

# Attribution of Weather and Climate Events

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## Keywords

extreme weather, risk assessment, probabilistic event attribution

## Abstract

Within the past decade, the attribution of extreme weather and climate events has emerged from a theoretical possibility into a subfield of climate science in its own right, providing scientific evidence on the role of anthropogenic climate change in individual extreme weather events, on a regular basis and using a range of approaches. Different approaches and thus different framings of the attribution question lead to very different assessments of the role of human-induced climate change. Although there is no right or wrong approach, the community is currently debating about the appropriate methodologies for addressing various stakeholder needs and scientific limitations. Tackling these limitations with more thorough model evaluation and meaningful bias corrections as well as going beyond the meteorological hazard and attributing the full impacts of extreme weather are the main challenges to face in the coming years.



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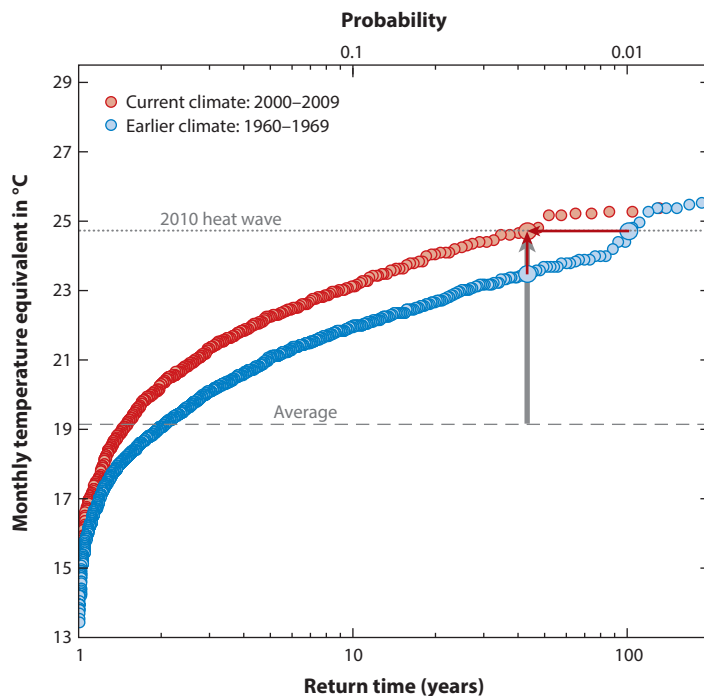
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## 1. INTRODUCTION

The detection and attribution of long-term trends in observed records (mainly temperature) have routinely been provided by the scientific community at least since the second Intergovernmental Panel on Climate Change (IPCC) report in 1995 (1). Attributing individual extreme events was, however, deemed impossible until Allen (2) described a methodology to assess whether and to what extent external drivers alter the likelihood of a specific extreme weather event occurring. Since then, the methodology has been applied in various contexts, with the first application (3) showing that the likelihood of the European heat wave of 2003 occurring was at least doubled due to human influence. Few studies followed in the years after these initial publications, until the science of extreme weather event attribution to anthropogenic climate change and other external drivers began to emerge with studies surrounding the Russian heat wave of 2010 (see 4 for a brief review) and the first annual special issue of the *Bulletin of the American Meteorological Society (BAMS)*, a collection of the extreme weather event attribution studies of the previous year (in this case, 2011; 5). Importantly, however, event attribution analyses are not a method to quantify a trend that is consistent with expectations from the global warming trend, and every attribution analysis has a priori four possible outcomes: (a) The event could have been made more likely because of anthropogenic climate change, (b) it could have been made less likely, (c) there is no detectable influence from anthropogenic climate change, or (d) with our current understanding and available tools we are unable to analyze the role of external drivers in the event. For example, Kay et al. (6) found that the likelihood of extreme precipitation in the spring in the United Kingdom has decreased because of climate change, despite a large-scale increase of rainfall in Northern Europe in a warming world. The reason for this discrepancy is that, although from thermodynamic considerations alone we expect more extreme rainfall in a warmer atmosphere that can hold more water vapor, higher ocean temperatures and higher greenhouse gas concentrations in the atmosphere also affect the atmospheric circulation, either in the same direction as the thermodynamics and thus increasing the effect or in the opposite direction. As such, the attribution of individual extreme events needs to be done if we want to understand regional impacts of climate change. At the same time, disentangling these two effects is one of the key challenges in the attribution of extreme events and requires a range of methodologies and modeling frameworks to obtain robust results.



**Figure 1**

Return time of extremely high monthly mean temperatures in Western Russia in the current climate (*red*) and an earlier climate (*blue*). The dashed line shows monthly average temperatures, and the dotted line shows the magnitude of the heat wave in 2010. The gray arrow shows the departure from the average in the magnitude, and the red vertical arrow depicts the role of climate change in that departure. The red horizontal arrow shows the increase in frequency of a 2010-like heat wave due to anthropogenic climate change. Adapted from Otto et al. (9).

Although necessary to quantify the uncertainty in attribution analysis and assess confidence levels, different methodologies can lead to very different quantitative and qualitative assessments of the role of anthropogenic climate change despite being scientifically valid. The Russian heat wave of 2010 arguably attained fame due to two high-profile attribution studies claiming a negligible role of human influence on climate change (7) on the one hand and a fivefold increase in the likelihood of record-breaking heat waves due to large-scale human-induced warming (8) on the other. These seemingly contradictory findings highlight that quantifications of the role of anthropogenic climate change or other external climate drivers are only meaningful if the framing of the attribution question is clear and, importantly, clearly communicated. An obvious difference that largely resolved the discrepancy around the heat wave of 2010 is whether the intensity of the event or the frequency of occurrence for an event of a given magnitude is analyzed (9); in this sense, the two articles showed no substantive contradiction, as Dole et al. (7) analyzed the role of anthropogenic climate change in the intensity, which is small compared to natural variability (**Figure 1**, gray arrow), whereas Rahmstorf & Coumou (8) analyzed how human-induced climate change increased the frequency of record-breaking heat waves in Western Russia.

But there are more subtle ways of framing a seemingly simple question: What is the role of anthropogenic climate change? Conditioning the analysis on the large-scale atmospheric conditions

or the observed sea surface temperatures (SSTs) versus on the long-term warming alone can lead to equally large discrepancies in the results (10).

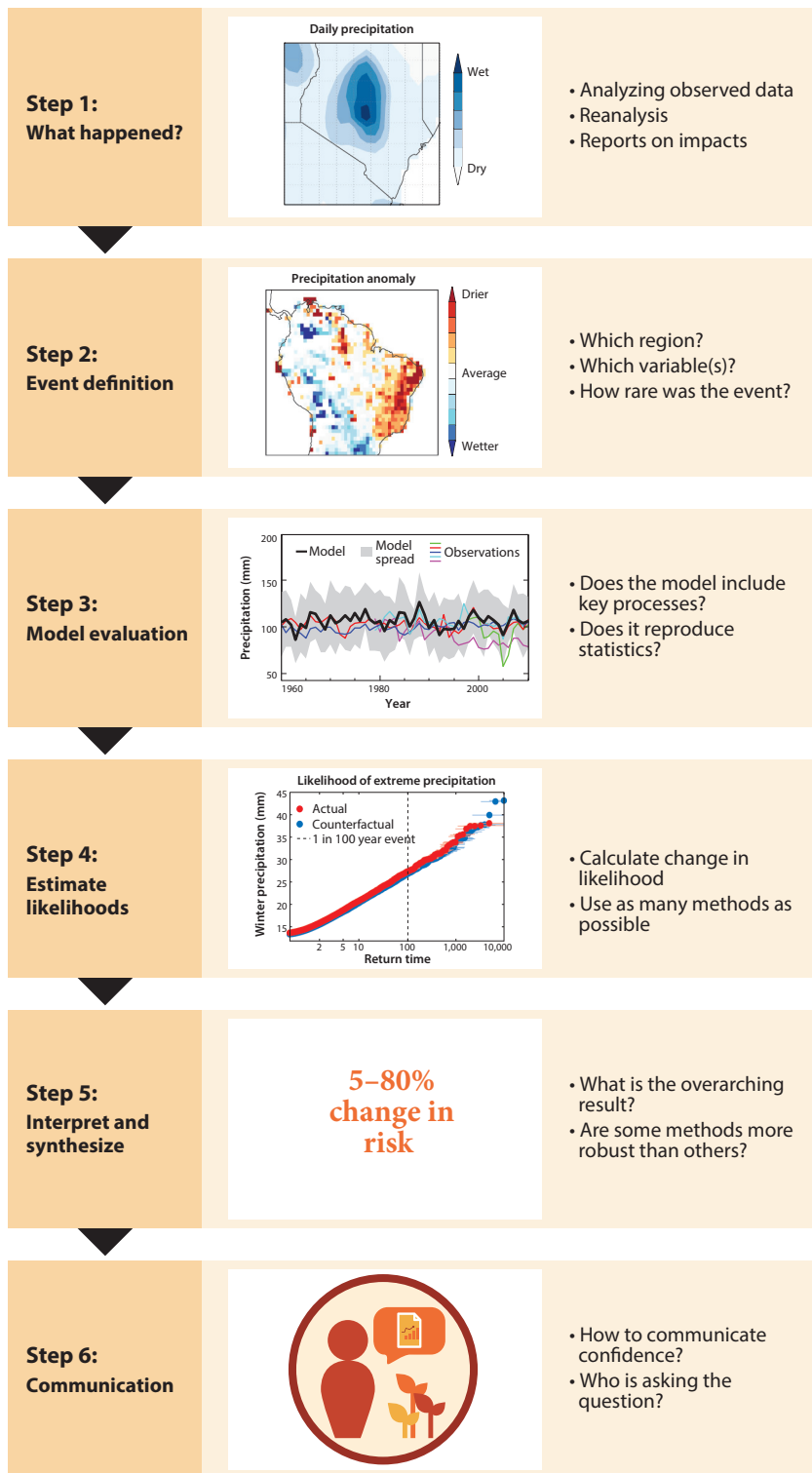
Apart from the framing of the question, the definition of the event itself determines the outcome of the attribution analysis. A study can identify an increase in the likelihood of a heat wave of an order of magnitude when simply looking at temperatures exceeding a threshold. The anthropogenic signal can, however, be very small for the same heat wave when analyzing changes in the heat stress on the human body (11). Depending on who is asking the question, one definition will be more appropriate than the other and a health professional might value the latter, whereas a farmer might have more interest in the former. The example also shows that a large signal in a meteorological variable does not necessarily translate into a change in impacts, and whether it depends to a large degree on the vulnerability and exposure as well as on the meteorological hazard; a holistic attribution study would need to look at both (12, 13). All of the studies cited so far have analyzed possible changes in a class of extreme events with the class being loosely or more narrowly defined with respect to an observed event. Recent attempts to put the art of attribution on a more theoretical framework and linking it to formal causality theory have tried to establish a different way of defining an extreme event in truly looking at the observed event with its multiple causes and occurrence probability of zero (14). Whether such an approach is really informative beyond academic circles is currently up for debate (15), but in so doing more of the implicit assumptions in the probabilistic approach are revealed arguable, moving attribution science from an ad hoc demand-driven conglomerate of methodologies to a theoretically based branch of science in its own right.

Lastly, event attribution studies require the study of extreme weather and climate-related events, as they would have been in a world without anthropogenic influence. Lacking observations of such a world, all studies necessarily depend on physical and statistical climate modeling and are thus all conditional on the assumption that the model reliably simulates the weather event in question. Depending on the type of event and region in the world this assumption is more or less justified. With approximately five years of methodological development and an increasing number of studies, it might now be possible to establish a typology of extreme events and their potential attributability (16) that will allow an a priori confidence assessment. Nevertheless, model evaluation and physically meaningful bias correction are (or should be) an integral part of every attribution study (**Figure 2**).

In the following section, we give a brief overview of key methodologies of event attribution studies, building on the earlier review by Stott et al. (17). Section 3 explores some key differences in the framing of the attribution question determined by the methodological approach, and Section 4 is dedicated to the importance of the definition of an extreme event and associated challenges. Section 5 is dedicated to the challenges of model biases and reviews the most recent approaches to overcome these. The final section briefly summarizes the key research questions the community is currently addressing and outlines the next steps in the maturing of an emerging science in its teenage years.

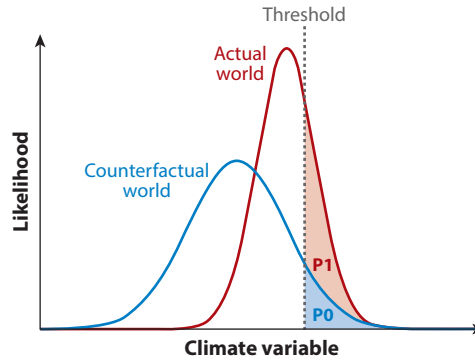
## 2. METHODS

In 2016, Stott et al. (17) aimed to review the main methodologies of extreme event attribution that have been developed over roughly the past decade. The methods reviewed by Stott et al. (17) employ the principle idea sketched out by Allen (2) and are referred to as either the risk-based approach (18) or the Oxford methodology (19). In the following both labels are used interchangeably.



**Figure 2**

A schematic demonstrating the six individual steps from identifying the meteorological drivers of an observed impact (what happened) to a robust attribution statement that can be communicated to stakeholders and the general public. Image in step 6 is from the Raising Risk Awareness project (<https://cdkn.org/climaterisk>; Attribution-NonCommercial-NoDerivs License).



**Figure 3**

Schematic of the distribution of a climatic variable under current climate conditions (*red*) and in a counterfactual climate that might have been (*blue*). The extreme event is defined by a simple threshold (*vertical dashed line*), and the different probabilities of such an event occurring (*red and blue shading*) are marked as P1 and P0.

## 2.1. The Risk-Based Approach

The principle approach behind the probabilistic event attribution methodologies is the assessment of possible weather events under current and preindustrial or counterfactual climate conditions to estimate the occurrence frequency of the event under different conditions. The idea is comparable to rolling dice, loaded and unloaded over and over again to identify whether and to what extent the dice are loaded (20).

In essence, every extreme weather event is unique and always the result of a combination of external drivers, natural and human-induced, as well as internal climate variability and noise; it is therefore impossible to say that an event could not have occurred without anthropogenic influence. However, in the same way that loading a die can increase the likelihood of rolling a six, the presence of an external driver such as anthropogenic climate change can alter the likelihood of the occurrence of an extreme weather event. To identify whether and to what extent this has happened, the risk-based attribution approach simulates possible weather under current climate conditions to identify the likelihood of occurrence of an event in question in today's climate (P1 in **Figure 3**) and compares this with the likelihood of occurrence of the same kind of event in a counterfactual climate with the human-induced drivers removed (P0 in **Figure 3**).

Estimating the likelihood of occurrence of an extreme weather event and thus its return time can be undertaken either on the basis of observed or reanalysis data (21) or on the basis of climate model simulations of possible weather in the current climate (22, 23). Each method has advantages and disadvantages. Observations are less biased compared to necessarily imperfect model simulations but records are often short and thus require assumptions about the properties of the underlying distribution to be made to infer the return times of rare events. In particular, atmosphere-only models can be used to simulate large ensembles, thus allowing for the statistics of rare events to be assessed without further assumptions about the statistical properties of the distribution of the event in question. Sippel et al. (24) compare in perfect model experiments both methods and find that the empirical model distributions do not always match with statistical modeling on a shorter subset of the data, in particular when simulating rainfall.

**2.1.1. Simulating the counterfactual.** While statistics of unloaded dice are known, those of weather and extreme events in a world without human influence are not. Hence, it is necessary

to simulate the counterfactual world. The simulation of the counterfactual is necessarily more uncertain than simulations of present day climate, as there are no observations of the counterfactual world. Using a model-based approach, the simulation of the counterfactual is conceptually straightforward and follows the protocol laid out in the Climate Model Intercomparison Project phase 5 (CMIP5) experimental design (25) for the Historical Nat simulations. In these simulations, greenhouse gases in the models' atmospheric forcing resulting from anthropogenic emissions are removed, as are the aerosols from anthropogenic activities. While the latter are comparably uncertain, the inventory of historic greenhouse gas emissions is rather comprehensive. For a coupled modeling approach, the counterfactual world is therefore well defined; differences in the simulation of the current climate and that of the counterfactual result from model differences and in particular the models' response to aerosol forcing rather than uncertainty in the counterfactual forcing itself.

Probabilistic event attribution studies based on large ensemble simulations using atmosphere-only modeling that requires SST forcings at each time step face the difficulty to not only remove the anthropogenic forcing from the atmosphere but also the magnitude and pattern of anthropogenic warming from SSTs. There are two main strategies to obtain such counterfactual SSTs. The primarily used methodology uses SSTs obtained from difference patterns in general circulation model (GCM) simulations (usually from the CMIP5 archive) of historical and historical natural (nat) simulations with the same coupled GCM. These patterns are subtracted from observed SSTs. To estimate the spread in possible warming patterns and the influence on extreme event simulations, usually more than one pattern is obtained (e.g., 13, 26). The sampling of possible warming patterns due to anthropogenic emissions is not a systematic sampling of possible warming patterns; it is based on a sample drawn from ensembles of opportunity such as CMIP5 and thus also represents an ensemble of opportunity.

An alternative approach of simulating a counterfactual world that might have been has been used in Pall et al. (27). In this study scaling factors from optimal fingerprinting analysis of coupled model simulations where a signal in the SSTs was detected are used to create counterfactual SST patterns. Similar to the methodology above, GCM simulations are the basis of the approach but in this case the distribution of scaling factors is used to create four ensembles from four GCM simulations rather than just the patterns obtained from the mean response over an averaged time period.

In probabilistic event attribution studies based on extreme value statistics of observed or re-analysis data, it is not possible to simulate a counterfactual world where only the influence of anthropogenic greenhouse gas and aerosol emissions is removed, and instead of simulating the world that might have been without anthropogenic influence on the climate, a historical period in time is used to estimate possible weather in a world where the anthropogenic influence is thought to be small. The comparison is of course different as observations of a historical period contain the influence of internal variability, as well as natural external forcings (volcanic and solar primarily) that are different from the current climate and potentially influence the likelihood of extreme weather events to occur. If the influence of these internal and natural forcings is, however, expected to be small compared to the anthropogenic signal, the counterfactual simulations in GCMs and the estimates of occurrence frequency of extreme weather in early historical observations will give very similar results.

Using the simulation of and observations from historical periods has the advantages of being readily available and thus allowing for relatively large ensembles of possible weather events. The methodology is thus widely used with historical periods taken to be "without" anthropogenic influence, which range from the end of the nineteenth century (28, 29) to the near end of the twentieth century. Although the end of the nineteenth century—in particular 1860–1880, when

no major volcanic eruption occurred (28), or even earlier (29)—provides the ideal baseline for a counterfactual world, high-quality observational data for historical periods only exists, if at all, from 1950 onward for most parts of the world and most variables, in particular when looking at extreme events that are small on spatial and temporal scales. Therefore, scientists must on a case-by-case basis take into account the trade-off between data availability and isolation of the anthropogenic signal to determine the definition of the counterfactual—whereby data availability is usually the limiting factor.

Extreme value statistics on a recent and a less recent period can of course not only be applied to observed and reanalysis data, but also to GCM and atmospheric GCM (AGCM) simulations of the historical period alone, thus allowing for a wide set of GCM simulations to be used in extreme event attribution studies without explicitly simulating the counterfactual world that might have been without anthropogenic climate change. Recent examples of how the different risk-based methodologies can be combined to estimate the overall change in risk of an extreme weather event can be found in publications from the World Weather Attribution (<http://www.climatecentral.org>) project.

## 2.2. The Boulder Approach

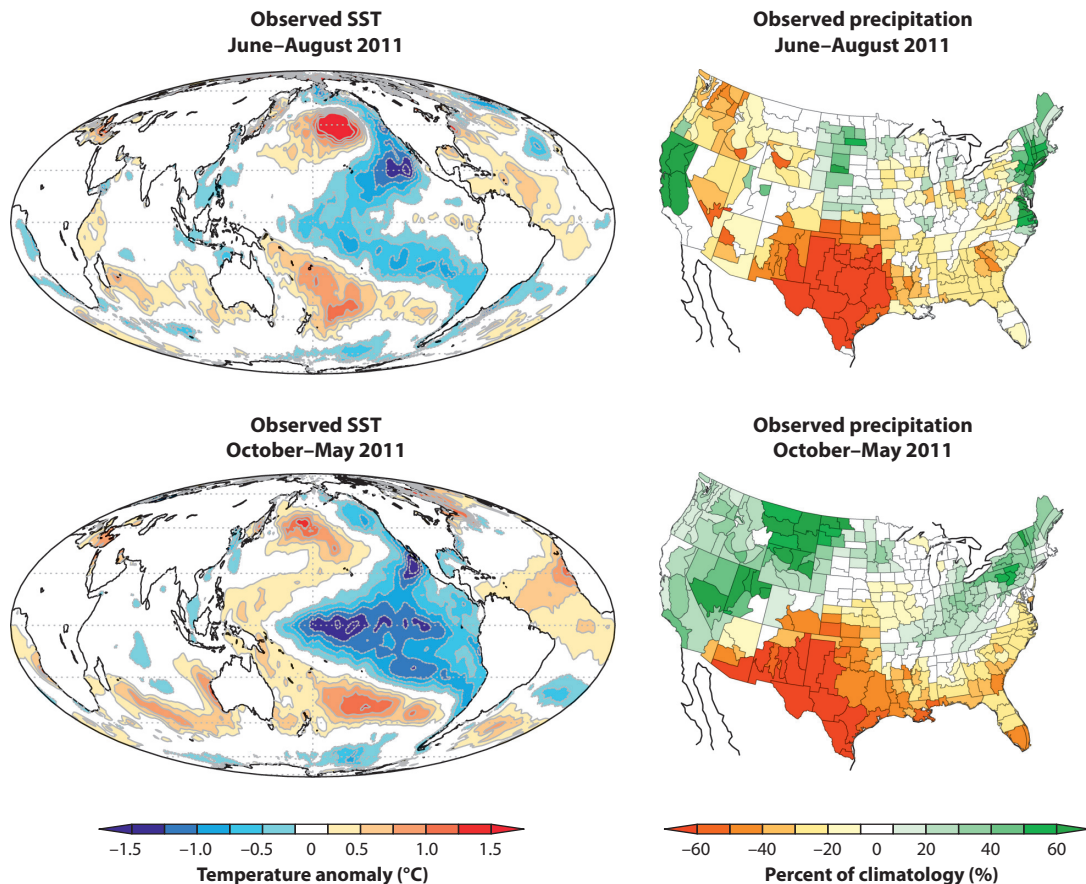
An alternative approach to extreme event attribution has been developed, e.g., by scientists at the National Oceanic and Atmospheric Administration (NOAA) in Boulder, Colorado, with key publications on African rainfall (30), the California drought of 2011–2014 (31), and the Russian heat wave of 2010 (7). Although the risk-based approach primarily aims at answering the question of whether and to what extent anthropogenic climate change altered the occurrence frequency of an extreme weather event, the Boulder approach aims to disentangle different causal factors leading to the event without necessarily quantifying the influence of these causal factors on the likelihood of occurrence. Studies applying the Boulder methodology in most cases focus on the influence of SST patterns and other large-scale circulation patterns. The tools used to identify causal factors of an extreme event are the same as those applied in the risk-based approach. In contrast to the risk-based approach, these extreme event autopsies (32) do not focus on simulating statistics of the extreme event; instead, they analyze an individual extreme event and its predictability from large-scale circulation patterns in small ensembles isolating different causal factors. **Figure 4** exemplarily shows the large-scale anomalies of SSTs and precipitation linked to the Texas heat wave of the summer of 2011 (32) and the conditions preceding it (October 2010–May 2011), which played a major role on the observed extreme summertime heat (32).

Dong et al. (33) identify causes of the European heat wave of 2015 by simulating the event with 2015 SSTs and greenhouse gas and aerosol concentrations of 2015, as well as with 2015 SSTs, but with a greenhouse gas and aerosol concentration from a control period (in this study 1964–1993), and a control experiment with SSTs and atmospheric forcing of the control period. This experimental design showed that two-thirds of the heat wave extreme event can be explained by the SSTs and atmospheric forcing, whereas one-third of the warming and dry conditions over Europe is due to internal atmospheric variability. The methodology, however, does not assess the overall likelihood of the event to occur and the potential changes in its frequency. In this particular example, as in other studies, applying the methodology of the role of the SST pattern in contrast to the overall increase of SSTs is not disentangled.

## 2.3. Circulation-Based Approaches

Stott et al. (17) cover partially another alternative methodological approach to the above: the analogs methodology. In this methodology primarily developed by scientists at the Laboratoire





**Figure 4**

(*Left*) Observed SST anomalies ( $^{\circ}\text{C}$ ) and (*right*) US precipitation anomalies (% of climatology), for (*top*) contemporaneous conditions for June–August 2011 and (*bottom*) antecedent conditions for October 2010–May 2011. All anomalies are relative to an observed 1981–2010 climatology. Abbreviation: SST, sea surface temperature. Adapted with permission from Reference 32.

des Sciences du Climat et de l'Environnement in France, the extreme event is defined by its circulation state either based on regime classifications or a simpler diagnostic (e.g., 34). Analogs to these circulation states are then calculated from either reanalysis data or model simulations where an increase in the number of analogs in more recent periods indicates a potential influence of anthropogenic climate change on the likelihood of the analogs occurring.

The methodology can also be applied on ensembles of current and counterfactual climate simulations and thus allow for a true attribution of the likelihood of circulation states to occur to a causal factor. Using this combination of the risk-based simulation approach with an analog event definition allows assessment of whether an overall change in the likelihood of an event occurring is due to the overall warming (thermodynamics) or results from changes in the atmospheric circulation—or a combination of both (35, 36).

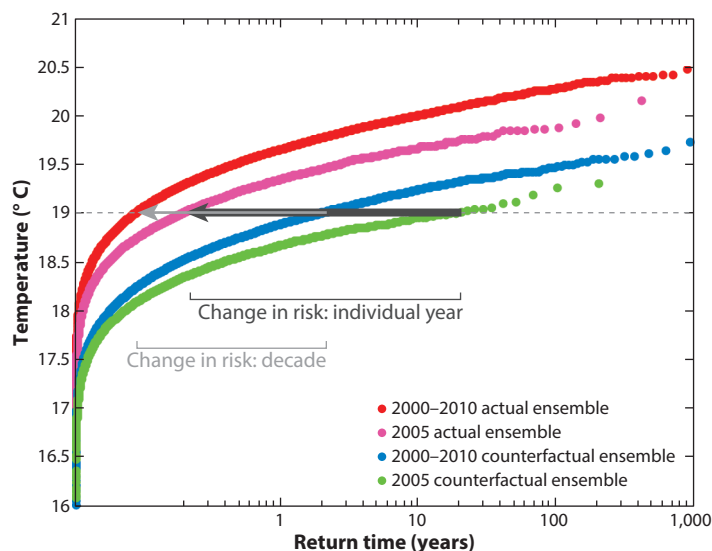
Trenberth et al. (37) and Shepherd (18) provide a further approach to assess contributions of human-induced climate change to individual extreme weather events. This storyline approach

conditions the analysis on the atmospheric circulation state and aims at assessing what the role of the thermodynamic increase in global mean temperatures and particularly ocean temperatures is in the event in question. While Trenberth et al. and Shepherd introduce the methodologies more in principle than by providing concrete case studies, Meredith et al. (38) provide a framework of how this methodology can be implemented using the case study of extreme rainfall over the Black Sea.

### 3. FRAMING THE ATTRIBUTION QUESTION

All methodologies currently applied in the emerging science of extreme event attribution are not directly comparable with each other, as the methodological differences result from or lead to subtly or fundamentally different questions being answered by the individual approaches. At the same time, an identical approach can give fundamentally different results with respect to the qualitative and quantitative role of an external driver dependent on the definition of the extreme event (see below in Section 4).

While the risk-based and storyline methodologies obviously attempt to answer different questions, the framing differences using methodologies based on the same overall approach are more subtle. Within the different methodologies used in the risk-based approach, a key difference stems from whether a counterfactual climate is explicitly simulated by removing a single (e.g., GHG) or a set of (e.g., all anthropogenic) external drivers from the model simulations or whether an earlier observed or simulated period in time is used as a proxy for preindustrial climate and weather simulations. Although results are often quantitatively comparable (39) between the observation-based approach and GCM simulations using counterfactuals, the question they answer is different. In the latter case, the question is as follows: What is the role of anthropogenic climate change in the frequency and magnitude of the extreme event occurring today? The former method answers the following question: How has the frequency and magnitude of this class of extreme events occurring changed over the past  $x$  decades? The latter approach includes usually the implicit or explicit assumption that anthropogenic climate change is the largest driver of change over this time period. This assumption is not as unreasonable as other known modes of long-term variability such as the El Niño Southern Oscillation or the Atlantic Multidecadal Variability/Oscillation can separately be accounted for and subtracted from the analysis and are not exerting a long-term trend. The model using the risk-based approach asks a slightly different question when simulating an individual year repeatedly with an atmosphere-only model using prescribed SSTs. Event attribution studies analyzing simulations of individual years answer the following question: Given all other conditions being equal, how has the risk of such an extreme event occurring changed as a result of anthropogenic emissions (40)? If the same modeling approach would be used to compare decadal long simulations instead, the interannual variability of large-scale oscillations in the SSTs is smoothed out, and the question answered is the following: Given all predictable (long-term) things being equal, how has the risk changed due to the global mean temperature increase and increase in greenhouse gas forcings (40)? **Figure 5** shows return time curves for an experiment addressing the latter question in red and blue and in magenta and green for an experiment simulating only a single year. In this example, the change in risk estimated differs by almost an order of magnitude. The analogs methodology as applied by Cattiaux et al. (34) belongs in the same methodological framework as that which asks how the event definition is significantly different from the threshold exceedance used in most other risk-based studies, but it also assesses the overall change in risk of the analogous circulation occurring. Another approach within the risk-based framework currently employed to enable fast analysis of the role of anthropogenic climate change within days or weeks after the event occurring is based on SSTs from seasonal forecasts instead



**Figure 5**

Return periods of daily minimum temperatures in July in East Africa in four different ensembles. The graph shows July minimum temperatures in the actual climate simulations of the year 2005 (*magenta*), the decade 2000–2010 (*red*), and July minimum temperatures in the counterfactual climate simulations of the year 2005 (*green*) and of the decade 2000–2010 (*blue*). The horizontal dashed gray line represents a threshold of 19°C. The arrows represent the increase in risk of exceeding the threshold of 19°C in the decadal (*light gray*) and individual year simulation approach (*dark gray*). Adapted with permission from Reference 40.

of observed SSTs for the season of interest. The analyses provide an answer to the following question: Given all predictable (short-term) conditions being equal, how has the risk of such an extreme event occurring changed as a result of anthropogenic emissions (10)?

Conditioning on the long-term trend only is in principle identical to coupled model approaches but using a different modeling framework, the question answered is therefore practically indistinguishable. The question asked in the other two cases is, however, different and the answer is conditional on the observed or forecasted SSTs. The methodology is henceforth not assessing the overall risk of the event occurring. This is of fundamental importance as it shows that the distinction between the risk-based approach and other methodologies is a distinction of degree and not of kind. Different degrees of conditioning require, however, different experimental designs so the degrees are not smooth and thus neither is their applicability in the context of decision making and disaster risk reduction strategies.

Although the distinction from risk-based approaches is not fundamental, the framing of the attribution question given when conditioning on the atmospheric circulation is a different one, as the overall risk or likelihood of an extreme event occurring is not estimated. This is a crucial distinction as these approaches are primarily attempting to understand the event and its development over up to a season independent of whether it is a 1-in-10-year event or a 1-in-1,000-year event. For the risk-based approach, the overall likelihood of the event is of crucial importance not only for the relevance outside of the scientific community but it also determines to a large degree the confidence in the result. Estimates of changes in the frequency of a 1-in-1,000-year event from 100 years of data will have much larger confidence intervals than estimating whether and to what extent frequency and magnitude of a 1-in-10-year event are influenced by anthropogenic

climate change. The return time of the overall event becomes rather unimportant if simulations are conditioned on the circulation state, in particular when the model is nudged toward the desired state (38). Shepherd (18) describes a theoretical framework where the conditional approach, or “storyline” in his words, is a special case of the overall risk-based framework, and the two approaches could thus be used in combination to complement each other. Although not formally applied in a single analysis, combinations of different approaches and hence framings have proven valuable in the past to enhance our understanding on extreme event development, the influence of external drivers, and the confidence in the results. The Russian heat wave of 2010, discussed above, is an example of how initially apparently contradictory results (7, 8) helped to provide a more comprehensive picture (9); however, for other events where several attribution studies have been conducted, with the California drought between 2011 and 2015 being a prominent example, many open questions remain (e.g., 31, 41, 42).

Hannart et al. (43) explore a different way of looking at the framing of event attribution studies that also allows for all different methodological approaches to be interpreted within the same framework. They show how the formalism developed under probabilistic event attribution approaches can be implemented in the formalism of causal theory as developed by scholars such as Judea Pearl (44). The key terminology introduced in the event attribution framework here is that of necessary and sufficient causality and the combination of the two. Necessary causation is handily equivalent to the fraction of attributable risk (FAR) introduced by Allen (2) as the risk ratio subtracted from one. A positive FAR thus corresponds to establishing necessary causality due to the external forcing analyzed, and hence necessary causality can be established in many cases. Sufficient causation in contrast is rarely established for extreme events but also depends solely on the likelihood of the event occurring in the current and counterfactual climate. Again, however, both measures crucially depend on the event definition. Although not necessarily providing new insights compared to other framings of the attribution question, linking results to causal theory will likely make it easier to interpret findings in an established context, in particular in a legal framing. As noted by the National Academy of Sciences (NAS) report (16), however, the FAR framing and formal causal theoretical language prohibit rather than help communicate scientific attribution results to lay audiences. Within the scientific community, the framework has, however, the potential to formally demonstrate the “in degree” nature of the different methodological approaches and could thus help to provide a comprehensive picture of event attribution methodologies. A formal incorporation of findings of different attribution studies on the same event within the causal theory is still outstanding, but ideas of how it could be done in a systematic way are brought forward by, for example, Hannart et al. (14), albeit using a very narrow (arguably too narrow) event definition.

Independent of whether and how different methodological approaches can be considered as part of an overarching theory, it is important for every extreme event attribution study to clearly state the framing of the attribution question being asked (15), including a clear definition of the extreme event being examined (**Figure 2**) [climatic variable(s), threshold(s), geographical region, temporal scale(s)], and whether the assessment is conditional on the atmospheric circulation, SST patterns or the long-term trend of the climate system (e.g., GHG forcings). Every study is always conditional on the methodologies applied being adequate to analyze the event and address the question that is being asked as explained below.

#### 4. THE DEFINITION OF AN EXTREME EVENT

In a way comparable to extreme event attribution in general and in particular to the different methodological approaches and the question of framing, the NAS report (16) has brought the

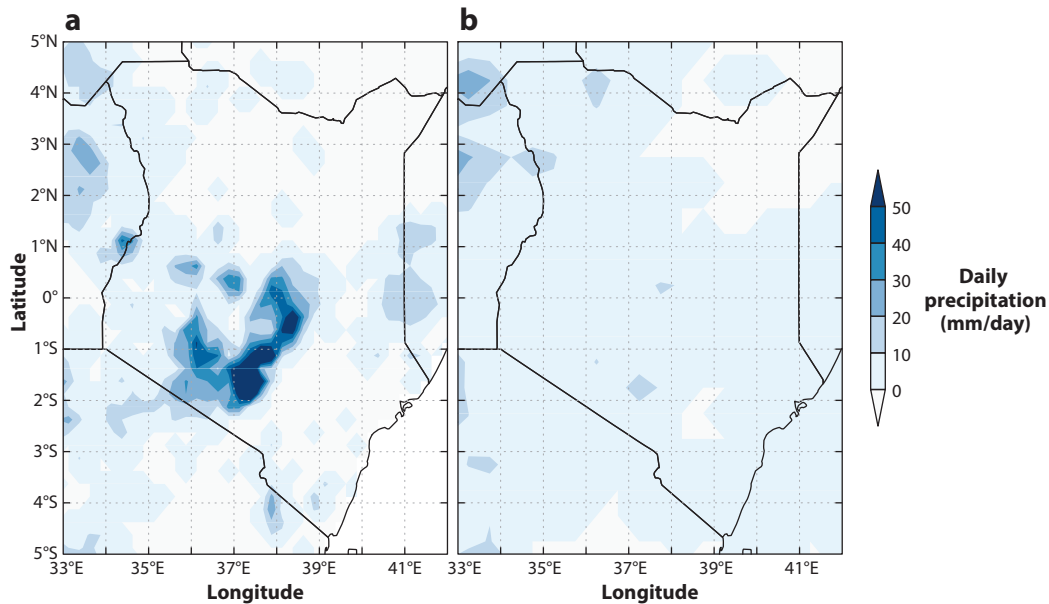
importance of event definition to the attention of the broader scientific community. In particular the report highlighted that different attribution approaches treat extreme events either as classes of events with an observed event being part of that class or singular events exactly as observed. By pointing out this crucial difference a major source of potential confusion could be avoided if “individual event” was well defined or a definition would be a priori obvious. Unfortunately however it is in practice almost impossible to determine what exactly is meant by an individual or singular extreme event in contrast to a class of events. While this distinction sounds like a rather straightforward difference this is only the case in theory. An individual extreme event is necessarily unique and hence all factors present in the event are required for the unique event to occur in exactly the way it was observed. An event, exactly as observed, will never happen again and the anthropogenic climate forcing as well as all other external and internal forcings are necessary for the event to unfold in exactly the way it did. All extreme weather events today are happening in a changing climate; thus, every extreme weather event is influenced by anthropogenic climate change. This is trivially true but therefore such a statement does not contain any new information neither on the likelihood of the event to occur or its magnitude nor on the short-term predictability or the importance of different causal factors. To estimate any of the latter some degree of abstraction from the singular event and thus “classification” of the event is necessary. Hence, there is no clear dichotomy between a class of extreme events and a singular event but the transition is fluid. In all but one approach (14), which so far has only been suggested in principle but not been applied to a real event, a class of extreme events is considered. In particular when climate models are used in the analysis a definition of the event is necessary to make it possible to identify the event in question in the climate model as well as in observations.

Although it is thus trivially necessary to classify extreme events, the definition of these classes is all but trivial and crucially the definition is based on choices that are not necessarily scientific but depend on who is asking the question and what the general aim of the attribution study is, respectively.

#### 4.1. What Happened?

The motivation behind most event attribution studies is to understand what happened after the event and assess whether and to what extent a changing climate leads to similar events happening more frequently. Scientific curiosity is usually inspired by an event that actually happened and rose to public awareness, either because of its meteorological exceptionality (“freak weather”) or, more commonly, because a meteorological event impacted society. In particular, when impacts of extreme weather events are high scientists are not the only ones wanting to understand the role of climate change; decision makers on all levels ask the attribution question as well (45).

The impacts of an extreme weather event are therefore often determining the definition of an extreme event (e.g., 39, 46). Depending on observations on the ground, an event definition would thus be based on short-term intense rainfall if the impacts were flooding of relatively small river catchments or rainfall over a whole season—or if the impacts leading to the attribution question being asked were, for example, groundwater flooding and flooding of larger catchments. Taking the example of a heat wave, heat stress on the human body (e.g., 47, 48) over at least three days might be the metric variable best describing the impacts. However, identifying the index most closely related to the relevant impacts needs to be balanced against availability of meteorological data and the variables that are likely to be best simulated by climate models. Observational records of meteorological variables at a length and density required to infer the rareness of an extreme event are sparse in many regions of the world, and records of variables other than temperature or precipitation as, e.g., required for calculating heat stress, often do not exist (49). This lack of



**Figure 6**

Daily precipitation in millimeters per day (mm/day) observed over Kenya on November 10, 2015, using (a) a product using data from low-orbit satellite microwave observations and station data (NOAA Climate Prediction Center Morphing Technique, CMORPH) (51) and (b) a high-resolution data product based on low-orbit satellite microwave observations alone (Climate Hazards Group Infrared Precipitation with Station, CHIRPS, data) (50).

observations is thus often what limits how close attribution studies are to the actual impacts of the extreme event. Typical problems even where observations do exist are mismatches between in situ observations and satellite data with respect to magnitude and location in particular for small-scale and high-frequency events.

**Figure 6** illustrates this by showing station data (NOAA Climate Prediction Center, CPC) and satellite observations (NOAA Climate Prediction Center Morphing Technique, CMORPH) from the same extreme rainfall event on November 10, 2015, in Kenya. The station data depict rainfall of more than 50 mm/day in Machakos County (0–1° S, 37–38° E), whereas the satellite observations miss the event to a large degree and show two smaller events further north and southwest instead. The decision on how to define the event might thus be further away from the impacts and closer to large-scale meteorological variables that are well observed and well captured in state-of-the-art weather and climate models. An event definition is always a trade-off between what happened in the real world, what has been observed, and what can reliably be simulated in a climate model.

At the same time as defining an extreme event closely related to its impacts, it is desirable to be able to compare findings of different assessments of extreme events either for the same event or, in particular, for similar events in the same region and around the world. To achieve this, an Expert Team on Climate Change Detection Indices came together to identify a list of indices and a common framework to calculate these indices that would be most useful for a broad range of extreme events and their impacts (52). The list incorporates 27 indices, some of which are rather specific, but measures such as  $TX_x$  (maximum value of daily temperature in a year or month) are now calculated in most risk-based attribution studies on extreme heat events, allowing for the



scientific community to slowly build an overview of the impacts of anthropogenic climate change today.

The nontrivial task of defining an extreme event relevant to the impacts requires, thus, experience with the observed data but also knowledge on specific vulnerabilities; hence, there will never be a “correct” definition, and different or multiple definitions might be most appropriate.

## 4.2. Event Definition and Conditional Attribution Approaches

All of the considerations above are relevant independent of the exact framing of the attribution question, but they apply particularly when intending to use a risk-based approach to an attribution study aiming at putting the risks of certain impacts occurring into a climate perspective. Approaches using conditional attribution approaches and the Boulder methodology tend to define the event with respect to the atmospheric circulation state at the time of the event and the development of the event. The primary question here is often that of predictability with attribution only the secondary objective. However, when focusing on attribution and highly conditional approaches, as suggested by, e.g., Trenberth et al. (37), the experiments and conditioning cannot define too narrowly the event such that every change, whether forcing or any other condition, leads to the event being irreproducible (15; see also H. Omrani et al. unpublished). A key motivation behind such conditional attribution is to only attribute the thermodynamic aspect of anthropogenic climate change while constraining the atmospheric circulation, assuming that climate models are in general better at representing the thermodynamics than the dynamical responses to external forcings. However, also constraining the flow or the large-scale circulation not carefully enough could be inadequate in some cases to make a straightforward statement on conditional attribution results of the thermodynamic response. The reason for this is, in particular, that coupling between the thermodynamics and small-scale dynamics can be very strong, so a nonlinear response of the extreme event to changes in the thermodynamics is expected, but also from any other perturbation. H. Omrani et al. provide criteria to avoid over- or underconstraining the flow in conditional event attribution studies. Following these criteria, such studies allow for an improved understanding on necessary and sufficient drivers of extreme events and in particular can lead to the identification of threshold behavior in the thermodynamic forcing (38).

## 5. MODEL EVALUATION AND BIAS CORRECTION

Extreme event attribution studies rely on data and can only be as good as the underlying data. As described above, high-quality observed data are crucial to understand what happened from a meteorological point of view and define the extreme event accordingly. Observed data are also necessary to calculate return times and estimate the change in likelihood and magnitude of extreme weather events due to observed climate change. Extreme event attribution is, however, impossible without the use of GCMs, which are the only type of model able to represent extreme weather, as they simulate the atmospheric circulation and thermodynamical processes. Lacking observations of the “world that might have been” without anthropogenic climate change, we rely on models to simulate this counterfactual world. Section 3 above describes the methodologies relying on GCMs to simulate the climate system. Although having made enormous progress largely because of increased resolution and the possibility to run ensemble simulations, GCMs are still far from true representations of the climate system and have large biases (53). Individual GCMs have individual strengths and weaknesses and a model-by-model evaluation is necessary to determine which aspects of the climate system they adequately address and where biases are large. For some kinds of extreme weather events, however, such as extreme rainfall associated with thunderstorms,

we know a priori that coarse resolution GCMs and also most regional climate models that can be run as ensembles are unable to reliably simulate them as they occur on spatial scales of the order of a few kilometers. Because observations of extremes are sparse (54), model evaluation for extreme events is particularly challenging and almost impossible for the counterfactual simulations. Even if climate models are able to represent the main processes, biases remain in the statistics of individual variables that can in some cases be corrected for.

Bias corrections are straightforward when the distribution is correct but just offset high or low, in which case analyzing anomalies instead of absolute values corrects for the bias. Most biases are, however, more complex and require more elaborate bias corrections. Although in some cases an additive or multiplicative adjustment of the variance in the model distribution might be possible (23), biases in the extremes only are corrected for by quantile mapping to achieve a match between observations and model output (e.g., 55). Although making the model distribution comparable to observations, quantile mapping is rather invasive and destroys the physical consistency between variables in the model output. When analyzing individual variables only and in cases where good observational statistics are available so that the distribution is actually matched with the “truth” (16), this might not be a problem, but when aiming to use the model output further in impact assessment, the physical inconsistencies are problematic (56).

An alternative to bias correction is to use an event definition that is not based on the observed magnitude of the event but on the return time of the event in the observational data. Such an approach not only corrects for offsets in the model data but makes it easier to compare different methodological approaches and to synthesize results from independent methodologies into an overall assessment of the change in risk due to an external forcing. With data not being free of biases and subtle differences in the framing of the attribution question leading to different quantitative answers, the use of such multiple lines of evidence is highly recommended (16), and to make this possible, not only the question asked should be transparent but also evaluation and bias correction standards need to be comparable to allow for synthesized assessments. Apart from resampling methodologies (56) and the use of anomalies, a simple statistical test to reject models that are not simulating distributions comparable to those observed is recommended (57). Community standards on model evaluation for event attribution do not yet exist, but could improve quality and acceptance of event attribution results (16).

The above approach is mainly relevant and recommended for the risk-based methodologies of event attribution as the use of multiple lines of evidence in conditional approaches is disproportionately more complicated with often complex experimental designs (38), but given that most studies are based on a single model (31, 33), model evaluation is of crucial importance and all event attribution studies are ultimately conditional on the model’s ability to simulate the event.

## 6. CONCLUDING REMARKS

With the development of different methodologies and also different conceptual approaches over the past few years, extreme event attribution has emerged as a subfield of climate science with its own growing community, which still mainly consists of the contributing and lead authors of Chapter 10 of the IPCC AR5 WG1 report (58); however, it includes increasingly scientists from other areas (59) and parts of the world that have not been represented previously (e.g., 60). Growing is never without pain and conflict, and it was recently remarked that the science of event attribution has left its childhood and entered the teenage years, which has led to slightly heated debates within the community about the “right” approach in event attribution and the robustness of different methodologies or philosophies (15, 18, 37, 61). Right and wrong are certainly not the right categories here; as described above, there are not strictly different approaches but also hybrids



between the Oxford and Boulder approaches and others fitting neither category (e.g., analogs). The annual *BAMS* special reports on attributing extreme events of the previous year (5, 62–65) demonstrate that there is great value in analyzing the same event using different methodologies. For a science standing very much in the public focus with every extreme weather event creating numerous headlines and the attribution question inevitably being asked, a public maturing process can be problematic and lead to distrust in the science if results appear to be contradictory. However, again, not least thanks to the *BAMS* special issues that bring the community together on an annual basis, large, inclusive research projects such as the European project EUCLEIA (<http://www.eucleia.eu>), and drawing on experience from climate science communication in the past, debates have been carried out in peer-reviewed publications, and scientists dealing with the media's reporting of the science has been appropriate and accurate. There are increasing findings that are providing scientific evidence for a debate that previously was mainly free of any science, with attribution statements being made not by scientists but politicians (45). This is a great achievement for an emerging science, but there is still a lot of methodological development to be done to produce more standard ways of framing the attribution question, which will make studies with different levels of conditioning more comparable (16). Moreover, further work needs to be done to develop the tools and methodologies to enable attribution studies on events currently not attributable, such as very small-scale weather events and hurricanes, where some progress has been made already (46, 66). A topic that has been particularly neglected in earlier attribution studies (e.g., 5, 62) is that of model evaluation and bias correction, although this negligence has been noticed by the community (56, 64, 65). More research and more standardized protocols are needed to make studies comparable and to assess the robustness of attribution findings.

Presumably the largest challenge for the event attribution community is, however, the attribution of the impacts of meteorological extreme events and to foster a close collaboration with the disaster risk reduction community. Today these two communities exist largely in parallel, with, e.g., Chapter 18 in the IPCC AR5 WG2 (67) addressing the impacts of climate change and IPCC AR5 WG1 (58) addressing the impacts of anthropogenic climate change. Although this mismatch has been recognized by few (68) and the crucial role of vulnerability and exposure highlighted (12), examples of attributing impacts rather than meteorological events are rare (13, 47, 56) and comprehensive methodological approaches are currently lacking, although their importance has been mentioned as early as 2005 (69).

## DISCLOSURE STATEMENT

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