) CliFlo: NIWA's National Climate Database on the Web, NIWA. https://cliflo-niwa.niwa.co.nz/

Noble IR, Huq S, Anokhin YA, Carmin J, Goudou D, Lansigan FP, Osman-Elasha B, Villamizar A (2014) In: Field CB, Barros VR, Dokken DJ et al (eds) Adaptation needs and options. Climate Change 2014: impacts, adaptation, and vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, U. K.

Nordhaus WD (1993) Rolling the 'DICE': an optimal transition path for controlling greenhouse gases. Resour Energy Econ 15(1):27–50

Nordhaus WD, Boyer J (1999) Roll the DICE again: economic models of global warming. Cambridge, MA: MIT Press

Noy I (2016) The socio-economics of cyclones. Nat Clim Chang 6:343

Noy I, duPont W (2018) The long-term consequences of disasters: what do we know, and what we still don't. Int Rev Environ Resour Econ 12(4):325–354

Olsson L, Opondo M, Tschakert P, Agrawal A, Eriksen SH, Ma S, Perch LN, Zakieldeen SA (2014) In: Field CB, Barros VR, Dokken DJ et al (eds) Livelihoods and poverty. Climate Change 2014: impacts, adaptation, and vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, U. K.

Otto FEL, Massey N, van Oldenborgh GJ, Jones RG, Allen MR (2012) Reconciling two approaches to attribution of the 2010 Russian heat wave. Geophys Res Lett 39(4):L04702

Otto FEL, Skeie RB, Fuglestvedt JS, Berntsen T, Allen MR (2017) Assigning historic responsibility for extreme weather events. Nat Clim Chang 7:757

Pall P, Aina T, Stone DA, Stott PA, Nozawa T, Hilberts AGJ, Lohmann D, Allen MR (2011) Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. Nature 470(7334):382–385

Parker HR, Boyd E, Cornforth RJ, James R, Otto FEL, Allen MR (2017) Stakeholder perceptions of event attribution in the loss and damage debate. Clim Pol 17(4):533–550

Pfahl S, Ogorman PA, Fischer EM (2017) Understanding the regional pattern of projected future changes in extreme precipitation. Nat Clim Chang 7(6):423–427

Philip S, Sparrow S, Kew SF, van der Wiel K, Wanders N, Singh R, Hassan A, Mohammed K, Javid H, Haustein K, Otto FEL, Hirpa F, Rimi RH, Islam AKMS, Wallom DCH, van Oldenborgh GJ (2019) Attributing the 2017 Bangladesh floods from meteorological and hydrological perspectives. Hydrol Earth Syst Sci 23(3):1409–1429

Pindyck RS (2013) Climate change policy: what do the models tell us? J Econ Lit 51(3):860–872

Pope VD, Gallani ML, Rowntree PR, Stratton RA (2000) The impact of new physical parametrizations in the Hadley Centre climate model: HadAM3. Clim Dyn 16(2):123–146

Risser MD, Stone DA, Paciorek CJ, Wehner MF, Angélil O (2017) Quantifying the effect of interannual ocean variability on the attribution of extreme climate events to human influence. Clim Dyn 49(9):3051–3073

Risser MD, Paciorek CJ, Stone DA (2019) Spatially dependent multiple testing under model misspecification, with application to detection of anthropogenic influence on extreme climate events. J Am Soc Stat Assoc 114(525):61–78

Rosier S, Dean S, Stuart S, Carey-Smith T, Black MT, Massey N (2015) Extreme rainfall in early July 2014 in Northland, New Zealand—was there an anthropogenic influence? Bull Am Meteorol Soc 96(12):S136–S140

Schaller N, Kay AL, Lamb R, Massey NR, van Oldenborgh GJ, Otto FEL, Sparrow SN, Vautard R, Yiou P, Ashpole I, Bowery A, Crooks SM, Haustein K, Huntingford C, Ingram WJ, Jones RG, Legg T, Miller J, Skeggs J, Wallom D, Weisheimer A, Wilson S, Stott PA, Allen MR (2016) Human influence on climate in the 2014 southern England winter floods and their impacts. Nat Clim Chang 6(6):627–634

Stott PA, Christidis N, Otto FEL, Sun Y, Vanderlinden J-P, van Oldenborgh GJ, Vautard R, von Storch H, Walton P, Yiou P, Zwiers FW (2016) Attribution of extreme weather and climate-related events. Wiley Interdiscip Rev Clim Chang 7(1):23–41

Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experiment design. Bull Am Meteorol Soc 93(4):485–498

Treasury, T (2013) Budget economic and fiscal update. pp 17–18

Wang G, Cai W, Gan B, Wu L, Santoso A, Lin X, Chen Z, McPhaden MJ (2017) Continued increase of extreme El Niño frequency long after 1.5 °C warming stabilization. Nat Clim Chang 7(8):568–572

Weitzman ML (2012) GHG targets as insurance against catastrophic climate damages. J Public Econ Theory 14(2):221–244

Wolski P, Stone D, Tadross M, Wehner M, Hewitson B (2014) Attribution of floods in the Okavango basin, Southern Africa. J Hydrol 511:350–358

Affiliations

David J. Frame[1] · Suzanne M. Rosier[2] · Ilan Noy[3] · Luke J. Harrington[1,4] · Trevor Carey-Smith[2] · Sarah N. Sparrow[4,5] · Dáithí A. Stone[2] · Samuel M. Dean[2]

[1]   New Zealand Climate Change Research Institute, Victoria University of Wellington, Wellington 6012, New Zealand

[2]   National Institute of Water and Atmospheric Research, Wellington 6021, New Zealand

[3]   School of Economics and Finance, Victoria University of Wellington, Wellington 6012, New Zealand

[4]   ECI, School of Geography and the Environment, University of Oxford, Oxford OX1 3QY, UK

[5]   Oxford e-Research Centre, 7 Keble Road, Oxford OX1 3QG, UK