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LETTER

When the fraction of attributable risk does not inform the impact associated with anthropogenic climate change

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Abstract

Weather and climate phenomena have outsized impacts on society when they are particularly extreme. Extreme Event Attribution (EEA) seeks to quantify the extent to which extreme weather and climate phenomena are the result of anthropogenic climate change (ACC), and thus it has implications for many pertinent climate change discussions, including those on potential legal claims of loss and damages and calculations of the social cost of carbon. The Fraction of Attributable Risk (FAR) is one metric that is used to quantify the proportion of an extreme weather or climate "event" associated with ACC. The FAR is typically applied to changes in the likelihood of exceeding some geophysical value chosen, post hoc, to represent the "event" (e.g., i.e., rainfall amounts, flood depths, drought measures, temperature values, etc.). The FAR has further been used to estimate the fraction of observed impacts (e.g., lives lost or economic damage) that can be associated with ACC by multiplying realized impacts by the FAR (IFAR = Impact×FAR). Here, we illustrate with a few stylized examples that this IFAR calculation only produces reliably useful results when the weather or climate phenomena in question can be easily conceived of as a discrete binary "event" (i.e., the entirety of the event either occurs or it does not). We show that the IFAR calculation can produce misleading results when the weather or climate phenomena in question are on a continuum, and ACC can be thought of as altering the intensity of the geophysical value that is used in the eventhood definition. Specifically, we show that the IFAR calculation inflates the impacts associated with ACC in these circumstances because it inaccurately assumes that there would have been zero impact had the geophysical value chosen to define eventhood not been exceeded. We illustrate that for weather and climate phenomena on a continuum (e.g., floods, droughts, temperatures, etc.), a clearer way of conceptualizing the impacts associated with ACC is to compare the expected value of the impact between the ACC and preindustrial conditions across the full continuum.

Keywords Extreme event attribution · Climate change impacts · Damage function · Social cost of carbon

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1 Introduction

The climate can be conceptualized as the full probability distribution (mean as well as all moments) of all weather and climate variables as a function of location, time of year, etc. (Hsiang 2016). Anthropogenic alterations of greenhouse gas concentrations and aerosol loading shift these probability distributions (anthropogenic climate change (ACC)). Since impacts on human and natural systems are particularly acute on the extreme tails of these probability distributions, there is a specific interest in the manifestation of ACC on these tails (Seneviratne et al. 2021). Quantifying the extent to which various extreme weather and climate "events" are manifestations of ACC is the topic of a rapidly developing field in climate science referred to as extreme event attribution (EEA) (Allen 2003; Otto 2017; Philip et al. 2020; Stott et al. 2016).

2 Extreme "event" attribution and the fraction of attributable risk

One metric that is sometimes used to quantify the extent to which various extreme "events" are manifestations of ACC is the fraction of attributable risk (FAR).

The fundamental idea behind the FAR is that it can quantify how a change in external conditions affects the risk of some outcome. The formula is

$$\mathrm{FAR} = 1 - \frac{P(\text{outcome}|\text{original condition})}{P(\text{outcome}|\text{altered condition})}. \tag{1}$$

The FAR has its origin epidemiology (Levin 1953); for example, it can quantify how exposure to a particular carcinogenic chemical affects the risk of contracting cancer over some period of time (Table 1 part a). In this case, the "outcome" in Eq. 1 would correspond to the contraction of cancer, "original condition" would correspond to a group not exposed to the chemical, and "altered condition" would correspond to a group exposed to the chemical.

If exposure to the chemical doubles the risk of cancer from 10 to 20% (Table 1 part a), then, the FAR is 0.5, and half of the cancer cases in an exposed group can be attributed to exposure. Or, thought of another way, if an exposed individual contracts cancer, then, half of the risk of their contraction of cancer can be attributed to exposure to the chemical.

This idea can be extended to quantify the portion of a downstream impact that is due to the altered conditions (exposure to the chemical). If we further imagine that treatment of this cancer universally costs US\$20,000, then it can be said that

$$\text{Impact} \times \mathrm{FAR} = \mathrm{IFAR} = \mathrm{US\$}20{,}000 \times 0.5 = \mathrm{US\$}10{,}000. \tag{2}$$

And, thus, US\$10,000 of a US\$20,000 medical bill could be blamed on exposure to the chemical.

The FAR (Stott et al. 2004) and IFAR concepts have been transferred from epidemiology to phenomena in the climate system. This was pioneered by Allen (2003), who wrote:

> *If at a given confidence level, past greenhouse-gas emissions have increased the risk of a flood tenfold, and that flood occurs, then we can attribute, at that confidence level, 90% of any damage to those past emissions.*

More recently, this same idea was articulated in the Sixth Assessment Report by the Intergovernmental Panel on Climate Change (O'Neill et al. 2022):

Table 1 Three examples of the IFAR calculation. The first two examples (a and b) are for phenomena that can be considered discrete and binary (i.e., Bernoulli random variables) and thus fit well into the IFAR framework. The third example (c) is for a phenomenon that cannot be considered discrete and binary and thus does not fit well into the IFAR framework

		Original condition	Altered condition			
a, Epidemiology example						
	Binary Outcome	No exposure	Exposure	Cost	FAR	IFAR
No event	No cancer	0.9	0.8	\$0		
Event	Cancer	0.1	0.2	\$20,000	0.5	\$10,000
b, Climate science example 1						
	Binary Outcome	Preindustrial climate	Anthropogenically altered climate	Cost		
No event	No Tropical Cyclone	0.9	0.8	\$0		
Event	Tropical Cyclone	0.1	0.2	\$1,000,000,000	0.5	\$500,000,000
c, Climate science example 2						
	Continuous random variable framed as binary outcome	Preindustrial climate	Anthropogenically altered climate	Cost		
No "event"	Daily rainfall $\leq$ 250 mm	0.9	0.8	Unknown but not \$0		
"Event"	Daily rainfall = 250 mm	0.1	0.2	\$10,000,000,000	0.5	X

Assuming that the extreme rainfall is a major driver of the total damages induced by the tropical cyclone, the contribution of anthropogenic climate forcing to the occurrence probability of the observed rainfall (Fraction of Attributable Risk) can also be considered the Fraction of Attributable Risk of the hurricane-induced damages or fatalities.

Finally, a more precise explanation is given by Clarke et al. (2021):

For any event with an attribution statement, the ACC-related impacts can be approximated by multiplying the total quantifiable impacts with the best-estimate FAR value. For example, the attributable insured losses I_{att} from a flood could be approximated as $I_{att} = \mathrm{I}_{total} \times FAR$, where I_{total} is the known total insured losses of the event….This method could equally be applied to any quantified impacts from an event, including overall economic loss or mortality.

Specifically, the IFAR calculation has been used to quantify the ACC contribution to human deaths associated with particularly high temperatures (Mitchell et al. 2016; Newman and Noy 2022) and rainfall amounts (Clarke et al. 2021; Newman and Noy 2022), as well as economic damage from particularly high rainfall amounts and measures of drought (Clarke et al. 2021; Frame et al. 2020b; Frame et al. 2020c; Li and Otto 2022; Newman and Noy 2022).

Recently, Perkins-Kirkpatrick et al. (2022) have drawn attention to the drawbacks of the IFAR calculation. They point out that it cannot be assumed that a FAR for an extreme weather or climate event is linearly related to the impact of that event. Thus, an improvement to the method is to perform the FAR analysis directly on the impact (using a transfer function) rather than performing FAR on the geophysical class of events and assuming that it transfers linearly to the impact. We endorse the major points made in Perkins-Kirkpatrick et al. (2022), but we argue here that the use of the IFAR method has even more fundamental problems that make it unsuitable to use on weather and climate phenomena on a continuum.

The transfer of the concept from the chemical-cancer example to a climate science application would be relatively straightforward so long as the "event" in question can be conceptualized as being discrete and binary, like the contraction of cancer. For example, it could be used to quantify the degree to which changes in the risk of landfalling tropical cyclones are a manifestation of ACC (Table 1 part b). In this case, the outcome would be the occurrence of a tropical cyclone over some region and timeframe, normal conditions would correspond to a preindustrial climate condition, and altered conditions would correspond to our current situation under ACC.

If, in some hypothetical region, ACC is associated with a doubling of the annual risk of tropical cyclone occurrence from 10 to 20% (Table 1 part b), and a tropical cyclone occurs, then the FAR is 0.5, and half of the tropical cyclone incidences can be attributed to ACC. Or, thought of another way, if a tropical cyclone occurs, then half of the risk of that occurrence can be attributed to ACC. If we further suppose that the impact of tropical cyclone occurrence is universally US$1bn, then it can be said that

$$\text{Impact} \times \text{FAR} = \text{IFAR} = \text{US\$1bn} \times 0.5 = \text{US\$500m}, \tag{3}$$

and thus US$500m of a US$1b impact could be blamed on ACC.

The key condition for the tropical cyclone example fitting into the framework is that the lack of tropical cyclone occurrence corresponds to a lack of impact. There is zero tropical cyclone cost if a tropical cyclone does not occur (Table 1 part b).

However, for the majority of cases in which IFAR has been applied in published climate science, the key condition above does not apply. This is because eventhood is defined post hoc by the exceedance of some geophysical value (e.g., crossing some rainfall total, temperature, and drought index) (Table 1 part c).

The IFAR calculation would be appropriate to apply to these cases if the impact could be assumed to be zero had the threshold not been crossed. This issue is made explicit in a caveat articulated in Frame et al. (2020b):

> *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.*

Frame et al. (2020b) go on to add appropriate caveats regarding how real-world complexities are lost in this simplifying assumption. These caveats are further expounded upon in Perkins-Kirkpatrick et al. (2022).

However, we argue here that treating the damage function as a step function when the phenomena in question is a continuous random variable and not best conceptualized as a discrete, binary outcome, causes the IFAR calculation to substantially over-attribute impacts to ACC.

In the example in Table 1 part c, 1 mm less rainfall would imply that the threshold used to define eventhood would not have been crossed, and thus the "event" would have been deemed to have not taken place. This is a conceptual problem for the IFAR calculation because, as discussed in, e.g., Brown (2016), Otto et al. (2012), and Seneviratne et al. (2021), change in the probability or frequency of exceeding a threshold (the so-called Oxford School of EEA) can be considered equivalent to changes in the intensity or magnitude of a phenomenon at a fixed probability or frequency (sometimes called the "Boulder School" of EEA (Easterling et al. 2016)). Thus, the "event" in Table 1 part c can just as easily be conceptualized as having been made more intense in the ACC condition. But "intensification" of the phenomena implies that much of its measurable quantity (e.g., much of the rainfall total in Table 1 part c) would have existed in the preindustrial condition as well. This means that much of the impact would have also existed in the preindustrial condition, and thus, it is incorrect to attribute all of the observed impact to the FAR of crossing the threshold.

3 Simple conceptual illustration of the problem with applying the IFAR calculation to geophysical variables on a continuum

Consider the following simple conceptual example that sacrifices some physical realism in an effort to sharpen the point above.

Suppose a location has a climate with a daily rainfall probability distribution that has an absolute hard limit on the maximum amount of rain that can fall in a day (bars in Fig. 1a). Suppose that, in the preindustrial condition, this maximum amount of rain that can fall in a day is between 249 and 250 mm (Fig. 1a gray bars). Assume further that at this extreme tail of the distribution, each additional millimeter of daily rainfall is associated with an additional US$0.1bn in economic damage from flooding (Fig. 1b). In the preindustrial climate condition, the most extreme daily rainfall possible (249 to 250mm) would be associated with US$9.9bn in damage (Fig. 1b).

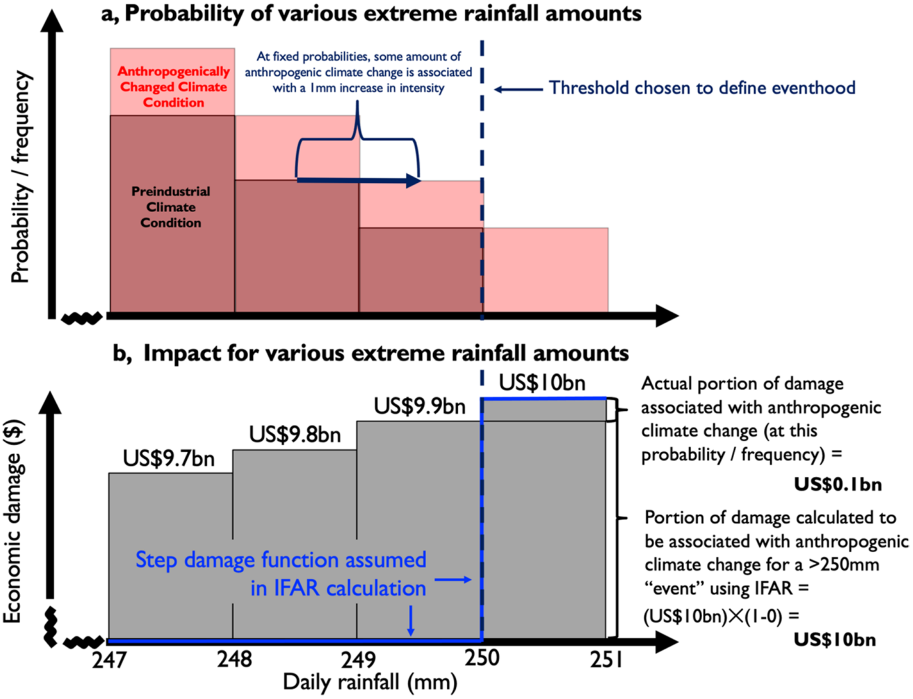

Fig. 1 Illustration of how the IFAR calculation can over-attribute impacts to anthropogenic climate change when the phenomenon in question is on a continuum and not easily conceptualized as a discrete binary "event"

Now, assume that under some marginal ACC, all of the most extreme daily rainfall values become more probable (red bars are higher than gray bars in Fig. 1a). Or equivalently, at any given probability/frequency, the intensity/magnitude of daily rainfall increases (the red histogram represents a shift to the right of the gray histogram). Specifically, suppose that at any given probability, the intensity of daily rainfall increases by 1 mm (i.e., the ACC condition's 250–251 mm bin has the same probability as the preindustrial condition's 249–250 mm bin; the ACC condition's 249–250 mm bin has the same probability as the preindustrial condition's 248–249 mm bin, etc.).

Now, suppose that under the ACC condition, the most extreme possible rainfall of 250–251 mm occurs (Fig. 1a). This has an economic impact of US$10bn (Fig. 1b).

The pertinent question is how much of this US$10bn impact is associated with ACC? In this example, ACC was associated with the intensity/magnitude of the most extreme daily rainfall amount being enhanced by 1 mm which corresponds to a US$0.1bn increase in damage. Thus, at this fixed probability, the portion of economic damage attributable to ACC is US$0.1bn (1% of the event's total economic damage).

In this example, the IFAR calculation would typically define eventhood as the exceedance of 250 mm of rain (black dashed line in Fig. 1). Greater than 250 mm of rain was impossible in the preindustrial condition [P(outcome|original conditions) = 0 in Eq. 1]. Thus, regardless of what its non-zero probability is in the ACC condition, the occurrence of > 250 mm of rain will have a FAR of 1.0. The proper interpretation is that *the risk of* > 250 mm, and thus, > US$10bn in damage is 100% associable with ACC (Perkins-Kirkpatrick et al. 2022), but this does *not* imply that 100% of the US\$10bn impact is associated with ACC. However, the IFAR calculation results in exactly the latter misinterpretation, associating *all* US\$10bn of the impact with ACC. In this example, this amounts to an 100× over-attribution of the impact to ACC.

This example further illustrates that the impact associated with ACC for a single "event" is more directly relatable to the change in magnitude at a fixed probability as opposed to a change in probability at a fixed magnitude (Perkins-Kirkpatrick et al. 2022; Wehner and Sampson 2021). However, in addition to quantifying the ACC contribution to the impact of a single extreme event, some published research that uses the IFAR calculation has also been motivated by the goal of improving estimates of annual mean damage functions (e.g., those included in integrated assessment models like DICE, PAGE, or FUND) and/or estimates of the social costs of carbon (Frame et al. 2020a; Frame et al. 2020c; Newman and Noy 2022). It is apparent from Fig. 1 that in order to make a holistic assessment of the impacts associated with ACC, it would be inappropriate to focus on just a single bin in the probability distribution. Thus, in the next section, we extend this example to a much wider range of a physically realistic probability distribution.

4 A more holistic quantification of impacts associated with anthropogenic climate change

Here, we expand the above example illustrated in Fig. 1 to a wider range of a more physically realistic probability distribution of rainfall, paired with a stylized but plausible damage function. The motivation of this stylized example is to gain insight on how to best conceptualize the full influence of ACC on some impact and to contrast this with what the IFAR calculation produces.

Our example uses daily rainfall distributions over a particular area simulated by the CESM2 global climate model (Danabasoglu et al. 2020). The ACC situation (altered conditions) is represented by CESM's simulation of 2050 to 2100 under RCP4.5 emissions, and the non-ACC situation (original conditions) is represented by CESM's simulation of 1850 to 1900 preindustrial conditions. Discrete daily rainfall distributions (histograms in Fig. 2a) are fit with generalized Pareto distributions on the right tail (lines in Fig. 2a) to smooth noise and extrapolate to extreme rainfall intensities not simulated in the 50-year spans.

CESM2 simulates a shift in the daily rainfall probability distribution such that ACC manifests as fewer days of rainfall below ~ 65 mm/day and more days of rainfall above ~ 65 mm/day (Fig. 2a). Thus, ACC is associated with greatly enhanced relative probabilities of extreme rainfall, and the more extreme the rainfall, the larger the fractional enhancement (Fig. 2a, b, and c). Exceedance of the most extreme 270 mm/day shifts its probability from a 1-in-6,101-year "event" in the preindustrial climate to a 1-in-608-year "event" under ACC (Fig. 2b), a roughly 10× increase (Fig. 2c). The 10× increase in exceedance probability for the most extreme value investigated corresponds to a FAR of 90% (Fig. 2d).

For economic damages associated with various daily rainfall amounts, we suppose a cumulative distribution function of the Gaussian distribution, where we use the error function (erf), with standard deviation $\sigma = 64$ mm, mean $\mu = 135$ mm, and $a = 5e + 9$:

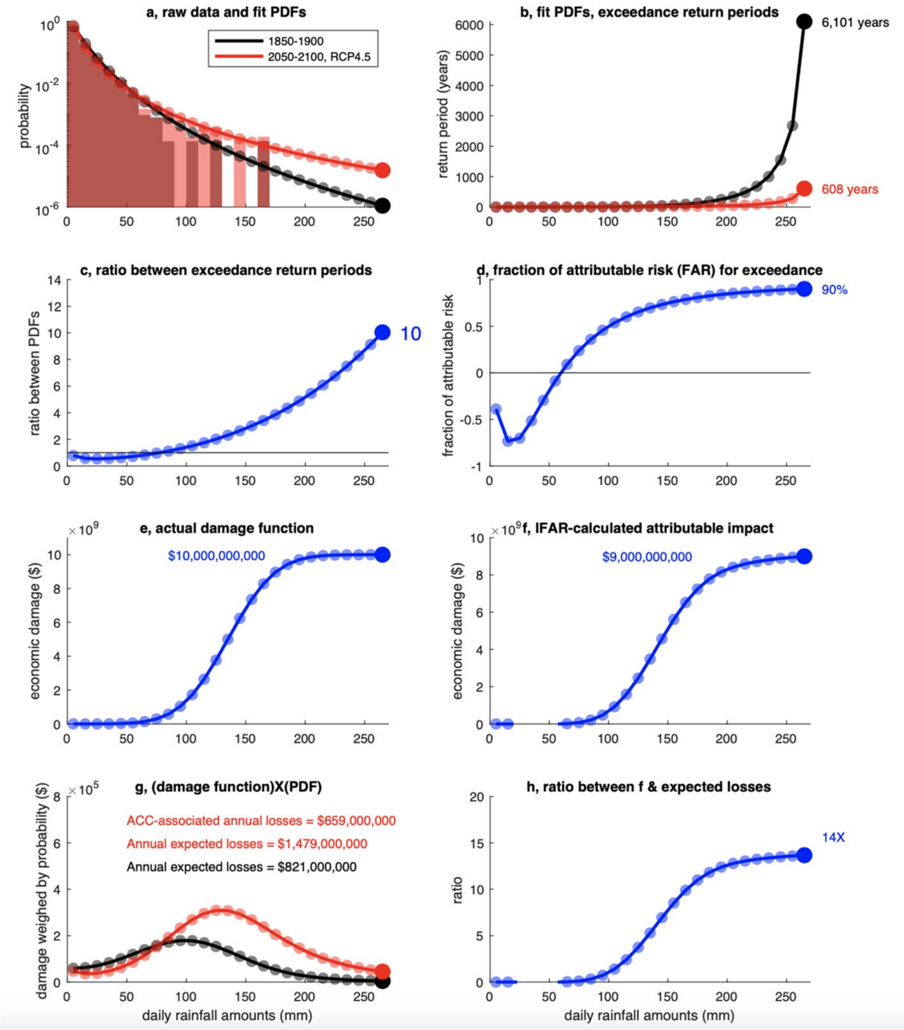

Fig. 2 Illustration of the difference between the IFAR calculation and annual expected losses attributable to anthropogenic climate change. The example uses the ACC-associated shifts in annual probabilities for daily rainfall, a geophysical variable on a continuum not easily thought of as a discrete "event." The data used is simulated daily rainfall totals from the CESM2 global climate model for the grid box nearest New York City, but the damage function should not be construed as representative of New York City. The two time periods being compared are 1850–1900 (black) and 2050–2100 under RCP4.5 emissions (red). Empirical frequency distributions are fit with generalized Pareto distributions over the 70% of the data on the right tail of the distribution in order to smooth out noise and to extrapolate to extremes not realized in the 50 years of simulation. **a** Histograms and fit probability distributions for simulated daily rainfall amounts in bins of 10-mm width. Note that the probabilities are on a log scale. We chose to consider changes in the probability distribution over a finite range of reasonable rainfall amounts because there are real physical constraints on how much rain can fall in a day that are not incorporated into theoretical probability distributions like the generalized Pareto distribution (where rainfall amount probabilities only reach zero as the rainfall amount goes to infinity). **b** Return periods for exceeding each rainfall total. **c** Ratio between the exceedance return periods in the two climate states. **d** Fraction of attributable risk (FAR) (Eq. 1) for exceedance. **e** Illustrative economic damage function (Eq. 4). **f** IFAR-calculated attributable costs assuming damage step function like Fig. 1b. **g** Damage function multiplied by the probability of occurrence for each bin, allowing for the calculation of an expected value of economic damages (Eq. 5) that is more comparable to damage functions incorporated into integrated assessment models. **h** Ratio between the IFAR-calculated attributable impact (f) and actual expected losses

$$\text{economic damage}_{\text{i}} = a \bullet \left(1 + \text{erf}\left[\frac{\text{rainfall}_{\text{i}} - \mu}{\sigma \bullet \sqrt{2}} \right] \right) \tag{4}$$

This function displays the plausible properties of registering very little damage for small daily rainfall amounts before increasing exponentially and then saturating (Ricke et al. 2016) at approximately US$10bn—as all property than can be flooded experiences flooding. This function is intended to be plausible for some hypothetical location but is for illustrative purposes only. The function is the same in both the ACC and non-ACC situations.

In this context, it is valuable to use the current example to illustrate the difference between IFAR-calculated impacts when an extreme event does occur and the impacts associated with ACC that would be expected in a typical year (i.e., what integrated assessment models incorporate).

In the current example, the damage function is assumed to be known, and thus, the true annual mean impact associated with ACC can be calculated by taking the difference of the expected values of the damages between the ACC condition and the preindustrial climate condition. In doing this, the economic damage function is weighted by the corresponding probabilities and then summed across all values:

$$\text{ACC associated annual expected losses} = 365 \bullet \sum_{i=1}^{n} P\left(\text{rain}_{\text{i}}|\text{altered}\right) \bullet \text{damage}_{\text{i}} - P\left(\text{rain}_{\text{i}}|\text{original}\right) \bullet \text{damage}_{\text{i}}, \tag{5}$$

where P is the probability, n is the number of bins considered, and i is the bin.

Using the particular representations of the probability distributions and the particular damage function described above, the expected annual impact associated with ACC would be ~ US$800 million (Fig. 2g). This number is an order of magnitude smaller than the US$9bn that would be calculated using IFAR on an observed 270 mm rainfall occurrence (Fig. 2f, h).

As stated in Frame et al. (2020b), the IFAR calculation performed on damages from observed extreme events is a different quantity and not directly comparable to annual mean economic damages. Nevertheless, it is sometimes argued that discrepancies between IFAR calculations and annual mean economic damage estimates incorporated into, e.g., integrated assessment models, are evidence that the annual mean estimates are too low (Frame et al. 2020a).

The example illustrates, however, that IFAR calculations being much higher than annual mean economic damage estimates are unsurprising in part because the rarity of the event is not accounted for in the IFAR calculation: If the occurrence of the event itself triggers the IFAR analysis, this selection bias obscures the property that the event would be extremely rare in both the preindustrial and ACC conditions.

Overall, the point being illustrated is that when a weather or climate phenomenon is on a continuum (i.e., a continuous random variable) and not easily conceptualized as a discrete binomial "event," shifts in probabilities across all magnitudes (as well as their interaction with an underlying damage function) must be taken into account when calculating a holistic impact associated with ACC. Considering the probability shifts over the entire continuum moves the focus of the analysis away from assessing the impact of a particular, extreme "event," but this is necessary if one wants to gain insight on annual mean damage functions or, e.g., the social cost of carbon.

This example also highlights the practical difficulty in estimating the full impact associated with ACC because it shows that the full impact function must be estimated. This is particularly challenging when one considers that the impact function should include downstream indirect effects that in the case of economic damages may be several times larger than direct damages (Frame et al. 2020c). Thus, further focus on these impact functions may be where the highest leverage is in terms of increasing the precision of the quantification of impacts associated with ACC.

5 Summary

The specific numbers from the stylized examples used here should not be taken seriously, but they serve to illustrate some points.

Specially, the IFAR calculation can provide useful information in situations where the "event" can be conceptualized as being discrete and binomial because, in those instances, it is valid to assume that there are no impacts when the "event" does not take place.

However, the IFAR calculation will inflate estimates of impacts associated with ACC when the phenomenon in question is on a continuum and not easily conceived of as a discrete binary "event" (i.e., rainfall amounts, flood depths, drought measures, and temperature values). This is because these phenomena can be thought of as being made more intense under the ACC condition (rather than simply more likely) which implies that *only* the impact associated with the *intensification* (not the impact associated with the entirety of the event) should be attributed to the ACC condition. Said another way, it is inappropriate in these situations to assume, as the IFAR calculation does, that there would be zero impact had the eventhood threshold not been exceeded.

We further illustrate that discrepancies between the IFAR calculation and annual mean estimates of impacts should be expected to diverge substantially, and thus, a discrepancy between the two is not strong evidence that annual mean damage estimates incorporated into integrated assessment models are biased low.

Data availability The CESM2 data can be downloaded at https://climexp.knmi.nl/start.cgi.

Declarations

Competing interests The author declares no competing interests.

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