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Primer

Attributing Extreme Events to Climate Change: A New Frontier in a Warming World

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https://doi.org/10.1016/j.oneear.2020.05.011

The emerging field of extreme-event attribution (EEA) seeks to answer the question: "Has climate change influenced the frequency, likelihood, and/or severity of individual extreme events?" Methodological advances over the past 15 years have transformed what was once an unanswerable hypothetical into a tractable scientific question—and for certain types of extreme events, the influence of anthropogenic climate change has emerged beyond a reasonable doubt. Several challenges remain, particularly those stemming from structural limitations in process-based climate models and the temporal and geographic limitations of historical observations. However, the growing use of large climate-model ensembles that capture natural climate variability, fine-scale simulations that better represent underlying physical processes, and the lengthening observational record could obviate some of these concerns in the near future. EEA efforts have important implications for risk perception, public policy, infrastructure design, legal liability, and climate adaptation in a warming world.

Looking beyond the Mean Climate

There is now an extremely high level of scientific confidence that human activities are the only plausible explanation for the observed ~1.2°C rise in global mean temperature, and a human fingerprint has likewise been found in numerous other changes in climate. However, although the mean climate is a useful metric of overall climate change, it remains a statistical construct: no place actually experiences its local mean. Moreover, the aspects of climate change that have the greatest effects on society and ecosystems—such as heatwaves, downpours, hurricanes, droughts, and wildfires—are inherently far from the mean. Therefore, to understand, mitigate, and adapt to climate changes that could harm the health and well-being of humans and ecosystems, it is imperative to understand how (and why) these climate-related extremes are changing in a warming world.

This branch of climate science, often referred to as extreme-event attribution (EEA), has evolved rapidly in recent years. This evolution has faced a number of challenges. In particular, structural limitations in process-based climate models, as well as temporal and geographic limitations of historical observations, lead to substantial challenges in quantification and validation. However, recent methodological advances, coupled with longer observational records and improved climate models, have opened the door to systematically addressing the question of whether climate change has influenced the likelihood and/or severity of individual extreme events.

Viewing Climate Change through an Extreme-Weather Lens

The news media and public often ask: "Did climate change cause this specific extreme weather event?" In a very literal sense, the answer to such a rigidly posed question will always be "no." All events in the dynamically coupled Earth system are ultimately the product of numerous complex, interrelated processes acting across a wide range of spatiotemporal scales. There will thus rarely (if ever) be a traceable singular cause for any specific event, and variability will always play an important role. Indeed, as recently as a decade ago, a common response from scientists was that "no single weather event can be attributed to climate change."

Weather and climate, of course, are not the same. Weather describes variations on very short day-to-day timescales, whereas climate integrates over much longer time horizons. A key step forward in the development of EEA has been the acknowledgment that weather and climate exist on a continuum. Because climate describes the aggregate statistical properties of weather—in other words, the plausible envelope of weather conditions at a particular point in time—it encompasses not only "typical" conditions but also rare, high-magnitude weather extremes. From this perspective, understanding multi-decadal climate change can reasonably be framed as an exercise in quantifying shifts in the overall probability distribution of day-to-day weather conditions.

As a result, climate scientists have increasingly recognized that the strict question of binary causality is ill posed. Because climate is inherently a probabilistic descriptor of largely stochastic underlying weather processes, it stands to reason that scientific investigations into the influence of climate change upon extreme weather events should also be framed in probabilistic terms. Additionally, a considerable body of evidence suggests that human-caused changes in the low-probability, high-consequence "tails" of the weather distribution could be considerably different from what might be inferred from extrapolating shifts in

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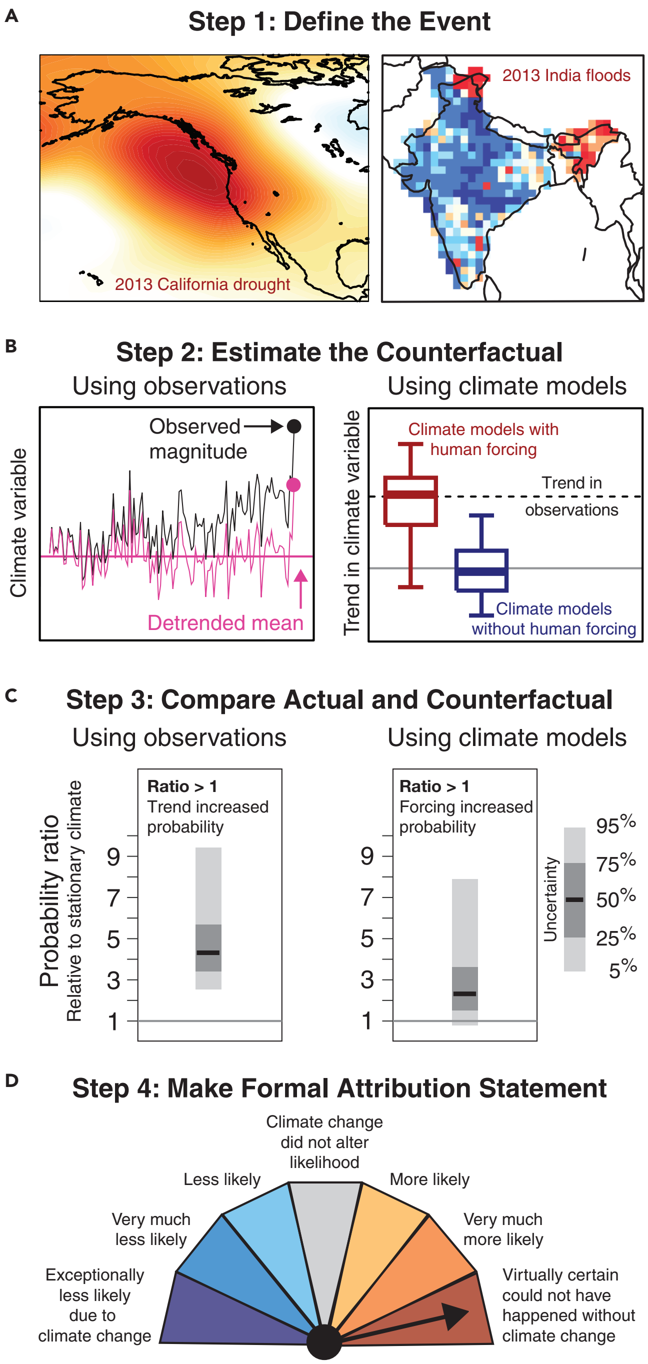

Figure 1. Four Key Steps of EEA

Illustration of the typical EEA workflow using examples from the existing literature.

(A) Define the extreme climate event, here illustrated by the magnitude of anomalous high pressure during a drought event (adapted from Swain et al., 2014, left) and of extreme precipitation during a flood event (adapted from Singh et al., 2014, right).

(B) Calculate the counterfactual climate by using real-world observations and/or climate models (adapted from Diffenbaugh et al., 2017).

(C) Compare actual and counterfactual climates, again by using real-world observations and/or climate models (adapted from Diffenbaugh et al., 2020).

(D) Make a formal attribution statement regarding whether anthropogenic climate change contributed to the likelihood and/or severity of the extreme event (adapted from Lewis et al., 2019).

the mean. Therefore, a growing number of studies have instead begun to ask a more nuanced question: "Has climate change influenced the frequency, likelihood, and/or severity of the extreme event?" This seemingly subtle shift in perspective transforms an essentially unanswerable question about absolute causality into one that is both scientifically tractable and practically actionable—and that can be directly addressed with existing observational and numerical modeling tools.

Diverse Attribution Approaches but Shared Epistemology

As the field of EEA has rapidly expanded over the past decade, different research groups have pioneered a range of novel approaches. Virtually all approaches share a common epistemology: using some combination of real-world observations, numerical climate-model simulations, and rigorous statistical techniques to separate the effects of actual human influence on the climate system from a counterfactual "climate without human influence." It is critical to understand both this general scientific framing and the specific methodological variations because results can be strongly dependent on the assumptions and analysis techniques employed. In the sections that follow, we first outline the basic methodological steps that are shared across most EEA studies (Figure 1) and then more deeply explore the range of approaches and assumptions that have historically been employed in different contexts.

Key Steps in EEA

1. Define the event. What spatiotemporal scale and physical variable(s) best characterize the event? Given an extreme heatwave, for instance, appropriate metrics might include daily maximum temperatures for a specific city, weekly average temperatures for a region, combined heat and humidity metrics, or underlying event drivers such as the strength of the atmospheric underlying high-pressure system.
2. Estimate the "counterfactual" climate. Quantifying the influence of global warming requires quantification of the magnitude and/or likelihood of the event in a counterfactual climate without human influence. One approach is to quantify changes in the probability of the event in climate-model simulations without anthropogenic climate forcing. Alternative approaches include removing the long-term trend from the historical climate time series, using statistical relationships between the climate variable and global temperature, and using observational data from a time period with little anthropogenic influence.
3. Compare actual and counterfactual climate. Are there statistically distinguishable differences in the probability and/or severity of the event between the actual and counterfactual climates? A number of different metrics have been used, including the fractional difference in event magnitude, the ratio of event probability (often called the "risk ratio"), and the portion of the total risk contributed by anthropogenic activities (i.e., the "fraction of attributable risk"). In addition, uncertainty quantification is a critical priority for both model- and observation-focused approaches. Key sources of uncertainty include the statistical quantification of the probability of the event,

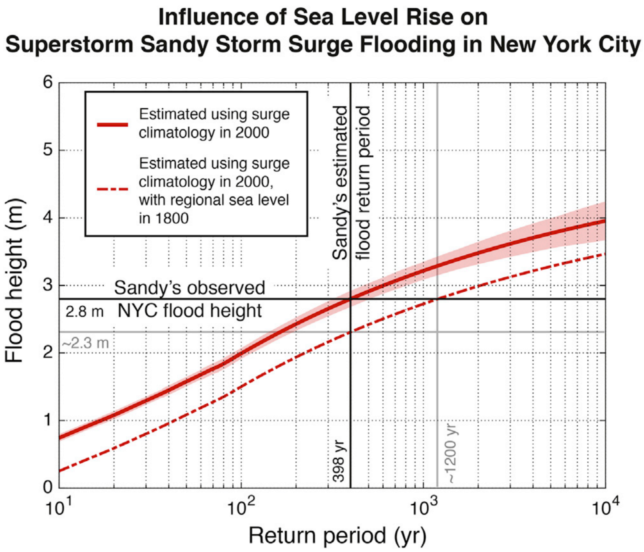

Figure 2. Example of a Conditional and Ingredient-Based EEA Assessment

Results from a conditional and ingredient-based EEA assessment of the influence of one particular aspect of climate change (sea-level rise) upon the observed level of coastal inundation during a specific historical storm event in New York City (Superstorm Sandy during October 2012). The upward and leftward shift of the red curve shows that sea-level rise increased the severity (depth) of the inundation by ~20% but increased the likelihood of the observed level of inundation (i.e., decreased the return period) by ~300%. Adapted from Lin et al., 2016.

the ability of climate models to accurately simulate the observed variability of the climate variable, the magnitude of the "forced response" simulated by different climate models, and the "irreducible uncertainty" in the forced response contributed by internal climate variability.

4. Make a formal attribution statement. Most EEA approaches use a very high bar for attribution: the typical null hypothesis is that human-caused climate change did *not* influence the magnitude or probability of the event, and rejecting that null requires a "beyond a reasonable doubt" standard. If there is sufficient evidence of a statistically distinguishable difference in the actual versus counterfactual climate, the null hypothesis can be rejected, and an affirmative attribution statement can be made at a specific confidence level. Given the multiple sources of uncertainty, attribution statements often include multiple components (i.e., "there is a 95% likelihood that global warming increased the probability of the event by at least a factor of 2.86"). New frameworks have been suggested to simplify the final attribution statement (Figure 1D).

Absolute, Conditional, and "Ingredient-Based" Approaches

Initial decisions regarding how to define the event can influence the entire EEA process described in Figure 1. In addition to the decisions regarding appropriate physical metrics and spatiotemporal scales, there is also a deeper philosophical choice regarding which aspects of the event are most important and how far down the chain of complex physical causality the attribution methodology can be reasonably extended. These decisions can ultimately shape the final EEA conclusion.

Consider an attribution study focused on the coastal inundation produced by a large hurricane making landfall at some specific location. One possible approach would be to consider the full sample of all hurricanes that affected the region and ask whether there has been a change in the likelihood of flooding exceeding the observed threshold. This might be referred to as an "absolute" approach because it considers overall changes in event likelihood without accounting for the specific initial conditions (i.e., the study is not preconditioned on the fact that a large hurricane occurred at that specific location and at that specific time) or the contribution of any particular contributing factor (e.g., sea level, precipitation intensity, and storm strength). As a result, absolute approaches can complicate efforts to understand which specific aspect of climate change has contributed to changes in the probability or severity of the extreme event. For example, without methods to isolate specific conditions, it would be difficult to differentiate between contributions from sea-level rise (which increase background water levels), increasing atmospheric water-vapor content (which contributes to the precipitation intensity of a given storm), and warming ocean temperatures and decreasing vertical wind shear (both of which act to intensify hurricanes).

Another approach, often referred to as the conditional or "storyline" approach, takes certain aspects of the event conditions as given (such as the large-scale atmospheric conditions at the time of the event) and asks whether climate change has had a detectable effect upon modulating the outcome of the event. Often, such attribution studies involve perturbing a subset of relevant physical variables characterizing the state of the real-world atmosphere and/or ocean by an increment commensurate with the effect of climate change. In the hurricane example, a conditional approach might involve using the real-world atmospheric conditions from 5 days before the storm made landfall as initial conditions in a model simulation but prescribing sea surface temperatures with the anthropogenic ocean warming trend removed. A key strength is that the conditional approach can help isolate the influence of specific physical aspects of climate change. A significant weakness is that this approach cannot diagnose changes in the overall probability of the event or the probability of individual constituent physical conditions.

An alternative to the absolute and conditional frameworks is the "ingredient-based" approach (Figure 2). Here, investigators first ascertain the most essential physical conditions known to contribute to the severity of a given event and then assess changes in the probability of these conditions. This approach aims to combine some of the key strengths of the absolute and conditional approaches because it (1) enhances understanding of how anthropogenic climate change is influencing the underlying physical drivers of extreme events, including the probability that they co-occur; (2) makes no assumptions regarding the specific set of initial conditions that produced the event; and (3) potentially enables attribution of event types that are poorly simulated in climate models and/or sparsely sampled in observational datasets.

Magnitude versus Frequency Definitions

Fundamentally, two aspects of extreme events are typically assessed in attribution studies: the probability and the severity

Examples of Collective Attribution

A

	Fraction of global surface area with individual attribution	
	Δ Return interval from historical trend	Δ Magnitude from anthropogenic forcing
Hottest monthly temperature	0.97	0.83
Hottest daily temperature	0.83	0.85
Driest annual precipitation	0.42	0.57
Wettest 5-day period	0.59	0.41

B

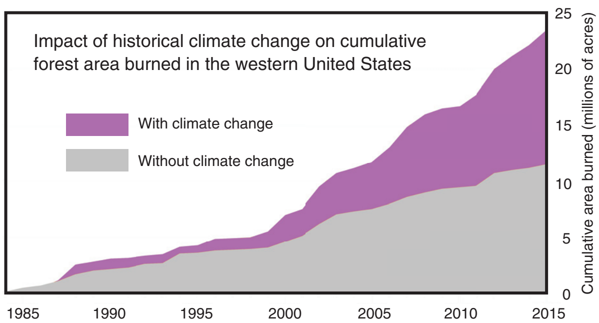

Figure 3. Example of Collective EEA Assessments

(A) Collective EEA for multiple physical event types (hot, dry, and wet events on different timescales) on a global scale with a large climate-model ensemble (adapted from Diffenbaugh et al., 2017).

(B) Collective EEA for a specific event type (wildfire risk, as measured by area burned) directly illustrates the contribution of climate change relative to a counterfactual climate without human influence (adapted from Gonzalez et al., 2018).

(Figure 2). The probability of an event is often defined as a rate of exceedance of a fixed threshold defined with a historical baseline—for instance, exceeding the 99.99th quantile of daily precipitation during the years 1920–1980. Conversely, the severity of an event is often defined as a magnitude associated with a given probability, such as "design floods" that are based on the magnitude of the 100-year recurrence interval.

The probability and severity definitions can be two sides of the same analytical coin (Figure 2). However, the differences between these definitions are sometimes highly consequential for both broader communication and practical decision making. For example, regional sea-level rise over the past two centuries increased the severity of Superstorm Sandy's flooding in New York City by 22% (from ~2.3 to ~2.8 m for an event of Sandy's observed probability). According to the same analysis (Lin et al., 2016), that same sea-level rise tripled the probability of the observed flooding (from ~1,200- to ~400-year return period for an event of Sandy's observed severity). In colloquial terms, a ~20% increase might sound modest, whereas a tripling sounds very large indeed—perhaps leading to a wide divergence in public perception regarding a study's outcome.

Yet, both of these are equally valid—and statistically consistent—metrics for quantifying the role of climate change, and both are potentially useful in different contexts. The probability-based metric, for example, could be highly relevant in a civil engineering context. Given that water infrastructure ranging from drainage culverts to large dams is typically designed to accommodate events defined by fixed historical thresholds (e.g., the amount of precipitation associated with a 100-year recurrence interval), increases in the probability of exceeding the original design threshold imply increased risk that the existing design capacity could be exceeded. The magnitude-based metric, on the other hand, is of heightened relevance in a legal and public policy context—instances in which it could be important to know the fraction of known losses contributed by climate change.

Individual versus Collective Event Attribution

Another key point of distinction is the difference between individual event attribution and what can be described as "collective event attribution." Individual event attribution seeks to answer the question: "Has global warming influenced the likelihood or severity of a specific observed historical event?" Conversely, collective event attribution seeks to answer the question: "Has global warming influenced the overall likelihood or severity of extreme events of a certain type?" (Figure 3). Individual event attribution might focus, for example, on whether the vegetation flammability in the vicinity of Paradise, California, in November 2018 (the time and location of California's deadliest and most destructive wildfire in modern history) was made more likely or more severe by global warming. Collective event attribution, on the other hand, might focus on whether climate change has increased the overall likelihood of high vegetation flammability in the western United States (and, hence, that the record-setting vegetation flammability was "consistent with" changes that would be expected from climate change).

Recently, research groups have begun to offer "rapid response" climate attribution targeted toward real-time weather events and sometimes make a formal attribution statement before the event even takes place. Emerging methods that apply an anthropogenic signal to numerical weather forecasts enable evaluations that are highly specific to the conditions of a given individual event. In addition, rapid statements can also be predicated on precomputed metrics via collective event-attribution methodologies that use large samples of observations and climate-model simulations to evaluate a particular type of extreme.

Similar collective attribution methodologies have also been used to quantify the fraction of a region or the globe over which anthropogenic forcing has already influenced the probability of record-setting events (Figure 3) and to verify event-attribution methodologies by using out-of-sample prediction-verification frameworks.

Scientific Stumbling Blocks

Although the science of EEA has advanced dramatically since the benchmark attribution study of the 2003 European heatwave (Stott et al., 2004), several substantial challenges remain. The most prominent relate to uncertainties surrounding the creation and analysis of the counterfactual climate. Researchers have used both statistical and climate-modeling approaches to quantify the counterfactual, although there is no consensus on which of these methods is the most suitable representation of event probability or severity in the absence of human influence.

The challenge of the counterfactual is exacerbated by the fact that, in many cases, it remains difficult to estimate the event probability in the current climate. For sufficiently severe events, the existing observational record might simply be too temporally and/or geographically limited to enable robust probability quantification. One option is to use parametric curve fitting or other statistical techniques from extreme value theory to approximate the

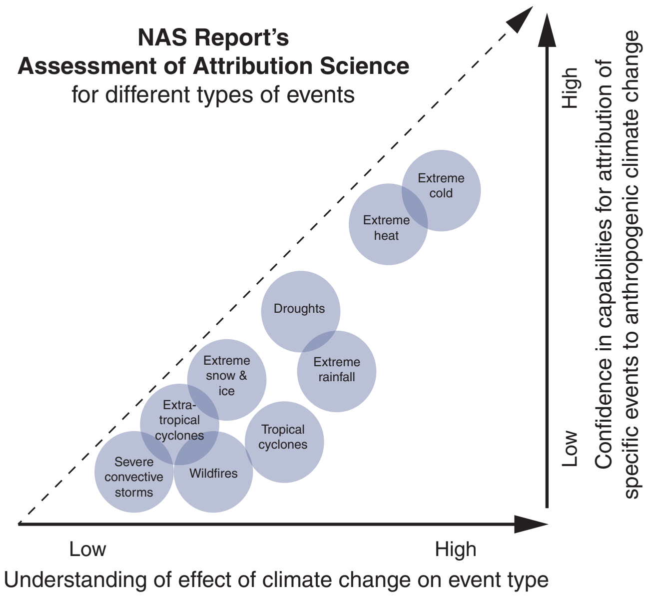

Figure 4. Confidence in EEA by Physical Event Type
Qualitative depiction of the relative levels of confidence in the ability to perform robust EEA as a function of physical event type. Such confidence varies considerably across different atmospheric and Earth system phenomena as a result of differences in understanding regarding how climate change can affect underlying drivers, as well as differences in how these processes are represented in observations and/or climate-model simulations. In general, confidence is highest for events most directly relating to temperature (such as extreme heat) and lowest for events occurring on small spatial scales (such as severe convective storms). Adapted from NASEM, 2016.

recurrence interval of the event. However, multiple studies have demonstrated that such statistical approaches are extremely sensitive to the assumed functional form of the underlying distribution and yield estimates of present-day probability that vary by orders of magnitude. Large climate-model ensembles, which offer much larger sample sizes, can help avoid the need to make such assumptions about the underlying distribution. Yet this alternative is still subject to the major caveat that present-generation climate models cannot always reliably capture the underlying physical processes responsible for certain types of events.

This caveat points to the larger question of whether climate models are fit for purpose in the context of EEA. A major challenge is the trade-off between the fine model resolution that is necessary for resolving the physical phenomena that produce certain types of extreme weather and the large ensembles and long integrations that are needed for fully characterizing internal climate-system variability and distinguish the signal of climate change. For instance, climate models are able to represent $\sim10^3$-km-scale high-pressure systems responsible for extreme heatwaves, but most are still too coarse to capture the full intensity and behavior of $\sim10^2$-km-scale tropical cyclones and face even greater challenges in simulating localized extreme precipitation events, which can occur on spatial scales that are smaller than a single global climate model grid cell. These climate-model limitations are a key reason why the level of confidence associated with EEA statements varies considerably by the type of extreme event (e.g., very high confidence for heatwaves versus only moderate confidence for tropical cyclones; Figure 4).

Together, these limitations raise the distinct possibility that studies finding no influence of climate change are simply reflecting the limitations of either the observational record or climate-modeling capabilities. A key philosophical consideration thus emerges: does an "absence of evidence" regarding the role of climate change mean that there is truly "evidence of absence"? Clarifying why it can be difficult to distinguish between these two possible interpretations of a negative attribution result is an important aspect of communicating the results of such studies to decision makers and the public.

The Way Forward

Recent developments in climate modeling and interdisciplinary Earth system science highlight the potential for rapid near-term advancement of EEA. Perhaps the most important development has been the growth of the EEA field, which has expanded the number of researchers developing, testing, and applying attribution methods to a wide variety of extreme events disrupting human and natural systems around the world. Efforts to systematically compare—and independently verify—different methods have begun to emerge. Further codification of these efforts and open access to underlying tools and data will help accelerate EEA capacity. In addition, efforts to develop clear and consistent shared language around communicating the specific characteristics or ingredients of the event being attributed, along with associated scientific uncertainties, will help the public and decision makers better understand the role of anthropogenic climate change.

Growth in supercomputing resources has enabled continued improvement in climate-model resolution, ensemble size, and integration length, allowing for increased physical realism in simulating processes that are critical in the evolution of extreme events. Indeed, targeted studies are now routinely conducted at sufficiently fine resolution that strong vertical motions—such as occur during many extreme precipitation events, severe thunderstorms, and tropical cyclones—can be explicitly represented. Although such "non-hydrostatic" simulations are still generally limited in their spatial and temporal scope, early indications are that this approach offers substantial promise for improving model representation of complex weather and climate phenomena. Similarly, the generation of multiple, single-model large ensembles (which use identical boundary forcings and model physics but perturbed initial conditions) is also a promising development for EEA because it allows for the intercomparison and refinement of predictive skill across individual model variations. It also enables more accurate quantification of the probability of an event within the context of historical climate variability, potentially offering a partial solution to the inadequacies of the existing observational record. Similarly, large "single-forcing" ensembles that isolate the influence of various anthropogenic greenhouse gases, aerosols, and land uses will help distinguish between the respective roles of potentially competing anthropogenic influences.

Given the rising public profile of climate change, the relevance of EEA for real-world applications in the legal, public-policy, and climate-adaptation arenas will only continue to increase. For example, as oil companies and other entities face potential civil liability for global warming, a key question in assigning culpability and subsequent penalties becomes whether climate change has demonstrably increased the likelihood and/or severity of extreme events that have caused loss and damage. Likewise, observed increases in destructive extreme events have increasingly factored into public investment decisions, including infrastructure funding requirements and state and federal disaster declarations. Civil engineering and design considerations are increasingly incorporating new information about the changing characteristics of extremes in order to maintain adequate safety margins and long-term resilience in a rapidly changing world.

Ultimately, it is clear that EEA is more than just a scientific exercise to improve communication of climate risks: it requires rigorous scientific methods to directly and quantitatively address an increasingly wide range of urgent, societally relevant questions that have long-term implications for human well-being. EEA can also help individuals and decision makers make sense of contemporary disasters, helping to contextualize real-world events relative to historical points of reference and aiding in disaster preparedness and climate-adaptation activities. Indeed, as EEA plays an increasingly prominent role in shaping public perception of climate risks, it could ultimately influence collective action to avoid levels of climate change that pose unacceptable risks to human and natural systems.

ACKNOWLEDGMENTS

D.L.S. was supported by a joint collaboration between the Institute of the Environment and Sustainability at the University of California, Los Angeles, the Center for Climate and Weather Extremes at the National Center for Atmospheric Research, and the Nature Conservancy of California. N.S.D. acknowledges support from Stanford University. D.S. acknowledges support from Washington State University. D.T. acknowledges support from University of California, Santa Barbara.

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