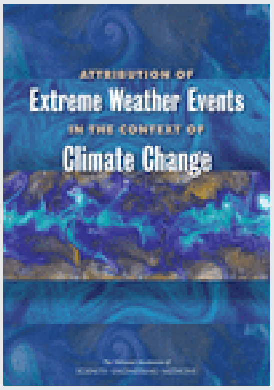

Attribution of Extreme Weather Events in the Context of Climate Change

DETAILS

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Preface

Extreme weather has affected human society since the beginning of recorded history and certainly long before then. Humans, along with every other living thing on the Earth, have adapted to a certain range of variability in the weather. Although extreme weather can cause loss of life and significant damage to property, people and virtually every other creature have, at least to some degree, adapted to the infrequent extremes they experience within their normal climatic zone.

Humans' use of fossil fuel since the start of the Industrial Revolution has begun to modify the Earth's climate in ways that few could have imagined a century ago. The consequences of this change to the climate are seemingly everywhere: average temperatures are rising, precipitation patterns are changing, ice sheets are melting, and sea levels are rising. These changes are affecting the availability and quality of water supplies, how and where food is grown, and even the very fabric of ecosystems on land and in the sea.

Despite these profound changes, climate change and its associated risks still may appear to many people as distant and remote in both time and space. The natural daily and seasonal variability of the weather can mask the changes in the overall climate. Yet, when people experience extreme events that they believe may be occurring with different—usually greater—frequency or with increased intensity, many ask about the connection between climate change and extreme events.

Effective, rigorous, and scientifically defensible analysis of the attribution of extreme weather events to changes in the climate system not only helps satisfy the public's desire to know but also can provide valuable information about the future risks of such events to emergency managers, regional planners, and policy makers at all levels of government. A solid understanding of extreme weather event attribution in the context of a changing climate can help provide insight into and confidence in the many risk calculations that underpin much of society's building codes; land, water, health, and food management; insurance; transportation networks; and many additional aspects of daily life.

There are compelling scientific reasons to study extreme weather event attribution as well. The basic physics of how the climate system works and the broad-scale impacts of rapid addition of greenhouse gases on the climate system are well understood. However, much is still to be learned about how the changing climate affects specific weather events. Improved attribution, and ultimately prediction of extreme events, will demonstrate an even more nuanced and sophisticated understanding of the climate system and will enhance scientists' ability to accurately predict and project future weather and climatic states.

The past decade has seen a remarkable increase in interest and activity in the extreme event attribution field. The first attempt at attributing an extreme weather event to climate change was published in 2004, analyzing the 2003 European summer heat wave that killed tens of thousands of people. In 2012 the American Meteorological Society started to publish a special annual issue of their *Bulletin*, compiling articles on extreme weather events of the past year. From 2012 to 2015, the number of research groups submitting studies to this issue has grown by more than a factor of five. A goal of this report is to provide a snapshot of the current state of the science of attribution of extreme weather events and to provide recommendations for what might be useful future avenues of both research and applications within this field.

Like all areas of study, terminology matters. As this field is relatively new, not everyone may be familiar with terms such as "counterfactual," "fraction of attributable risk," or "selection bias." Because the committee chose to use the terminology as it is defined and used in the relevant literature we have included a Glossary that defines these key terms.

A reoccurring theme of this report is the importance of the framing of any attribution question. Although climate scientists are frequently asked "Was a given observed weather event caused by climate change?" we believe this is a poorly formed (or ill-posed) question that rarely has a scientifically satisfactory answer. The report discusses appropriate ways to frame attribution questions as well as the interplay between meteorological and human-made factors in the realization of extreme events.

In addition to exploring framing and attribution methods, the report provides a synopsis of the attribution of nine specific types of extreme events. Not every type of event discussed is a pure meteorological event. Droughts, floods, and wildfires, for instance, all have human, as well as natural, components. Land management, controlled burning, and dams and levees impact the magnitude and frequency of these extreme events. The committee believes there is a large weather and climate signal to these types of events, however, and climate scientists are frequently asked to comment on them.

I want to thank our numerous sponsors: the David and Lucile Packard Foundation, the Heising-Simons Foundation, the Litterman Family Foundation, the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric

Administration (NOAA), and the U.S. Department of Energy, with additional support from the Arthur L. Day Fund of the National Academy of Sciences. In addition to meeting the needs of our sponsors, the committee hopes this report will be of use to the scientific community, the media, and policy makers who are interested in this topic.

Over the course of just 3 months the committee held a number of webinar meetings, met twice in person, and conducted a widely attended community workshop where we heard a diversity of views from the international community working on event attribution. During these meetings the committee gathered information, discussed and debated their views, and crafted this report. Over the course of the study, the committee engaged with international and U.S. scientists who spearheaded development of extreme event attribution approaches, as well as with the broader detection and attribution and climate science communities. (See Appendixes B and C for the names of the experts the committee consulted.)

In closing, I want to personally thank my fellow committee members for their sustained hard work and exceptional dedication to this report. When we started this process, many people believed that it would take more than 1 year to produce such a report. That *Attribution of Extreme Weather Events in the Context of Climate Change* was produced within 6 months is a testament to the focus and commitment of each member of this committee. I also want to thank and note with great appreciation the incisive and thoughtful comments of our reviewers, whose efforts significantly improved this report, and to thank everyone who gave of their time and expertise to speak at our workshop, on our webinars, or otherwise communicate with the committee during our study process. Finally, I want to acknowledge the superb efforts of the National Academies of Sciences, Engineering, and Medicine staff, led by Katie Thomas took our many disparate inputs, made them into a collective whole, kept us focused and on schedule, and did so with constant grace, cheerfulness, and good humor. Thank you.

David W. Titley, *Chair*
Committee on Extreme Weather Events and Climate Change Attribution

Acknowledgments

This report has been reviewed in draft form by individuals chosen for their diverse perspectives and technical expertise. The purpose of this independent review is to provide candid and critical comments that will assist the institution in making its published report as sound as possible and to ensure that the report meets institutional standards for objectivity, evidence, and responsiveness to the study charge. The review comments and draft manuscript remain confidential to protect the integrity of the deliberative process. We wish to thank the following individuals for their participation in the review of this report:

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Although the reviewers listed above have provided many constructive comments and suggestions, they were not asked to endorse the conclusions nor did they see the final draft of the report before its release. The review of this report was overseen by M. Granger Morgan, Carnegie Mellon University, Pittsburgh, PA; and Andrew Solow, Woods Hole Oceanographic Institution, Woods Hole, MA, who were responsible for making certain that an independent examination of this report was carried out in accordance with institutional procedures and that all review comments were carefully considered. Responsibility for the final content of this report rests entirely with the authoring committee and the institution.

The committee would like to thank the following individuals who shared their expertise with the committee through presentations and discussions: Myles Allen, University of Oxford; Elizabeth Barnes, Colorado State University; Heidi Cullen, Climate Central; Timothy DelSole, George Mason University; Noah Diffenbaugh, Stanford University; Randall Dole, National Ocean and Atmospheric Administration (NOAA) Earth Systems Research Laboratory; Kerry Emanuel, Massachusetts Institute of Technology; Chris E. Forest, Pennsylvania State University; Stephanie Herring, NOAA National Centers for Environmental Information; Martin Hoerling, NOAA Earth Systems Research Laboratory; David Karoly, University of Melbourne/University of Oklahoma; Eric Kasischke, National Aeronautics and Space Administration; Thomas Knutson, NOAA Geophysical Fluid Dynamics Laboratory; Kenneth Kunkel, NOAA Cooperative Institute for Climate and Satellites; Jay Lawrimore, NOAA National Centers for Environmental Information; Geert Jan van Oldenborgh, The Royal Netherlands Meteorological Institute (KNMI); Naomi Oreskes, Harvard University; Friederike Otto, University of Oxford; Tim Palmer, University of Oxford; Judith Perlwitz, NOAA Earth Systems Research Laboratory; Thomas Peterson, NOAA National Climactic Data Center; Fernando Prates, European Centre for Medium-Range Weather Forecasts; David Rupp, Oregon State University; Leonard Smith, University of Oxford; William Sweet, NOAA National Ocean Service; Michael Tippett, Columbia University; Jeffrey Trapp, University of Illinois; Kevin Trenberth, National Center for Atmospheric Research; Steven Vavrus, University of Wisconsin; Mike Wallace, University of Washington; Michael Wehner, Lawrence Berkeley National Laboratory; Antje Weisheimer, European Centre for Medium-Range Weather Forecasts; and Pascal Yiou, Climate and Environmental Sciences Laboratory (LSCE), France.

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Glossary[1]

Attribution: The process of evaluating the relative contributions of multiple causal factors to a change or an event with an assignment of statistical confidence (Hegerl et al., 2010).

Bias: A term used by statisticians to mean the difference between the true quantity and the estimates of that quantity based on data from repeated studies with statistically equivalent samples of data.

Causal factors: Influences on the climate system, including both external forcings—which may be either anthropogenic (greenhouse gases [GHGs], aerosols, ozone precursors, land/water use) or natural (volcanic eruptions, solar cycle modulations)—and slowly varying components of the system (sea-surface temperatures [SSTs], sea ice, soil moisture, snow cover) that are known to influence climatic conditions on seasonal timescales.

Causality: The relationship between something that happens or exists and an effect, result, or condition for which it is responsible.

Conditioning: The process of limiting an attribution analysis to particular types of weather or climate situations. For example, an attribution study may assess whether human influence on the climate plays a role in a given type of event when El Niño "conditions" prevail.

Counterfactual: From the perspective of attribution studies, *counterfactual* or *counterfactual world* refers to a hypothetical "control" world that has only been impacted by natural forcings and internal variability. In practice it usually refers to the observed climatic conditions (e.g., a specific sea-surface temperature [SST] distribution) as they might have occurred had anthropogenic forcing been absent.

Detection: Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense without providing a reason for that change (Hegerl et al., 2010).

Dynamic: Concerning the motion of bodies under the action of forces. In the context of event attribution, dynamics would include both large-scale circulation patterns—which can modulate temperature and precipitation extremes—and storms.

[1] The Intergovernmental Panel on Climate Change reports and the National Climate Assessment are excellent resources for climate-related definitions.

Ensemble: A collection of similar entities. In climate science, the term usually refers to a collection of simulations by a single model but with different initial conditions (hence different internal variations) or to a set of simulations of similar design by different climate models.

Exceedance probability: Probability that a quantity (e.g., temperature or precipitation) will exceed some specified threshold.

Extreme event: A weather or climate event that is rare at a particular place (and, sometimes, time of year) including, for example, heat waves, cold waves, heavy rains, periods of drought and flooding, and severe storms. Definitions of rare vary, but an extreme weather event would normally be as rare as or rarer than a particular percentile (e.g., 1st, 5th, 10th, 90th, 95th, 99th) of a probability density function estimated from observations expressed as departures from daily or monthly means.

Factual: From the perspective of attribution studies, *factual* refers to the currently observed world as it exists in the context of climate change.

(External) Forcing: A term that refers to a forcing agent outside the climate system causing a change in the climate system. Examples include volcanic eruptions, solar variations and anthropogenic changes in the composition of the atmosphere, and land use change.

Fraction of attributable risk (FAR): The fraction of the likelihood of an event that is attributable to a specific causal factor.

Framing: The process of posing scientific questions that arise when an event occurs and establishing the context within which they are answered (e.g., whether some kind of conditioning is involved). Framing may include translation of a question such as "Did human-induced climate change cause this event?" into one or more questions that science may be better able to answer: for instance, "Has human influence on the climate increased the frequency or intensity of events like the one that has just occurred?"

Internal variability: The technical term that is often used to describe the natural, unforced, chaotic variability that occurs continually in the climate system. It is a component of natural variability.

Model: A set of ideas; a physical representation or set of formulas that describe a process or system. In climate science, and in this report, the term usually refers to a set of equations describing the physical laws governing the behavior of the atmosphere, ocean, sea ice, land surface, and other components of the Earth system, whose solutions simulate the time evolution of the system.

Natural variability: Internally (such as El Niño–Southern Oscillation) and externally (e.g., volcanic eruptions or changes in solar radiance) induced natural climate variability that occurs without anthropogenic forcing.

P_0: Counterfactual probability p_0 (i.e., the probability of an event in a world without human influence on climate).

P_1: Factual probability p_1 (i.e., the probability of an event in the currently observed world as it exists in the context of climate change).

Return time: A return time (or period) is a commonly used metric of probability; for example, a 100-year return time means that in any given year, there is a 1-in-100 chance of the threshold being reached. If the climate were not changing, return time could also be interpreted as the average time between events, but it should not be interpreted as the time that will pass before an event occurs again.

Risk ratio: The ratio of probabilities under two different conditions or settings; in event attribution this is generally the ratio of the probability under anthropogenic forcing (the factual scenario) to that under the counterfactual scenario. While well established in epidemiology, the term is a misnomer because it is a ratio of probabilities and does not involve risk as formally defined to account for both probability and magnitude of impact.

Selection bias: A term used by statisticians to describe the systematic errors in probabilistic inference that can arise when the data that are collected or analyzed are not representative of the population of interest. A famous example is the mis-prediction of the outcome of the 1948 U.S. presidential election (Dewey versus Truman) based on a telephone survey, because in those days only the wealthier members of society had their own telephones.

Thermodynamic: Concerning heat and temperature and their relation to energy and work. In the context of event attribution, thermodynamics would include behavior related to the warming and increased moisture-holding capacity of the atmosphere.

Variance: A term used by statisticians to mean the variability of an estimate of a quantity based on one sample of data around the average estimate of that quantity that would be calculated based on data from repeated studies with statistically equivalent samples of data.

Summary

The observed frequency, intensity, and duration of some extreme weather events have been changing as the climate system has warmed. Such changes in extreme weather events also have been simulated in climate models, and some of the reasons for them are well understood. For example, warming is expected to increase the likelihood of extremely hot days and nights (Figure S.1). Warming also is expected to lead to more evaporation that may exacerbate droughts and increased atmospheric moisture that can increase the frequency of heavy rainfall and snowfall events.

The extent to which climate change influences an individual weather or climate event is more difficult to determine. It involves consideration of a host of possible natural and anthropogenic factors (e.g., large-scale circulation, internal modes of climate variability, anthropogenic climate change, aerosol effects) that combine to produce the specific conditions of an event. By definition, extreme events are rare, meaning that typically there are only a few examples of past events at any given location.

Nonetheless, this relatively new area of science—often called event attribution—is rapidly advancing. The advances have come about for two main reasons: one, the understanding of the climate and weather mechanisms that produce extreme events is improving, and two, rapid progress is being made in the methods that are used for event attribution. This emerging area of science also has drawn the interest of the public because of the frequently devastating impacts of the events that are studied. This is reflected in the strong media interest in the connection between climate change and extreme events, and it occurs in part because of the potential value of attribution for informing choices about assessing and managing risk and in guiding climate adaptation strategies. For example, in the wake of a devastating event, communities may need to make a decision about whether to rebuild or to relocate. Such a decision could hinge on whether the occurrence of an event is expected to become more likely or severe in the future—and, if so, by how much.

The ultimate challenge for the science of event attribution is to estimate how much climate change has affected an individual event's magnitude[1] or probability[2] of occurrence. While some studies now attempt to do this, most consider classes of events that are similar to the event that has been observed. Irrespective of whether a specific

[1] In this report "magnitude" and "intensity" are used synonymously.
[2] In this report "probability" and "frequency" are used synonymously.

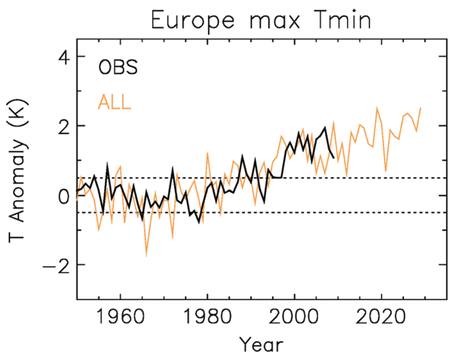

FIGURE S.1 This figure shows a time series of the annual maximum nighttime temperature averaged over the European Region. Temperatures are plotted as anomalies, or deviations from normal (in this case, 1961-1990), in degree Kelvin (K). Observed temperatures are represented by the black lines and are based on Caesar et al. (2006; updated). The orange lines come from model simulation (Martin et al., 2006). Both observations and model output show an increasing trend in nighttime temperature anomalies over time. The horizontal dotted lines denote the uncertainty range (5-95%) due to natural climate variability. SOURCE: Stott et al., 2011.

event or a class of events is studied, results remain subject to substantial uncertainty, with greater levels of uncertainty for events that are not directly temperature related. The conclusions drawn also depend, in general, on choices made when selecting the events, framing the questions asked about the role of climate change, designing the modeling setup, and selecting statistical tools to quantify uncertainty.

More and more event attribution studies are being published every year, and study results are increasingly requested very quickly after events occur. Some of the study methods are still relatively novel, however, and there are a range of views about how to conduct and interpret the analyses. This report examines the science of attribution of specific extreme weather events to human-caused climate change and natural variability[3] by reviewing current understanding and capabilities. It assesses the robustness of the methods for different classes of events and attribution approaches, provides guidance for interpreting analyses, and identifies priority research needs (the full statement of task can be found in Appendix A). This study is sponsored by the David and Lucile Packard Foundation, the Heising-Simons Foundation, the Litterman Family Foundation, the National Aeronautics and Space Administration (NASA), the National Oceanic and

[3] In this report, the term "natural variability" encompasses both externally forced variations other than anthropogenic as well as the chaotic component of the atmosphere that is not externally forced. See Glossary.

Atmospheric Administration (NOAA), and the U.S. Department of Energy (DOE), with additional support from the Arthur L. Day Fund of the National Academy of Sciences.

EVENT ATTRIBUTION APPROACHES

Event attribution approaches can be generally divided into two classes: (1) those that rely on the observational record to determine the change in probability or magnitude of events, and (2) those that use model simulations to compare the manifestation of an event in a world with human-caused climate change to that in a world without. Most studies use both observations and models to some extent—for example, modeling studies will use observations to evaluate whether models reproduce the event of interest and whether the mechanisms involved correspond to observed mechanisms, and observational studies may rely on models for attribution of the observed changes.

Some types of observation-based approaches to event attribution use the historical context in order to determine changes in the rarity of an observed event based on long-term data. For example, this might involve comparing the statistical probability of an event in today's climate to its probability in some previous time several decades earlier when the concentration of anthropogenic greenhouse gases (GHGs) was much lower. In practice, historical observations are often not available for a long enough period to enable a reliable statistical evaluation of whether there has been a significant change in event frequency or intensity.

Another observational approach is based on analyzing the characteristics of a given weather event (e.g., the large-scale circulation pattern) and looking for historical analogues in order to determine how meteorologically similar events have changed. These studies might compare the amount of rainfall in the current event to similar past events to estimate how the long-term increases in atmospheric temperature and moisture affected the event. As such, this approach does not address how climate change may have influenced the conditions that gave rise to a particular weather pattern. Some studies have also diagnosed the frequency of circulation states in order to determine if these may explain or counteract any change in extreme events. In general, it will be challenging to attribute any such changes to anthropogenic climate change.

Weather and climate model-based approaches to extreme event attribution compare model-simulated weather and climate phenomena under different input conditions: for instance, with and without human-caused changes in GHGs. Many studies rely on coupled atmosphere-ocean climate models, while others may use global atmospheric models, regional models, or models that are constructed specifically to represent a particular class of weather events, such as hurricanes. Multiple simulations can be conducted to test how changes in sea-surface temperature (SST), the levels of atmospheric CO_2 or aerosols, or other variables affect the extreme event of interest. Simulations are often repeated many times with small changes in the initial atmospheric or other conditions to estimate some uncertainties and sensitivities. Figures S.2 and S.3 provide examples of model-based attribution for the extreme heat events in Russia during the summer of 2010 and the extreme flooding events in England and Wales during the autumn of 2000, respectively.

Many studies have used climate models to understand just how unusual observed conditions are with respect to the distribution of possible conditions in a world that is unperturbed by humans. Models are often used to estimate the probability of occurrence of an event with human-caused climate changes (p_1) and without these changes (p_0). These estimated probabilities are often used to estimate the fraction of attributable risk (FAR)—FAR = $(p_1 - p_0)/p_1$—or the risk ratio (RR)—RR = p_1/p_0. These model-based estimates of attributable risk or RR hinge on the model used being able to reliably simulate both the event in question and any changes in this event that may occur due to human-caused climate change or another considered factor.

Some recent studies also have used models to attempt to follow the evolution of a particular extreme weather event—for example, through the use of a set of short-term forecasts using a weather model. This allows detailed study of particular extreme events with a model capable of representing those specific events with fidelity and quantification of the effect of certain aspects of climate change (e.g., increased moisture-holding capacity of a warmer atmosphere) in which there is high confidence. Such studies cannot fully address frequency of occurrence because the results are highly conditional both on the initial state of the atmosphere and land surface that is specified to the model and on the specific sea-surface conditions that prevailed at the time of the event. With these constraints, it may be possible to estimate changes in event magnitude or changes in the frequency of exceedance above or below a given event magnitude, conditional on all else that is required to be specified to make the short-term forecasts. It is not possible, however, to study whether the likelihood of the occurrence of similar initial states and sea-surface conditions has changed.

ASSESSMENT OF CURRENT CAPABILITIES

Event attribution is more reliable when based on sound physical principles, consistent evidence from observations, and numerical models that can replicate the event. The ability to attribute the causes of some extreme event types has advanced

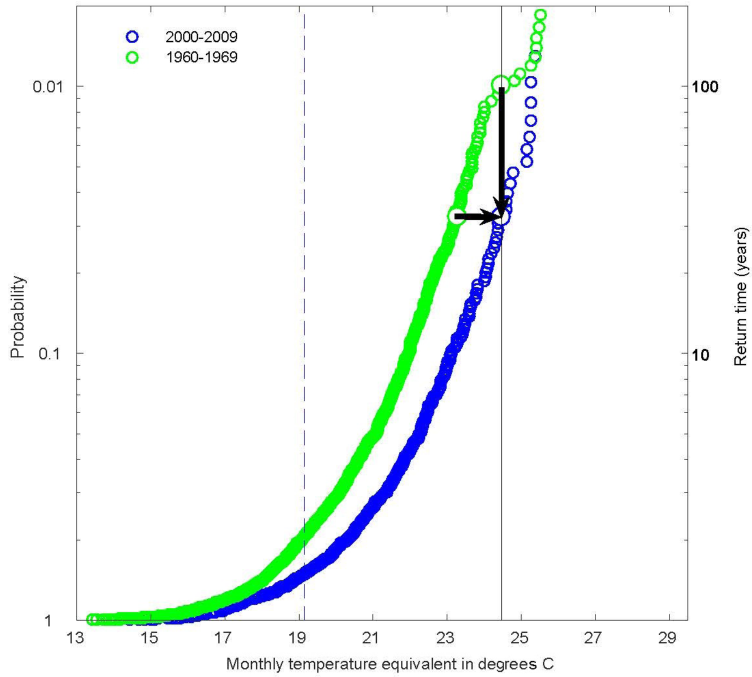

FIGURE S.2 Western Russia experienced several heat waves in the summer of 2010, leading to average temperatures in July 2010 exceeding the long-term observed average by more than 5°C. This extreme heat prompted questions about the potential effect of human-caused climate change. To address this question, Otto et al. (2012) used an atmospheric general circulation model to produce hundreds of simulations of the climate of the 2000s (blue circles) and of the 1960s (green circles). Defining heat waves as having high temperatures and anti-cyclonic circulation anomaly (associated with persistent conditions), they examined how likely it would be for temperature to exceed a given magnitude. Using this approach, the authors concluded that the average observed temperature during July 2010 of nearly 25°C was significantly more likely in the 2000s than in the 1960s, corresponding to a shift from a 99-year return time to a 33-year return time (downward black arrow; horizontal arrow explained in Figure 2.1). SOURCE: Figure courtesy of Friederike Otto, adapted from Otto et al. (2012).

rapidly since the emergence of event attribution science a little more than a decade ago, while attribution of other event types remains challenging. In general, confidence in attribution results is strongest for extreme event types that

- have a long-term historical record of observations to place the event in an appropriate historical context;

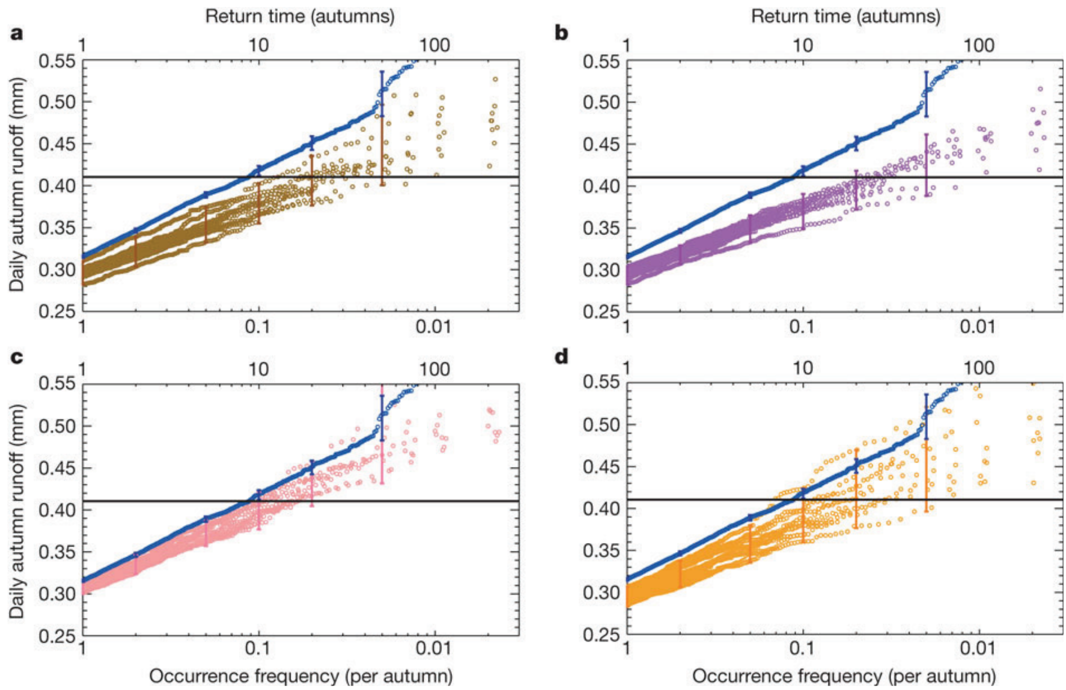

FIGURE S.3 In England and Wales, October and November 2000 were the wettest autumn months since records began in 1766, resulting in widespread flooding and substantial damages. Pall et al. (2011) examined the sensitivity of the change in the frequency of occurrence of extremely high river runoff in England and Wales for autumn 2000 using different climate models to simulate a world in which humans were not influencing climate (see Chapter 3). Blue is the modeled return time for 2000 runoff (identical in each panel) against frequency of occurrence, while colored dots show the return times in a world that might have been, constructed by removing the pattern of human influence on sea surface temperatures (SSTs) from four different climate models: HadCM3 (brown, a), GFDL (purple, b), PCM (pink, c), and MIROC (orange, d). The horizontal black line on each panel corresponds to the highest daily runoff observed during these 2 months. SOURCE: Pall et al., 2011.

- are simulated adequately in climate models[4]; and
- are either purely meteorological in nature (i.e., the event is not strongly influenced by built infrastructure, resource management actions, etc.) or occur in circumstances where these confounding factors can be carefully and reliably considered.

[4] By "adequately" the committee means that, at a minimum, climate models used for event attribution need to accurately capture the spatial patterns and variability of relevant climate-related phenomena. See Table S.1 and Box 4.1 for the committee's assessment of the capabilities of climate models to simulate each event type.

Non-meteorological factors can limit the accuracy of model simulations of extreme events and confound observational records. Drought and wildfire are examples of events for which non-meteorological factors can be especially challenging in attribution studies.

Furthermore, confidence in attribution results that indicate an influence from anthropogenic climate change is strongest when there is an understood and robustly simulated physical mechanism that relates a given class of extreme events to long-term anthropogenic climate changes such as global-scale temperature increase or increases in water content of a warmer atmosphere.

More frequent occurrences of extreme heat and less frequent occurrences of extreme cold are examples of changes that are consistent with increasing global mean temperatures.

Using this set of criteria (i.e., sound physical principles, consistent evidence from observations, and numerical models that can replicate the event) the committee assessed their confidence in event attribution capabilities for different extreme event types, as illustrated in Figure S.4 and Table S.1.

Confidence in attribution findings of anthropogenic influence is greatest for those extreme events that are related to an aspect of temperature, such as the observed long-term warming of the regional or global climate, where there is little doubt that human activities have caused an observed change. For extreme heat and cold events in particular, changes in long-term mean conditions provide a basis for expecting that there also should be related changes in extreme conditions. Heavy rainfall is influenced by a moister atmosphere, which is a relatively direct consequence of human-induced warming, though not as direct as the increase in temperature itself. The frequencies and intensities of tropical cyclones and severe convective storms are related to large-scale climate parameters whose relationships to climate are understood to varying degrees but, in general, are more complex and less direct than are changes in either temperature or water vapor alone. Nevertheless, atmospheric circulation and dynamics play some role in the development of an extreme event, which is different for different event types. Changes in atmospheric circulation and dynamics are generally less directly controlled by temperature, less robustly simulated by climate models, and less well understood.

Event attribution can be further complicated by the existence of other factors that contribute to the severity of impacts. For example, while many studies have linked an increase in wildfires to climate change, the risk of any individual fire depends on past forest management, natural climate variability, human activities in the forest,

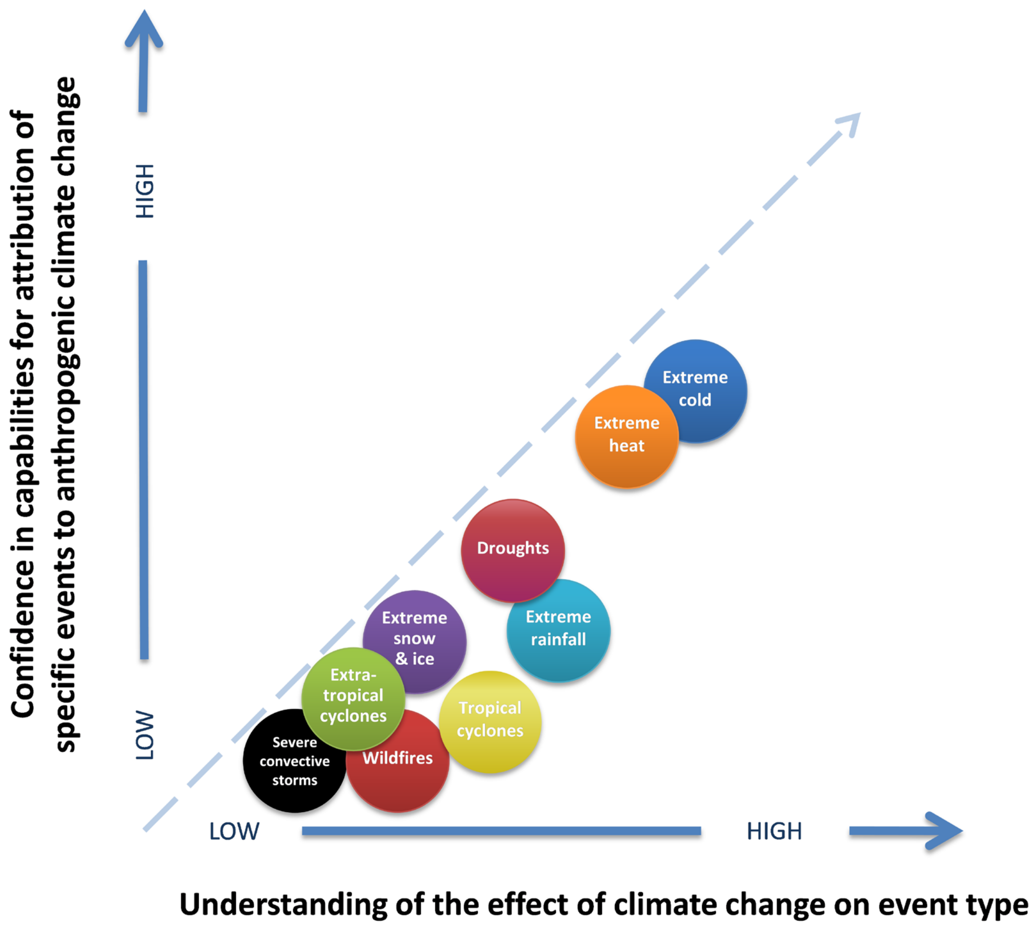

FIGURE S.4 Schematic depiction of this report's assessment of the state of attribution science for different event types. The horizontal position of each event type reflects an assessment of the level of understanding of the effect of climate change on the event type, which corresponds to the right-most column of Table S.1. The vertical position of each event type indicates an assessment of scientific confidence in current capabilities for attribution of specific events to anthropogenic climate change for that event type, which draws on all three columns of Table S.1. A position below the 1:1 line indicates an assessment that there is potential for improvement in attribution capability through technical progress alone (such as improved modeling, or the recovery of additional historical data), which would move the symbol upward. A position above the 1:1 line is not possible because this would indicate confident attribution in the absence of adequate understanding. In all cases, there is the potential to increase event attribution confidence by overcoming remaining challenges that limit the current level of understanding. (See Box 4.1 for more details.)

TABLE S.1 This table, along with Figure S.4, provides an overall assessment of the state of event attribution science for different event types. In each category of extreme event, the committee has provided an estimate of confidence (high, medium, and low) in the capabilities of climate models to simulate an event class, the quality and length of the observational record from a climate perspective, and an understanding of the physical mechanisms that lead to changes in extremes as a result of climate change. The entries in the table, which are presented in approximate order of overall confidence as displayed in Figure S.4, are based on the available literature and are the product of committee deliberation and judgment. Additional supporting information for each category can be found in the text of Chapter 4, summarized in Box 4.1. The assessments of the capabilities of climate models apply to those models with spatial resolutions (100km or coarser) that are representative of the large majority of models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5). Individual global and regional models operating at higher resolutions may have better capabilities for some event types, but in these cases, confidence may still be limited due to an inability to assess model-related uncertainty. The assessments of the observational record apply only to those parts of the world for which data are available and are freely exchanged for research. Most long records rely on *in situ* observations, and these are not globally complete for any of the event types listed in this table, although coverage is generally reasonable for the more densely populated parts of North America and its adjacent ocean regions.

● = high ◉ = medium ○ = low	Capabilities of Climate Models to Simulate Event Type	Quality/Length of the Observational Record	Understanding of Physical Mechanisms That Lead to Changes in Extremes as a Result of Climate Change
Extreme cold events	●	●	●
Extreme heat events	●	●	●
Droughts	◉	◉	◉
Extreme rainfall	◉	◉	◉
Extreme snow and ice storms	◉	○	◉
Tropical cyclones	○	○	◉
Extratropical cyclones	◉	○	○
Wildfires	○	◉	○
Severe convective storms	○	○	○

and possibly other factors, in addition to any exacerbation by human-caused climate change.

Confidence in attribution analyses of specific extreme events is highest for extreme heat and cold events, followed by hydrological drought and heavy precipitation. There is little or no confidence in the attribution of severe convective storms and extratropical cyclones. Confidence in the attribution of specific events generally increases with an increased understanding of the effect of climate change on the event type. Gaps in understanding and limitations in the historical data lead to differences in confidence in attribution of specific events among different event types.

Attribution of events to anthropogenic climate change may be complicated by low-frequency natural variability, which influences the frequencies of extreme events on decadal to multidecadal timescales. The Pacific Decadal Oscillation and the Atlantic Multidecadal Oscillation are examples of such variability. Characterization of these influences is uncertain because the observed record is too short to do so reliably or to assess if climate models simulate these modes of variability correctly.

PRESENTING AND INTERPRETING EXTREME EVENT ATTRIBUTION STUDIES

Given the relative newness of the event attribution field, standards have not yet been established for how to present results, which can make their interpretation difficult, particularly if conflicting evidence is available. Most event attribution studies are subject to substantial uncertainty. Results also hinge on how the event that is analyzed is defined, the specific questions that are posed, the assumptions made when analyzing the event, and the data, modeling, and statistical tools used to conduct the analysis. It is therefore essential to communicate the event definition, event attribution questions, assumptions, and choices clearly when reporting on the outcome of an event attribution study. The technical nature of this information makes it challenging to accurately communicate results, uncertainties, and limitations to the broader public.

There is no single best method or set of assumptions for event attribution, as these depend heavily on the framing of the question and the amount of time available to answer it. Time constraints may themselves affect framing and methodological choices by limiting analyses to approaches that can be undertaken quickly.

A definitive answer to the commonly asked question of whether climate change "caused" a particular event to occur cannot usually be provided in a deterministic sense because natural variability almost always plays a role. Many conditions must align to set up a particular event. Extreme events are generally influenced by a specific weather situation, and all events occur in a climate system that has been changed by human influences. Event attribution studies generally estimate how the intensity or frequency of an event or class of events has been altered by climate change (or by another factor, such as low-frequency natural variability). Thus, examples of questions that the scientific community can attempt to address include:

- "Are events of this severity becoming more or less likely because of climate change?"
- "To what extent was the storm intensified or weakened, or its precipitation increased or decreased, because of climate change?"

Statements about attribution are sensitive to the way the questions are posed and the context within which they are posed. For example, when defining an event, choices must be made about defining the duration of the event (when did it begin and when did it end) and the geographic area it impacted, but this may not be straightforward for some events (e.g., heat waves). Furthermore, different physical variables may be studied (e.g., drought might be characterized by a period with insufficient precipitation, excessively dry soil, or reduced stream flow), and different metrics can be used to determine how extreme an event was (e.g., frequency, magnitude). Whether an observation- or model-based approach is used, and which observations and/or models were available for studying the event, will also constrain the sorts of questions that can be posed.

Attribution studies of individual events should not be used to draw general conclusions about the impact of climate change on extreme events as a whole. Events that have been selected for attribution studies to date (e.g., events affecting areas with high population and extensive infrastructure attract the greatest demand for information from stakeholders) are not a representative sample. Also, events that are becoming less likely because of climate change (e.g., cold extremes) will be studied less often because they occur less often than events whose frequency is increasing because of climate change. Furthermore, attribution of individual events is generally more difficult than characterizing the statistical distribution of events of a given type and its dependence on climate. For example, it may be possible to make confident statements about how some class of extreme events is expected to change because of human-induced climate change, while at the same time an attribution study of an individual event of that type may be unable to make a confident statement about the human influence on that one specific event. Thus, for all of these reasons, counts of available attribution studies with any positive, negative, or neutral results are not expected to give a reliable indication of the overall importance of human influence on extreme events.

ATTRIBUTION OF EXTREME WEATHER EVENTS IN THE CONTEXT OF CLIMATE CHANGE

Unambiguous interpretation of an event attribution study is possible only when the assumptions and choices that were made in conducting the study are clearly stated and uncertainties are carefully estimated. The framing of event attribution questions, which may depend strongly on the intended application of the study results, determine how the event will be studied and can lead to large differences in the interpretation of the results. Event attribution studies presented in the following manner are less likely to be misinterpreted:

- Assumptions about the state of one or more aspects of the climate system at the time of the event (e.g., SST anomalies, atmospheric circulation regimes, specific weather situations) are clearly communicated.
- Estimates of changes in both magnitude and frequency are provided, with accompanying estimates of uncertainty, so users can understand the estimated degree of change from the different perspectives.
- Estimates of changes in frequency are presented as a risk ratio—that is, in terms of the ratio of the probability of the event in a world with human-caused climate change to its probability in a world without human-caused climate change. Equivalently, one can compare the return periods of the event (i.e., how rarely an event occurs) in the world without climate change to that in the world with climate change.
- The impact of assumptions (e.g., of how estimates of changes in magnitude and frequency depend on SST anomalies or atmospheric circulation regimes) is discussed.
- Statements of confidence accompany results so users understand the strength of the evidence.

Bringing multiple scientifically appropriate approaches together, including multiple models and multiple studies helps distinguish results that are robust from those that are much more sensitive to how the question is posed and the approach taken. For example, robust attribution analyses typically show that the results are qualitatively similar across a range of event definitions, acknowledging that quantitative results are expected to differ somewhat because of differences in definition. Utilizing multiple methods to estimate human influences on a given event also partially addresses the challenge of characterizing the many sources of uncertainty in event attribution.

Examples of multiple components that can lead to more robust conclusions include:

- Estimates of event probabilities or magnitudes based on an appropriate modeling approach that has been shown to adequately reproduce the event and its circumstances, such as the dynamic situation leading to the event.

- Reliable observations against which the model has been evaluated and that give an indication of whether the event in question has changed over time in a manner that is consistent with the model-based attribution.
- Assessment of the extent to which the result is consistent with the physical understanding of climate change's influence on the class of events in question.
- Clear communication of remaining uncertainties and assumptions made or conditions imposed on the analysis.

THE PATH FORWARD

Improving Extreme Event Attribution Capabilities

Continued research efforts are necessary to increase the reliability of event attribution results, particularly for event types for which attribution is presently poorly understood. Some of this research is covered in the ongoing work to understand the connection between climate change and long-term statistics of extremes. Improvements in attribution capability for all event types require improvements in observations, models, theoretical understanding of the links between climate change and extremes, and analysis techniques.

A focused effort to improve understanding of specific aspects of weather and climate extremes could improve the ability to perform extreme event attribution. Because extreme event attribution relies strongly on all aspects of the understanding of extremes and their challenges, the committee endorses the recommendations identified in the white paper sponsored by the World Climate Research Programme "WCRP Grand Challenge: Understanding and Predicting Weather and Climate Extremes" (Box S.1; Zhang et al., 2014) as necessary to make advances in event attribution.

In particular, this committee recommends research that aims to improve event attribution capabilities, which includes increasing the understanding of

- the role of dynamics and thermodynamics in the development of extreme events;
- the model characteristics that are required to reliably reproduce extreme events of different types and scales;
- changes in natural variability, including the interplay between a changing climate and natural variability, and characterization of the skill of models to represent low-frequency natural variability in regional climate phenomena and circulation;
- the various sources of uncertainty that arise from the use of models in event attribution;

BOX S.1
KEY RECOMMENDATIONS FROM THE WHITE PAPER "WCRP GRAND CHALLENGE: UNDERSTANDING AND PREDICTING WEATHER AND CLIMATE EXTREMES"

- substantial advances in modelling (including but not limited to model resolution)
- advances in the understanding of the physical mechanisms leading to extremes
- increased effort to extend the historical observational record, including planned climate quality reanalyses over longer historical periods
- improvements in remote sensing products that extend long enough to document trends and sample extremes

SOURCE: Zhang et al., 2014.

- how different levels of conditioning (i.e., the process of limiting an attribution analysis to particular types of weather or climate situations) lead to apparently different results when studying the same event;
- the statistical methods used for event attribution, objective criteria for event selection, and development of event attribution evaluation methods;
- the effects of non-climate causes—such as changes in the built environment (e.g., increasing area of urban impervious surfaces and heat island effects, land cover changes), natural resource management practices (e.g., fire suppression), coastal and river management (e.g., dredging, seawalls), agricultural practices (e.g., tile drainage), and other human activities—in determining the impacts of an extreme event;
- expected trends in future extreme events to help inform adaptation or mitigation strategies (e.g., calculating changes in return periods to show how the risk from extreme events may change in the future); and
- the representation of a counterfactual world that reliably characterizes the probability, magnitude, and circumstances of events in the absence of human influence on climate.

Research efforts targeted specifically at extreme events, including event attribution, could rapidly improve capabilities and lead to more reliable results. In particular, there are opportunities to better coordinate existing research efforts to further accelerate the development of the science and improve and quantify event attribution reliability. Also, it would be beneficial to encourage interdisciplinary research at the interface between the climate, weather, and statistical sciences to improve analysis methods. Event attribution capabilities would be improved with better observational records, both near–real time and for historical context. Long, homogeneous observed records are essential for placing events into a historical context and evaluating to what extent climate models reliably simulate the effect of decadal climate variability on extremes.

Event attribution could be improved by the development of transparent community standards for attributing classes of extreme events. Such standards could include an assessment of model quality in relation to the event/event class. They also could include use of multiple lines of evidence, developing a transparent link to a detected change that influences events in question and the clear communication of sensitivities of the result to how the question of event attribution is asked.

Systematic criteria for selecting events to be analyzed would minimize selection bias and permit systematic evaluation of event attribution performance, which is important for enhancing confidence in attribution results. Studies of a representative sample of extreme events would allow stakeholders to use such studies as a tool for understanding how individual events fit into the broader picture of climate change. Irrespective of the method or related choices, it would be useful to develop a set of objective event selection and definition criteria. This would help to reduce selection bias and, in some cases, lead to methodological improvements. This also is a prerequisite for the development of a formalized approach to evaluating event attribution results and uncertainty estimates, similar to the existing approaches used to evaluate weather forecasts.

Event Attribution in an Operational Context

As more researchers begin to attempt event attribution, their efforts would benefit from coordination to make sure that there is a systematic approach and that uncertainties are explored across methods and framing. Event attribution can benefit from links to operational numerical weather prediction where available. Some groups are moving toward the development of operational extreme event attribution systems to systematically evaluate the causes of extreme events based on predefined and tested methods. Objective approaches to compare and contrast the analyses among multiple different research groups based on agreed event selection criteria are yet to be developed.

In the committee's view, attributes of a successful operational event attribution system would include the following:

- objective event-selection criteria to reduce selection bias so stakeholders understand how individual events fit into the broader picture of climate change;

ATTRIBUTION OF EXTREME WEATHER EVENTS IN THE CONTEXT OF CLIMATE CHANGE

- provision of stakeholder information about causal factors within days of an event, followed by periodic updates as more data and analysis results become available;
- clear communication of key messages to stakeholders about the methods and framing choices as well as the associated uncertainties and probabilities; and
- reliable assessments of performance of the event attribution system through evaluation and verification processes utilizing observations and seasonal forecasts and skill scores similar to those used routinely in weather forecasting.

Some future event attribution activities could benefit from being linked to an integrated weather-to-climate forecasting effort on a range of timescales. The development of such an activity could be based on concepts and practices within the Numerical Weather Prediction community. Ultimately the goal would be to provide predictive (probabilistic) forecasts of future extreme events at lead times of days to seasons or longer, accounting for natural variability and anthropogenic influences. These forecasts would be verified and evaluated using observations, and their routine production would enable the development and application of appropriate skill scores. The activity would involve rigorous approaches to managing and implementing system enhancements to continually improve models, physical understanding, and observations focused on extreme events. Although situating some future event attribution activities in an integrated weather-to-climate forecasting effort would lead to more coordination, the committee encourages continued research in event attribution outside of an operational context to ensure further innovation in the field.

CONCLUDING REMARKS

The ability to understand and explain extreme events in the context of climate change has developed very rapidly over the past decade. In the past, a typical climate scientist's response to questions about climate change's role in any given extreme weather event was, "We cannot attribute any single event to climate change." The science has advanced to the point that this is no longer true as an unqualified blanket statement. In many cases, it is now often possible to make and defend quantitative statements about the extent to which human-induced climate change (or another causal factor, such as a specific mode of natural variability) has influenced either the magnitude or the probability of occurrence of specific types of events or event classes. The science behind such statements has advanced a great deal in recent years and is still evolving rapidly. Still further advances are necessary, particularly with respect to evaluating and communicating event attribution results and ensuring that event attribution studies meet the information needs of stakeholders. Further improvement will depend not only on addressing scientific problems specific to attribution but also on advances in the basic underlying science, including observations, modeling, and theoretical understanding of extreme events and their relation to climate change.

CHAPTER ONE

Introduction

Extreme weather and climate events (e.g., heat waves, droughts, heavy rainfall, hurricanes) have always posed risks to human society. A matter of growing interest, however, is the degree to which humans are changing these risks through anthropogenic climate change. This concern has been driven by the growing impacts on ecosystems, communities, and infrastructure of recent extreme events across the United States and the world.

Efforts to attribute the causes of individual extreme events need to be understood in the broader context of what we already know about climate change. Humans have contributed to warming of the climate system globally (predominantly due to anthropogenic greenhouse gas [GHG] emissions). This finding is supported by multiple lines of evidence that originate from data from observing systems across the globe on land and sea and in the atmosphere and from structurally different analyses of multiple components of the climate system. A substantial body of evidence also shows that climate change has led to discernible and quantifiable changes in the intensity and/or frequency of some types of extremes (Donat et al., 2013; IPCC, 2014; Melillo et al., 2014; Seneviratne et al., 2012; Figure 1.1).

Extreme weather is one way that people experience climate change. Extreme events are abrupt, occur in the present, and are highly visible, as opposed to long-term climate change trends that seem abstract, distant, gradual, and complicated (Howe et al., 2014). The global news includes reports on extreme weather or climate events on a regular basis: for example, in 2015 there was a May-June India-Pakistan heat wave, both a "1,000-year rainfall event" in South Carolina (Figure 1.2) and Hurricane Patricia, the "strongest eastern Pacific or Atlantic hurricane in the historical record," in October, as well as widespread flooding in northern England in December. Each of these cases has led to questions from the media and the public about whether the events were "caused" by climate change. Attribution draws the explicit connection between climate science as a whole and the specific event in the news, making the science concrete in a way that statements about broader trends and future projections do not.

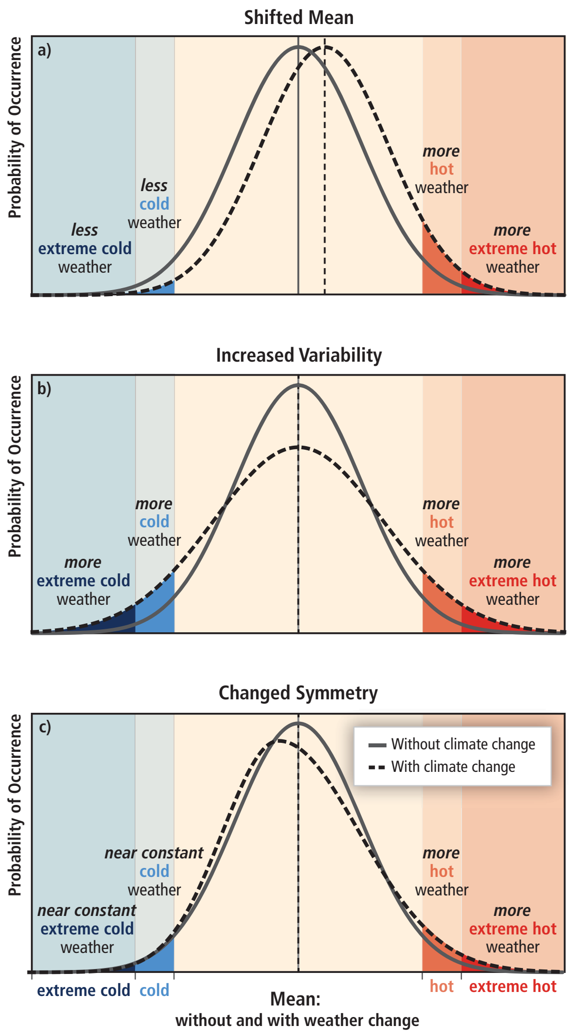

FIGURE 1.1 This probability density function captures the likelihood of specified events resulting from a given temperature distribution and its changes. As with any bell curve, those events that fall near the center (events occurring in a mid-range temperature state) are most likely, and events that occur in lower and upper temperature extremes have smaller probability. A world with climate change could have different effects on the probability of extreme values of the distribution. For example, in (a) a simple shift of the entire distribution toward a warmer climate could lead to fewer cold weather and extreme cold weather events and more hot weather and extreme hot weather events. Alternatively, in (b) increased temperature variability without a shift in the mean could lead to more extreme cold and heat events, with lower probability of mid-range temperature events. In a third example (c), an altered shape of the temperature distribution could result in no change in the mean but differing likelihoods in extreme events on both ends of the temperature spectrum (in this example, a change in asymmetry toward the hotter part of the distribution). SOURCE: IPCC, 2012.

FIGURE 1.2 Historic flooding in South Carolina in October 2015. SOURCE: Chuck Burton/Associated Press.

WHY INVESTIGATE THE CAUSES OF EXTREME EVENTS?

Given that climate change affects the climate system globally, it is impossible to rule out some contribution from climate change to any extreme event. Each extreme event, however, has a host of possible natural and anthropogenic causes in addition to anthropogenic climate change. Examples of natural causes include large-scale circulation, internal modes of climate variability, and some aerosol effects (e.g., marine aerosol, stratospheric and volcanic aerosol). Furthermore, the resulting impacts of that event can be mitigated or exacerbated by other factors (e.g., the local topography, land use).

There are several motivations for investigating the causes of individual extreme events. From a scientific perspective, these studies increase our understanding of how and why the frequency and intensity of extremes has changed over time. These studies may also spur model improvements to ensure that the models used in event attribution studies adequately represent the event being studied. There is an element of scientific curiosity, but the primary motivation for event attribution goes beyond science.

Extreme events are directly traceable to loss of life, rising food and energy prices, increasing costs of disaster relief and insurance, fluctuations in property values, and concerns about national security. Extreme events can and have evoked policy changes: for example, Superstorm Sandy led to supplemental Congressional legislation to increase the National Weather Service's numerical weather modeling capacity.[1] Furthermore, global insurer Munich Re calculated that natural disasters caused more than $90 billion in overall losses and $27 billion in insured losses in 2015 alone (NatCatSERVICE, 2016).[2] A study in the *Bulletin of the American Meteorological Society* (BAMS) (Lazo et al., 2011) noted that weather affects about 3.4% of the U.S. Gross Domestic Product, or more than $500 billion per year.

The strong societal impacts of extreme events explain public and policy maker interest in understanding their underlying causes. In addition, it is important to assess what is known about climate and non-climate causes of such events in order to evaluate whether they are likely to pose increasing risks to life and property in particular regions in the future. As is established in this report and many others, the climate contribution to risk associated with some kinds of extreme events is expected to increase over time as the concentration of GHGs in the atmosphere increases. Some of the anticipated impacts can be reduced, however, through such management strategies as land use planning if the connections between climate change and extreme events like intense precipitation are better understood. Such planning would ideally be based on a broad risk assessment, including projections of future trends in extreme events, and it need not rely specifically on attribution of individual events.

As they improve, event attribution studies can be a tool for informing choices about assessing and managing risk and guiding adaptation strategies. Such information may be critical to multiple decision makers, among them insurers, elected officials and policy makers, local and regional land and resource managers, zoning and infrastructure planners and engineers, litigators, and emergency managers who focus on disaster risk reduction.

OVERVIEW OF EXTREME EVENT ATTRIBUTION RESEARCH

In the past decade, the field of extreme event attribution has moved from generalized statements about expecting certain events to increase in frequency or magnitude,

[1] See https://www.ametsoc.org/boardpges/cwce/docs/profiles/MurphyJohnD/2013-08-SCM.pdf (accessed May 31, 2016).

[2] NatCatSERVICE is a natural catastrophe loss database that analyzes approximately 1,000 events every year.

to documented increases in frequency or intensity of extreme events, to probability-based attribution of individual events. Following an extreme climate or weather event, the standard response from scientists has typically been that global warming does not "cause" any single event in a deterministic sense, but it can make some of them more likely to occur or more intense when they do. Because of advances in the relatively young science of extreme event attribution, however, it is now possible in some cases to provide quantitative information about how climate change may have impacted the probability or intensity of an individual event and to cast this within a probabilistic causal framework.

In perhaps the first attempt at extreme event attribution, Stott and colleagues (2004) showed that climate change had at least doubled the chance of the record-breaking 2003 European summer heat wave that has been associated with the death of more than 70,000 people by some accounts (Robine et al., 2008). Since then, advances in the field have prompted numerous studies (e.g., the 2010 Russian heat wave [Dole et al., 2011; Otto et al., 2012]; the Texas drought and heat wave in 2011 [Hoerling et al., 2013; Rupp et al., 2012]; and the ongoing California drought [Cheng et al., 2016; Diffenbaugh et al., 2015; Williams et al., 2015]). BAMS now publishes annual special issues on event attribution (Herring et al., 2014, 2015b; Peterson et al., 2012, 2013b), which include a compilation of short studies on events that occurred during the previous year. An indication of the developing interest in event attribution is highlighted by the fact that in 4 years (2012-2015), the number of papers increased from 6 to 32.

Detection and Attribution of Long-Term Changes

Many elements of extreme event attribution research are derived from the more mature field of detection and attribution of long-term changes in the characteristics of the climate, such as changes in the frequency or intensity of extremes as well as changes in average climatic conditions.

The primary approach used in detection and attribution research is to compare observations (e.g., of spatial patterns of decadal mean temperatures) to expected changes, which are derived from climate model simulations. The methods used for detection of change continue to evolve, but repeatedly they have been demonstrated to be robust (see, e.g., Allen and Stott, 2003; the appendices in Hegerl et al., 2007, and Bindoff et al., 2013; the review of Hegerl and Zwiers, 2011; and recent papers that suggest further changes to the methods, such as Ribes et al., 2013, 2015; Ribes and Terray, 2013; and Hannart et al., 2015b).

Considerations Specific to Attribution of Extreme Events

Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with an assignment of statistical confidence[3] (Hegerl et al., 2010). Many causal factors impact any given extreme event, so attribution to any of them could be studied in principle. Our statement of task covers attribution to both human-induced climate change and natural variability. In a number of respects the scientific issues are similar, whether human influence or natural variability is being assessed in an attribution study, so much of our discussion is general. Where attribution to human influence raises distinct scientific issues, our discussion prioritizes those, and our conclusions and recommendations do as well.

The occurrence of any individual extreme event, by itself, does not prove or disprove that the climate is changing. Nevertheless, event attribution studies seek to calculate how much human-induced climate change has affected an individual event's magnitude or probability of occurrence (Stott et al., 2015).

Conclusions regarding attribution of extreme events are strongly affected by the way "extreme" is defined by scientists. Seneviratne and colleagues (2012) define climate extremes (extreme weather or climate events) as "the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable." In fact, the threshold that is selected as "extreme" is generally based on 20th-century observations, but the baseline of what is "normal" is changing over time. In the future, events that are currently considered extreme may eventually be considered normal. Therefore, scientists generally establish metrics to characterize the extreme nature of the event being attributed in the context of a baseline period.

There are several important challenges related to event attribution (discussed in more detail in other chapters), including defining and interpreting an "event" and characterizing a "cause," or a causal link. Further issues arise from the many different ways that scientists (who are often working with different sources of data and models) describe the degree of certainty about their findings and characterize the uncertainty.

THIS STUDY AND THE COMMITTEE'S APPROACH

This committee was asked to examine the science of attribution of extreme weather events to human-caused climate change and natural variability by reviewing current

[3] In practice, not all attribution studies include statistical confidence.

understanding and capabilities; assessing the robustness of the methods; providing guidance for interpreting analyses; and identifying priority research needs (see Appendix A for the full statement of task).

This study is sponsored by the David and Lucile Packard Foundation, the Heising-Simons Foundation, the Litterman Family Foundation, the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), and the U.S. Department of Energy, with additional support from the National Academy of Sciences' Arthur L. Day Fund. Beyond the sponsors, the intended audiences for this report are the scientific community, decision makers, and the media. The committee's goal for this report is to provide these audiences with guidance in interpreting new attribution studies and about the robustness of extreme event attribution science. The committee also hopes that this report guides future support and development of high-priority attribution and detection projects.

Although it is clear to the committee that communication is a critical issue in extreme event attribution, communication is not discussed in detail in this report, as it is not part of the committee's charge. Indeed, a careful and comprehensive treatment of the many issues associated with science communication related to climate attribution could be a study in its own right. The committee recognizes the importance of communicating clearly and accurately framing any climate-related issue, however. Framing of event attribution questions—how they are posed, and the context within which they are posed—is a key issue, both in terms of communicating study results and in designing and conducting event attribution studies (e.g., Otto et al., 2013, 2015b; Trenberth et al., 2015). Different event framing can lead to large differences in the interpretation of evidence regarding whether human influence on the climate system played a role. The committee has included a detailed discussion on the framing of extreme event attribution questions in Chapter 2 and offers guidance on communicating event attribution study results in Chapter 3.

Although this report focuses almost exclusively on the physical aspects of the causes of extreme events, including the effect of anthropogenic climate change, it is important to acknowledge that significant human aspects (other than human-induced GHG emissions) do influence the severity of extreme events. This includes the perception of what is regarded as being "extreme" and the role that human activity plays in creating the vulnerability and exposure that determine the impacts of extreme events (Cardona et al., 2012). Event attribution is important because of its relationships to risk perception, disaster risk, climate change adaptation, disaster risk reduction, communication, and decision making. Human behavior can either exacerbate or mitigate the impacts of extreme events. For these reasons, understanding the social, ethical, and

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human behavior issues that are connected to the experience of extreme events is an important research need.

REPORT ROAD MAP

This report focuses on several topics related to the committee's statement of task. Chapter 2 discusses the framing of event attribution questions. Chapter 3 discusses the challenges and uncertainties associated with the implementation of the different approaches to extreme event attribution. In Chapter 4 the committee provides an evaluation of the robustness of the attribution work that has been completed for specific types of extreme events as well as identifies anticipated progress in research efforts. Chapter 5 provides guidance for future research.

CHAPTER TWO

Framing

"What we observe is not nature itself, but nature exposed to our method of questioning."
—Werner Heisenberg

To answer a question scientifically, the question needs to be posed in a way that is amenable to scientific analysis. The question often asked by the public and the media, "Was this extreme event caused by anthropogenic climate change, yes or no?" is not well posed because the word "cause" can have several different meanings. For a record-breaking extreme event, a potential rephrasing of this question might be "Could an event of this severity have happened in this location and time of year without climate change?" Generally speaking the answer will be "yes" because observational records are too short to have well sampled the full range of climate possibilities. In this case a more informative rephrasing of the question could be "Are events of this severity becoming more or less likely because of climate change?" For a weather event such as a storm, which in detail is always unique, a potential rephrasing of the question might be "To what extent was the storm intensified, or its precipitation increased, because of climate change?"

How event attribution questions are posed, and the context within which they are posed, is referred to as *framing*. The developing literature on event attribution has shown that the framing of questions is fundamental to the choice of method that is used and can lead to large differences in the interpretation of evidence regarding whether human influence on the climate system played a role. This chapter explores the different ways in which event attribution studies can be framed.

The chapter begins with a number of framing issues that arise in any event attribution study. It goes on to discuss the additional framing issues that arise when the attribution is conditional on the state of the climate system (e.g., for a given sea-surface temperature [SST] pattern, such as that associated with El Niño–Southern Oscillation [ENSO]), a naturally occurring source of interannual variability). Because all event attribution is performed and interpreted within the broader context of the scientific understanding of climate change, this too represents part of the framing and so is explicitly discussed in that vein. The interest in extreme events is typically driven by their impacts on society, which raises further framing issues when non-climate anthropogenic factors come into play. Finally, because the choice of which events to study is

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another aspect of framing, the possible role of selection bias in affecting the interpretation of collections of attribution studies also is discussed.

GENERAL CONSIDERATIONS

The traditional and perhaps easiest-to-interpret approach to event attribution posits that the probability of an event is related in some way to the observed event and thus uses model simulations or observational data. It does this for both the *factual (currently observable) world as it exists in the context of climate change* and a hypothetical *counterfactual world without climate change*; the difference between the factual and counterfactual probabilities is taken to represent the effect of climate change.

Attribution refers to causation, but there are different kinds of causation. In the classical (deterministic) context, causation can be either *necessary* or *sufficient*, and these concepts have probabilistic counterparts (Hannart et al., 2015a; Pearl, 2009). Necessary causation means that the event can occur only in the presence of the causal factor, but it could be that other causal factors are necessary too. Multiple causation is typical with weather-related extremes, where many conditions must align to set up a particular event. An example would be a record-breaking heat wave that occurred in the presence of a summertime blocking[1] anti-cyclonic circulation, a condition known to lead to heat waves. One possibility is that the observed temperature conditions could have occurred in either the factual or the counterfactual world (and just had not previously been observed because of the shortness of the observational record), but that the likelihood is substantially higher in the factual world because of the increase in mean temperature. Another possibility is that the temperature conditions would have been effectively impossible in the counterfactual world and were possible in the factual world (though still rare) only because of the mean warming. In this latter case, it may be said that the event could only have occurred because of climate change.

In contrast, sufficient causation concerns whether the presence of the causal factor alone is enough to produce the event. For extreme events, for which the probability of an event is generally low, climate change (which is always present in the factual climate) cannot be a sufficient cause. Sufficient causation would arise only when climate change has caused an event to have become very likely and no longer be extreme in the current climate (relative only to the historical baseline).

[1] "Blocking" is a disruption of the prevailing westerly flow that is associated with anomalous warm and cool temperatures.

Interpretation of Single Events and Causation

Event attribution questions are often posed in terms of a specific actual event, but definitive attribution of a specific event in a deterministic manner is generally not possible. This is because on the one hand, most events could have happened in the counterfactual world (so the probability of necessary causation is less than 100%), while on the other hand, the entire climate system, and therefore all extreme events, are being affected by climate change (as discussed further below), thereby obviating the question. Therefore, event attribution is usually a matter of changing probabilities rather than a deterministic yes or no. For example, a scientific researcher might repose the question "Was Hurricane Sandy caused by climate change?" as "How much did human influence on climate increase the odds of a tropical or post-tropical storm with winds greater than 65 knots making landfall in northern New Jersey?" Moreover, analysts necessarily estimate relevant probabilities using more than just the event in question. In fact, probabilities are usually estimated using a definition of an event that differs from the specific event, such as by estimating the probability of an event as *or more* extreme than the event of interest. As a result, the answers obtained are no longer directly about the actual event. Epidemiology concentrates heavily on such a probabilistic framing, which is discussed in relation to other possible framings in Parascandola and Weed (2001). For example, Rothman's *Epidemiology: An Introduction* (Rothman, 2012) frames strength of causation as relating to probabilities that pertain to collections of events, in contrast to his deterministic perspective on individual events: "With respect to an individual case of disease, however, every component cause that played a role was necessary to the occurrence of that case."

Hannart and colleagues (2015a) present a causal framework for event attribution that provides probabilities of necessary and of sufficient causation. They show that the metric known as the fraction of attributable risk (FAR), which was introduced to extreme event attribution by Allen (2003), can be interpreted as an estimate of the probability of necessary causation (by anthropogenic forcing) of an event. It is interesting to note that the argument made by Allen (2003) for interpreting the FAR as applying to an individual event was actually a legal one rather than a physical one: namely, that an uninsured loss should be equated with the cost of insurance against a similar loss.

The FAR, however, is perhaps the easiest to interpret when an "event" is taken to be a class of events (e.g., all events as intense or more intense than the event that has been observed) rather than an individual event. In this case, a FAR of 80% would mean that four of five events belonging to the class of events in the factual world would not have happened in the counterfactual world. This interpretation corresponds to the prob-

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abilities that are currently estimated in event attribution studies, which are not those of the actual event but are of a broader class.

While Hannart and colleagues (2015a) provide some very useful insights, a focus on formal analysis of causation may distract attention from important questions about changing probabilities of extreme events and their impacts on risk, which may be the more important questions from scientific and impacts/adaptation perspectives. Physically, the notion that an event may not have been affected by climate change can be difficult to justify in a climate system in which everything is connected. This point is made by Hansen and colleagues (2014b), Solow (2015), and Trenberth (2012), who suggest that given the pervasive effects of anthropogenic influence on the climate—unlike, for example, the isolated effect of smoking on an individual smoker—it may not make sense to speak about whether an event has or has not been caused or affected by anthropogenic influence. In reality, all events are occurring in a world influenced by anthropogenic climate change, but one can still clearly talk about changes in probability.

Frequency Versus Magnitude

If an extreme event truly is rare in the current climate, then almost by definition it required some unusual meteorological situation to be present, and the effect of climate change is only a contributing factor. For example, a heat wave induced by an unusually persistent summertime atmospheric high pressure system situation (i.e., blocking) would be exacerbated by anthropogenic warming of several degrees Celsius (C) (leaving aside possible amplifiers such as soil-moisture feedbacks, for simplicity), but it may have been a heat wave nonetheless. In this case, to reach the recorded temperature extreme both the unusual blocking situation and the anthropogenic warming were necessary conditions. Attribution in such a case with several necessary causal factors is heavily dependent on the framing and also is liable to misinterpretation. In studies of the 2010 Russian heat wave, for example, one study concluded that the event was largely natural because the temperature anomalies were greatly in excess of those explainable by long-term trends (Dole et al., 2011), whereas another concluded that the anthropogenic influence was significant because long-term climate change, though small, greatly increased the probability of exceeding specified temperature thresholds (Rahmstorf and Coumou, 2011). This apparent contradiction in conclusions can be reconciled by understanding that these two studies aim at answering the attribution question in two different ways. In this particular case, a small change in the magnitude of the mean can correspond to a large change in the frequency of extremes (Otto et al., 2012; see Figure 2.1) because of anthropogenic influence. Interpretation therefore

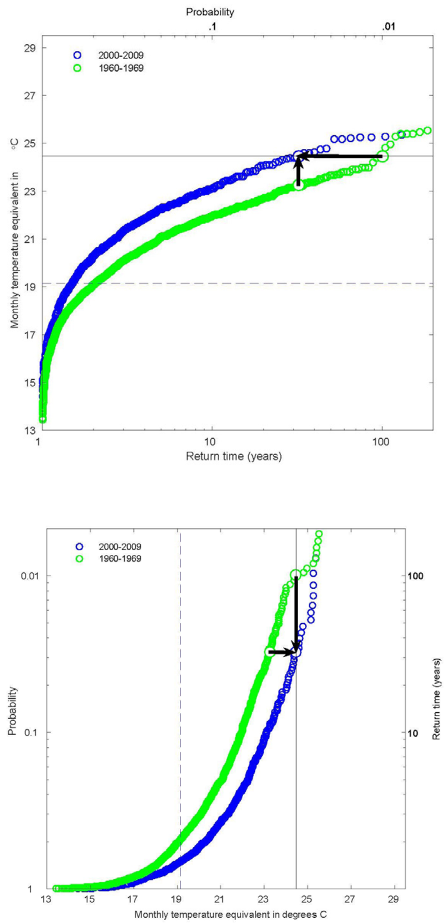

FIGURE 2.1 Different ways of describing the effect of anthropogenic climate change on July heat waves over western Russia, motivated by the extreme heat wave of summer 2010. Heat waves are defined here by a combination of high temperature and anti-cyclonic circulation anomaly (associated with persistent conditions). Both figures show model estimates of the likelihood of occurrence of an extreme of at least the given magnitude for conditions in the 1960s (green) and 2000s (blue), expressed either as a return time or as a probability. The top figure shows magnitude versus probability (or return time), whereas the bottom figure shows the same data plotted as probability (or return time) versus magnitude, which is related to the *cumulative distribution function* commonly encountered in statistics but here shows probability of exceedance rather than the usual probability of non-exceedance. In both panels the magnitude of the July 2010 Russian heat wave (indicated by the thin black line) corresponds to a large change in likelihood arising from climate change (from a 99-year return time to a 33-year return time, indicated by the horizontal arrow in the top figure and the vertical arrow in the bottom figure), but to a small (compared to the overall anomaly of 2010 with respect to average July conditions [dashed line]) relative change in magnitude (indicated by the vertical arrow in the top figure and the horizontal arrow in the bottom figure). SOURCE: Figure courtesy of Friederike Otto, adapted from Otto et al. (2012).

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ultimately depends on whether the interest in a particular type of event is predominantly related to changes in frequency for a given magnitude—which might be the case if, for example, exceedance of a fixed extreme temperature threshold leads to a marked impact such as a reduction in crop yield—or to changes in magnitude for a given frequency—which might be the case if, for example, it was required to design structures capable of withstanding the event magnitude associated with a prescribed return time.

Event Definition

In order to facilitate probabilistic analysis, a particular event is usually generalized to a broader class of event. Analyses may use the magnitude of an actual event and quantify probabilities of exceeding that observed magnitude, or they may use a percentile from the climatology in place of the magnitude of an actual event. Analyses also may focus on events over a longer timescale and larger region than those of the event itself, considering the causes of the prevailing climatic conditions that provide the context for the event rather than the specifics of the event itself (e.g., Stott et al., 2004). Generally speaking, using a larger spatio-temporal footprint will emphasize more strongly the anthropogenic role (e.g., Fischer et al., 2013).

Furthermore, in some cases different physical variables may be considered. For example, studies of the recent California drought focusing on precipitation deficit have tended to find no discernible anthropogenic influence (Seager et al., 2015), while those focusing on a combination of precipitation deficit and high temperature (which affects evaporation) have tended to find an anthropogenic influence (Diffenbaugh et al., 2015; Williams et al., 2015). These different definitions of drought can lead to confusion if the difference is not recognized.

Event definitions should take the limitations of both observations and models into account. For example, if an observationally based approach (see Chapter 3) is to be used to estimate changes in the probability or magnitude of an event by comparing an earlier period with a recent period, then it would be necessary to ensure that (1) the observational data are of high quality (e.g., free of non-climatic heterogeneities), (2) the record is long enough to allow reliable comparison of extremes between two subperiods, and (3) human influences are accounted for in a defensible manner and that natural influences or non-climatic human influences do not confound the estimate. In the case of model-based approaches (see Chapter 3), event definitions should be constrained in such a way that the focus is on events that the model can simulate reliably and for the correct reasons.

A robust attribution analysis would show that results are qualitatively similar across a range of event definitions, acknowledging that quantitative results are expected to differ somewhat because of differences in definition. Results for particular spatial regions or scales or for particular temporal periods, seasons, or scales may differ from results for other regions, scales, or periods, but for a robust result, one would expect that results would be similar for events defined by similar characteristics, without strong sensitivity to the exact definition. One would hope, too, that results using different magnitudes for defining an event class would be similar, though as the magnitude becomes either non-extreme or very extreme, quantitative results are expected to differ. For instance, using structurally different methods, different regions, and different seasonal temperature thresholds, Christidis and colleagues (2014) and Sun and colleagues (2014) develop qualitatively similar estimates of the FAR of an extremely warm summer in China.

Fraction of Attributable Risk Versus Risk Ratio

Another aspect of framing concerns how the difference between the factual probability p_1 and the counterfactual probability p_0 (that is, the probability of the same event in a world that is identical but for the human influence on climate) is expressed. One choice is to express it as FAR = $(p_1 - p_0)/p_1$. The limitations of FAR are well recognized in other fields: see, for example, the World Health Organization statement concerning the equivalent metric used in attributing causes of disease risk.[2] One difficulty in any interpretation of the FAR is its tendency to saturate at values near one for very rare events: that is, events for which the estimated p_0 is very close to zero. For such events, even small increments in the estimated likelihood of p_1 of the event when considering the effects of human influence lead to a FAR close to 1, with little discrimination between smaller and larger increments in p_1 relative to p_0. Additionally, it is not designed for describing cases where the likelihood decreases, which can be the case with climate change (e.g., of cold extremes, which in some regions have become substantially less frequent [see, e.g., Cattiaux et al., 2010], and assessment in Bindoff et al., 2013). Hannart and colleagues (2015a) show that the probability of necessary causation is the maximum of 0 and the calculated FAR, and therefore it will be zero in cases of decreasing likelihood. Hence, the aggregation of attribution results using this metric would provide a biased overview of human influences on extreme events.

Another important limitation occurs when events have more than one causal factor, as will generally be the case for extreme events (as discussed above). For example, one

[2] See http://www.who.int/healthinfo/global_burden_disease/metrics_paf/en (accessed May 31, 2016).

can easily imagine an extreme event that was affected both by anthropogenic factors and by a particular SST anomaly pattern (e.g., ENSO) such that both factors cause an increase in the probability of the event, but neither factor on its own is sufficient to make its frequency exceed a certain threshold. (Treating the factors separately assumes that the particular SST anomaly pattern is unrelated to climate change, an assumption that may or may not be justified.) If p_0 is sufficiently small, then the FAR could be close to one for both causal factors. In an event attribution study of such an event, if only anthropogenic factors were considered, then a FAR near one could easily be interpreted to mean that anthropogenic factors are fully responsible for the event even when there are other causes. Rothman (2012) points out that the sum of FAR values of multiple causes is not constrained to sum to one. Failure to appreciate this feature of the FAR can lead to apparently conflicting viewpoints concerning a specific event.

Another potential weakness of the FAR is that the strength of necessary causation may be confused with the strength of the statistical evidence. For example, as a probabilistic extension of necessary causality, a FAR of 0.8 could be interpreted as there being an 80% likelihood that anthropogenic forcings were a necessary cause of the event. In analyses using statistics, however, "likely" is generally used to refer to the strength of the statistical evidence. To give a concrete example, a person could have little statistical certainty in an estimated FAR of 0.8 with a broad confidence interval of (0.1, 0.95) that indicates considerable ignorance about the true FAR. A reader, though, might be inclined to believe that the person is confident of the result if the focus is solely on the single value 0.8. Alternatively, a person could have high statistical certainty in a small FAR with a confidence interval of (0.05, 0.15) around an estimated FAR of 0.1, indicating little uncertainty about the true FAR. The difficulty lies in the fact that event attribution studies estimate a probability, so the discussion of likelihood may pertain to the magnitude of the estimated probability or to the uncertainty about that probability.

An alternative way of comparing probabilities is the risk ratio (RR)—RR = p_1/p_0. The FAR and the RR are mathematically equivalent—there is a one-to-one mapping between the two quantities—but the RR directly frames the result in terms of the relative probabilities under the two scenarios and is analogous to how epidemiological results are presented to the public. For instance, a member of the public is apt to be familiar with a statement such as "Smoking increases the probability of lung cancer by a factor of X." Although the RR does not have the same causal interpretation as the FAR (Hannart et al., 2015a), that may not be disadvantageous if, as suggested earlier, the probabilistic causal interpretation of individual extreme events (as opposed to collections of events) is inappropriate in the case of climate extremes. Furthermore, a probabilistic analysis done using model output can always be framed as reporting a ratio of probabilities explicitly *as estimated based on the model* such that this dependence on model quality is very clear. In contrast, a causal statement about a single real-world event is a much stronger statement directly about the real world, and the dependence on the model to estimate the causal quantity may not be as easily communicated and is easily overlooked.

The Null Hypothesis

Estimating the unconditional probabilities of very rare events is extremely challenging because of observational and model limitations, and it is difficult to quantify the uncertainties in the calculations. In addition, it becomes more difficult to discern human influence at smaller spatio-temporal scales (Angelil et al., 2014; Bindoff et al., 2013; Fischer et al., 2013) because analysis on these scales offers less opportunity to reduce the magnitude of natural variability through spatial and temporal averaging or other techniques. Although it is perfectly reasonable—and even advisable (Nicholls, 2001) to report an estimated magnitude of effect with an uncertainty interval that includes zero (i.e., no effect)—there is a tendency in climate science to regard such results as null results of there being no effect. That interpretation is incorrect, however: Failure to reject the null hypothesis of no effect should not be regarded as evidence in favor of there being no effect. An inability to rule out there being no effect (i.e., lack of statistical significance) does not necessarily mean that the effect is small; it may just mean that the uncertainties are large. Therefore, it could be misleading to report a result of no detectable effect of climate change as no effect of climate change. To avoid any misunderstanding, it is always advisable to focus on effect size and to report confidence intervals (or Bayesian analogues) rather than focusing on statistical significance (Nicholls, 2001).

CONDITIONAL ATTRIBUTION

Rather than attempting to answer questions about changes in probability or intensity considering only the influence of external forcing, a person may attempt to answer these questions after limiting or constraining the state of one or more slowly varying parts of the climate system. This "conditional attribution" approach has been used in many recent studies (see Chapter 3) that investigate the role of external forcing conditional upon the prevailing pattern of SST anomalies. The reasoning is often that the SST anomaly structure likely had an influence on the atmospheric circulation that prevailed during the event, and that the effect of external forcing can be more clearly assessed by controlling for such internal influences.

A very similar approach involves conditioning on the state of the large-scale atmospheric circulation (Cattiaux et al., 2010; Yiou et al., 2007). While to date this has been applied mainly to observational analysis (see Chapter 3), it could in principle be applied to a climate model through some kind of nudging.[3] For example, specifying the state of the stratosphere seems sufficient to constrain the winter-mean North Atlantic Oscillation in climate models (Douville, 2009), and spectral nudging of winds (leaving the thermodynamic quantities free to respond to forcing) is an established method in regional climate modeling (von Storch et al., 2000; Waldron et al., 1996). One also could imagine conditioning on the state of the tropical atmosphere (thereby overcoming potential model errors in the local response to tropical SSTs) or anomalous Arctic sea-ice extent or other such factors. In short, a logical extension of conditioning on the prevailing pattern of SST anomalies is to condition on various aspects of the large-scale circulation or the atmosphere's lower-boundary conditions (sea-ice, snow cover, soil moisture, etc.) that are known to be important in altering the likelihood of extreme events.

One can go even further and condition on the specific weather situation (see Chapter 3), asking how large-scale, long-term changes in thermodynamic quantities of the atmosphere such as temperature or humidity—which are more directly attributable to greenhouse gas increases than is any specific weather event (e.g., Bindoff et al., 2013)—may have changed the severity of an event (Trenberth et al., 2015). For instance, given the landfall of a hurricane at a certain point, how might its intensity have changed because of SST or atmospheric humidity anomalies along its path, and to what extent might those anomalies (defined relative to long-term historical averages) be attributable to human influence? How was the coastal flooding the storm induced increased by long-term sea level rise? How were rainfall amount and intensity and subsequent inland flooding affected by the warmer, moister atmosphere? These could be useful questions for local authorities who use past extremes as benchmarks to ask when planning future resilience. Although the attribution question is now framed in a deterministic manner—uncertainties in the calculations need to be estimated, but that is a different issue (see "Uncertainty Quantification" in Chapter 3)—this approach can be given a probabilistic interpretation if one adopts a "nowcasting" perspective:

[3] Nudging is a well-known scientific technique in which observations are used to guide a dynamic model, such as a climate or weather model. Nudging (Lorenc et al., 1991) is an example of a type of data assimilation, which refers to a broad class of methods that are used to introduce observations into dynamic models. Improvement in data assimilation techniques has been a key factor in the steady improvement of the weather forecast skill that has been achieved over the past three decades.

Given the state of the atmosphere as estimated from the meteorological observing system, what is the probability distribution of specific weather features such as intense rainfall in a particular catchment? But, the probability distribution is certainly narrower than would result when conditioning on a large-scale circulation state or SST anomaly (see Shepherd, 2016).

Probabilistic Formulation

The trade-off involved in conditioning is that it improves the signal-to-noise ratio of the anthropogenic influence while providing a more realistic simulation of the event, but a full estimate of the change in likelihood of the event would require an explicit estimate of the change in the probability or intensity of the anomalous climatic or weather state on which the inference is conditioned (see below). Such a change could either increase or decrease the conditional anthropogenic effect. (Strictly speaking, it also may require an estimate of the change in probability when the conditional state is absent, but this would not be relevant if the conditional state was necessary for the event to occur [Shepherd, 2016].) Note that this issue applies as much to conditioning on an SST pattern as it does to conditioning on a specific weather situation. Whether it is necessary to make the additional effort to estimate the change in probability of the climatic or weather state would be a matter for the user of the information to determine (Otto et al., 2015c). Trenberth and colleagues (2015) argue that for extreme weather events that cannot be adequately simulated in global models it is the only credible approach. Even for large-scale circulation patterns, if anthropogenic changes in their likelihood did matter, then one would need to assess one's confidence in the simulated changes. This would seem to be extremely challenging, given the low confidence in these aspects of climate change compared with thermodynamic aspects (Bindoff et al., 2013; Shepherd, 2014).

When considering the probability of an event, use of the RR rather than the FAR would allow one to represent conditional analyses in their broader context. For a simple example, consider a conditional analysis of an event under El Niño conditions (e.g., Zhang et al., 2010). The conditional RR (see equation 2.1) for the probability of the event, conditioning on the El Niño conditions, denoted N, is

$$\frac{P_f(E\,|N)}{P_c(E\,|N)} \qquad (2.1)$$

where P_f is the probability under the factual world (i.e., the currently observable world as it exists in the context of climate change) and P_c is the probability under the counterfactual world without anthropogenic influence. If we now want to add information about how forcings affect El Niño conditions (see equation 2.2), we can consider

$$\frac{P_f(E\,|N)}{P_c(E\,|N)} \times \frac{P_f(N)}{P_c(N)} = \frac{P_f(E,N)}{P_c(E,N)} \qquad (2.2)$$

to get an unconditional RR concerning the joint occurrence of the event and El Niño in the factual and counterfactual worlds. This multiplication of risk ratios is not possible if one uses the FAR. Note that the product above is now the RR for an altered event definition that includes the condition of the system and the meteorological outcome (such as heavy precipitation), as opposed to either an unconditional RR that considers the meteorological outcome under all possible states or a conditional RR that considers the meteorological outcome under a specified climatic state. This is analogous to what was done in Figure 2.1, where the anti-cyclonic circulation associated with a high-pressure system was part of the definition of the heat wave, and is often a sensible choice if the extreme can occur only under unusual dynamic conditions. If there is little information about the RR for the dynamics, it may be sensible to concentrate on the conditional RR, treating the ratio for the dynamics as one. This is the approach taken by Diffenbaugh and colleagues (2015) in their analysis of the recent California drought, where precipitation is controlled by storm-track dynamics, which are highly variable and uncertain, but the persistent warming is leading to an increasing risk of drought conditions. Cattiaux and colleagues (2010) also use such a factorization of the RR via conditioning to argue that cold extremes are becoming less likely despite the occurrence of the cold European winter of 2010, although their results also suggest that the probability of the circulation situation itself has not changed.

As discussed above, one also can consider multiple causes of an event, such as anthropogenic influence and El Niño, such that we have an RR for each (see equation 2.3),

$$\frac{P_f(E)}{P_c(E)} \text{ and } \frac{P_f(E\,|N)}{P_f(E\,|N^c)} \qquad (2.3)$$

respectively, where N^c indicates non-El Niño conditions. These RR values cannot be used together in a quantitative fashion, however, because different variables are being conditioned on.

USE OF BACKGROUND KNOWLEDGE ABOUT CLIMATE CHANGE

In conditional attribution, background knowledge about climate change is explicitly included through the choice of the counterfactual conditions, for instance, the counterfactual SSTs. Background knowledge also is often included in unconditional attribution, however, by couching the event attribution within the broader context of climate change science. A firmer basis for an event attribution result identifies a human influence if one can demonstrate that there has been human influence on a related aspect of the climate—that is, if detection and attribution results demonstrate that human influence has altered the mean state in some way in the region where the event occurred. That is almost certain to be the case for temperature-related events, but the detection and attribution literature on precipitation generally deals with precipitation change on very large scales, as the signal of precipitation change is emerging more slowly due to high climate variability (e.g., Zhang et al., 2010; see Bindoff et al., 2013; Collins et al., 2013; Kirtman et al., 2013).

In general, there is a higher degree of confidence concerning the understanding of purely thermodynamic aspects of climate change associated with warming and increased moisture-holding capacity of the atmosphere compared with dynamic aspects of climate change (Shepherd, 2014). The latter include both large-scale circulation patterns, which can modulate temperature and precipitation extremes, and storms. Thus, in any event attribution study, it is important to distinguish between the purely thermodynamic and the dynamic drivers. If the response of the dynamic drivers to climate change is a significant component of the anthropogenic influence, then the plausibility of that response needs to be established. Confident attribution is not possible in the absence of adequate understanding (see further discussion in Chapter 4 and Figure 4.7).

OTHER FACTORS AFFECTING IMPACTS OF EXTREME EVENTS

Attribution of extreme events is primarily anchored in discussions about anthropogenic climate change, yet many extreme events also are affected by other types of anthropogenic processes, which raise additional framing issues in terms of event impacts. Human-related activity not directly linked to anthropogenic climate change can worsen an extreme event. The urban heat island effect is an example of such an effect of human activity on temperature extremes. Heat wave characteristics such as duration and magnitude may be increasing in large U.S. cities because of the combination of global warming and urban heat (Habeeb et al., 2015; Zhou and Shepherd, 2010).

Beyond heat waves, increases in temperature also can lead to other kinds of extreme events, including drought and wildfire. The occurrence of these events is closely related to the drying effect associated with higher temperatures when evapotranspiration is moisture-limited, and this depends strongly on the nature of the land cover (Seneviratne et al., 2016).

An important effect of intense precipitation is related to flooding of the land surface, which is affected by a wide range of factors other than changes in the climate. For example, the intensity of flooding is affected by a range of human land use decisions, including urbanization and river channelization efforts (Melillo et al., 2014). In particular, precipitation is falling onto more impervious surfaces. Du and colleagues (2015) confirm that an increase in impervious surfaces associated with rapid urbanization has led to greater peak discharge and flood volume in parts of China over the past 30 years. Shepherd and colleagues (2011) also note increased flow rates of floodwater in cities due to impervious surfaces. In some cases, upstream flood control efforts actually increase damages downstream in the same watershed. Furthermore, the "extreme" nature of flooding is often defined in human terms because the impact of flood events is often calculated in dollars. These costs are directly affected by the value of infrastructure that has been constructed in the floodplain (Downton and Pielke, 2005; Downton et al., 2005).

Increasing temperatures and changes in precipitation are related in multiple ways to evaporation from the land surface and the water demand of plants (transpiration). In fact, feedbacks from the land surface and land management practices have been shown to affect local and regional drought events. A classic example is the so-called Dust Bowl period that coincided with heat waves in 1934 and 1936, where land management was a factor exacerbating the drought through dust (e.g., Seager, 2011). More recently, drought conditions in Brazil may be amplified by Amazon deforestation due to decreases in dry season latent heat flux (Bagley et al., 2014; Nazareno and Laurance, 2015).

Wildfires may also be affected by land management decisions. For example, there is substantial evidence that past fire control practices have increased the likelihood of large-scale wildfires because of the buildup of fuels that occurs when natural, lower-intensity fires are suppressed (Allen et al., 2002). Likewise, the decision to build homes at the wildland-urban interface (e.g., in Southern California; see Figure 2.2) greatly increases the costs associated with fires and firefighting.

Perhaps the best example of the intersection of land use decisions and extreme events is in coastal areas: Not only have people made major changes to the morphology of coasts that in some cases exacerbate the impacts of coastal storms, many of the major cities around the globe are located in or near coastal areas as well. Storm surges that historically might have been blunted by barrier dunes or wetlands now directly impact urban infrastructure. Furthermore, dredging and other coastal modifications may be linked to increases in minor flooding after the 1980s in parts of the mid-Atlantic United States (Ezer and Atkinson, 2014). The costs of these coastal flood-

FIGURE 2.2 Aerial view of wildland-urban interface and fire damage (located at the top of the image). SOURCE: Image courtesy of National Park Service.

ing events are high, in part because of the high value of coastal investments, much of it knowingly constructed in areas of high vulnerability. The "extreme" nature of coastal flooding is therefore a product of a combination of different anthropogenic impacts, some of which have little to do with climate-mediated effects like sea level rise.

Human-related activity not directly linked to anthropogenic climate change (such as urban impervious surfaces, land cover changes, and dredging) can worsen an extreme event. Therefore, attribution studies should clearly distinguish such climate factors from the effects of climate change, and the results should be framed accordingly. Apart from more accurately isolating the anthropogenic climate change effect, this also has the benefit of identifying risk factors that could potentially be mitigated at the local level.

Selection Bias and Systematic Event Attribution

Most of the currently available literature on event attribution focuses on events selected by researchers. In recent years, collections of such studies have been published in *Bulletin of the American Meteorological Society* (BAMS) yearly supplements (e.g., Herring et al., 2014, 2015b; Peterson et al., 2012, 2013b). There is a desire to summarize anthropogenic influence across all of the events and to ask whether it is causing a change in extreme events generally. This has led to the presentation of a summary of the BAMS results in tabular form, from which one might calculate the proportion of events for which anthropogenic influence is found. As the editors acknowledge, however, the studies presented in the supplements are not a representative sample of any well-defined population; hence, summarizing across the studies does not provide direct information about changes in extreme events collectively.

Scientifically, a "bias" refers to an unintentional but systematic error in a quantitative estimate arising from the particular way in which the estimate was made, and it is to be distinguished from random errors due to insufficient data or an intentional selection of cases to achieve a predetermined result. In statistics, "selection bias" refers specifically to potential systematic errors in probabilistic inference arising when the data that are collected or analyzed are not representative of the larger population about which one wants information. In the context of event attribution, selection bias can arise when the studies are based on events that actually occurred and that are chosen for study by the researcher. Selection bias does not affect the validity of any particular result, but it is relevant for meta-analyses of collections of results.

Potential biases in attribution results are of concern for collective assessment of anthropogenic influence on extreme events, but they may not be relevant if the focus is on a climatological understanding of events or on the implications of attribution analyses for adaptation and planning in specific contexts. Some of the issues discussed below also arise in meta-analysis in the medical literature, in which the goal is to improve statistical power by analyzing results from multiple studies that assess the same scientific question.

What follows is a list of several potential forms of selection bias, with shorthand labels for each provided in parentheses:

1. bias from studying only events that occur (occurrence bias),
2. bias from choosing to study events for which the researcher suspects either anthropogenic influence in general or an increase in likelihood from anthropogenic influence specifically (choice bias),

3. bias from publishing studies about events for which the study finds either anthropogenic influence in general or an increase in likelihood from anthropogenic influence specifically (publication bias), and
4. bias in choosing regions or event definitions of interest to the analyst (type bias).

Occurrence bias is more subtle and likely more easily overlooked than the other types of selection bias listed above. The simplest example of occurrence bias is an event class for which p_1 is zero or vanishingly small, while p_0 is rather larger. Such events will never occur in the current world and never be analyzed. As a result, few publications in the literature exist that find event classes that are *much* less likely in the factual world.

Similarly, the influence of occurrence bias can occur in less drastic settings. Occurrence bias could result in a scientific literature that suggests that extreme events are generally becoming more common because of anthropogenic influence. Suppose there are 100 event classes (across regions and types of events) that can occur, and we consider the probability of occurrence over the course of 1 year. Further suppose that for 50% of those event classes p1 = 0.04 and p2 = 0.02 and that for 50% of the classes the reverse is true: p1 = 0.02 and p2 = 0.04. An example of a generally decreasing likelihood of an event class under climate change is cold events. Collectively, the probabilities across all event classes are equal under both scenarios. Now consider the events that occur in a given year. On average, there will be six events, four representing classes that are more frequent under the factual world and two representing classes that are more frequent under the counterfactual world. If a study of each event is done, and assuming the study can determine the RR or FAR without statistical uncertainty, four of the six studies will show that the event is more likely under the factual world and two of the six less likely under the factual world. A general conclusion across the six studies would be that extreme events are more likely because of anthropogenic influence. A more realistic scenario is that because of statistical uncertainty, no firm conclusions can be drawn in some of the studies. For those studies in which anthropogenic influence is found, however, a similar imbalance would persist, with more studies showing an increase in extreme events in the factual world than a decrease.

The remaining three types of bias are more straightforward to understand. Choice bias could arise because scientists are actively interested in finding events that are related to climate change or simply to subtle factors in the choice of what events to study. Publication bias is a well-known problem that distorts results obtained from doing collective analysis across published studies. Finally, a clear example of type bias is simply the geographic bias where attribution studies are done, focusing more attention on understanding extreme events in areas such as North America and Europe, although this is beginning to change. Due to these biases, a meta-analysis of event attribution results based on tabulating results from an ad hoc collection of studies could be severely misleading.

The potential for selection bias does not contradict that there can be good reasons to examine particular events if one is interested in those events themselves, such as for reasons of public curiosity or of liability or as historical benchmarks for resilience.

GUIDANCE FOR FRAMING EVENT ATTRIBUTION QUESTIONS

The notion that an event may not have been affected by climate change can be difficult to justify in a climate system in which everything is connected. In any extreme event, multiple contributing factors are involved (both human-induced and natural). Therefore, results of event attribution studies should not be framed as the cause being either anthropogenic or natural, as frequently it will be a combination of both.

Statements about attribution are sensitive to the way the questions are posed and the context within which they are posed. Results of event attribution studies with respect to the extent of anthropogenic influence can differ depending on how the results are framed. Therefore, in any attribution analysis, one should be explicit about the framing choices and explain why those particular choices were made. Framing choices include:

- how single events are interpreted;
- the type of conditioning involved, if any;
- whether changes in frequency or in magnitude of an event are assessed;
- how the event is defined;
- how the factual and counterfactual probabilities are compared (e.g., FAR versus RR); and
- whether the results are cast as a null hypothesis significance test.

The RR has many advantages over the FAR and is less prone to misinterpretation. The RR directly frames the result in terms of the relative probabilities under a world with anthropogenic climate change and a world without. The FAR, by contrast, does not represent a share of causation because for any given event, multiple factors can have FARs that are close to one. Further framing issues arise for impacts of extreme events because other anthropogenic factors (e.g., land use) apart from climate change often significantly affect the magnitude of impacts.

It also is useful to present results in more than one way (e.g., magnitude and frequency), so that users understand there are different ways of looking at the event. Relevant quantities (probabilities or magnitudes) should be estimated, with accompanying uncertainty intervals, to help users understand the strength of the evidence. This approach is more useful and less prone to misinterpretation than is null hypothesis significance testing. Furthermore, results should be presented in terms of the overall understanding of the climate system, as this is important prior information that affects the interpretation of the result.

An essential part of the framing involves whether or not the attribution is conditioned (e.g., on the current climatic or specific weather state) because that affects the quantitative estimates of the extent of anthropogenic influence and more closely relates the study to the factors driving the particular event. An unconditional attribution analysis of a joint probability can be considered a product of conditional attribution analyses (see equation 2.4), i.e.,

$$\frac{P_f(E,N)}{P_c(E,N)} = \frac{P_f(E\,|N)}{P_c(E\,|N)} \times \frac{P_f(N)}{P_c(N)} \tag{2.4}$$

where E is the event, N is a conditioning factor (such as SST anomaly pattern), P_f is the probability under the factual world (i.e., the currently observable world as it exists in the context of climate change), and P_c is the probability under the counterfactual world that might have been without anthropogenic influence. If the response of N to climate change is highly uncertain, then the last factor might be assumed to be one in which case the unconditional and conditional probabilities are equal.

Various sources of selection bias are almost inevitable in event attribution applied to individual events. Such selection biases interfere with the ability to draw general conclusions about anthropogenic influence on extreme events collectively.

Overall, it is useful to perform event attribution with all factors explicitly assessed and discussed: thermodynamic and dynamic aspects of anthropogenic climate change, non-climate anthropogenic factors, and natural variability. This helps the user understand the uncertainties in the calculation, the resilience to current climate variability, and other anthropogenic factors that might be relevant.

CHAPTER THREE

Methods of Event Attribution

The findings of event attribution studies are influenced both by how questions about a human or natural influence on an event are asked and by the methods used to answer the questions. A natural first step in event attribution, for example, is to study observations in order to determine the rarity of the event in historical context, or to study the circulation and other aspects of the state of the climate that prevailed when the event occurred. While observations are useful, attribution studies generally use climate models, which incorporate knowledge of the physics of the climate system, to quantify how human or natural influences have changed the frequency or intensity of events like the observed event relative to a baseline forcing scenario. Climate and other numerical models are useful because they can be used to investigate responses to controlled forcing (see conditioning in the previous chapter) and also to generate a larger sample size than is possible from observations—for example, "control" runs of 1,000 years with no changes in greenhouse gas (GHG) forcing. The various options for using observations and models for event attribution are discussed in subsequent sections.

METHODS BASED ON OBSERVATIONS

The Role of Observations

Observations are used to a varying extent in all approaches to event attribution. Many studies determine the rarity of an observed event in the context of long-term historical data, often using statistical methods. For example, Swain and colleagues (2014) fit a statistical distribution to Northeastern Pacific circulation anomalies related to the recent California drought in order to determine that the very persistent ridge type of circulation pattern[1] that sustained the drought is extremely rare in the historical context (see Figure 3.1). Also, many studies begin by setting out the dynamic context from observations as an analysis of the combination of factors and events that contributed to the extreme event, and often later as a benchmark for model simulations of similar events (e.g., Hoerling et al., 2013; Pall et al., 2011).

[1] A circulation pattern is an elongated area of relatively high atmospheric pressure; the opposite of trough.

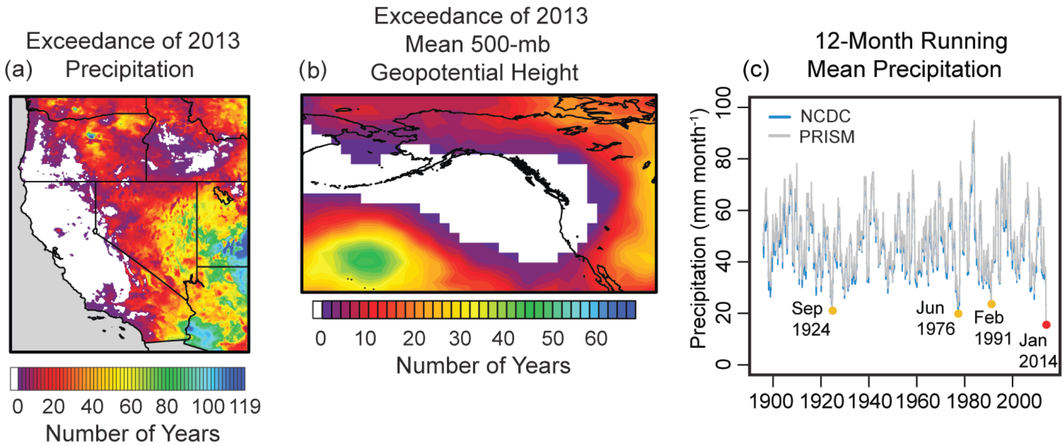

FIGURE 3.1 Example of an observational analysis supporting an event attribution analysis: Number of years in the past that 2013 California precipitation anomalies (panel a) and geopotential height values were exceeded in the historical record (panel b) in comparison to a time series of California mean precipitation (panel c). SOURCE: Swain et al., 2014.

A requirement for the attribution of a change in probability of events to human (or natural) influence is detection of a change either in observations of the event analyzed or in appropriately related climate variables (see Hegerl et al., 2010). In practice, statistically confident detection of a change in the frequency or the intensity of the event type itself is possible only for a subset of event types (the most common example being temperature extremes) because it takes a long observational record and well-observed statistics of extremes to be able to do so (e.g., King et al., 2015). It is often challenging to detect trends because of the limitations of the observational record (both quality and record length). Trend detection is also complicated by unforced natural variability that can cause apparent trends that may last decades.

The limitations of trend detection in the frequency or intensity of extreme events imply that event attribution must often rely on the understanding of long-term changes in variables that have a close physical relationship to the event in question and are expected to affect the frequency or the intensity of the event in question. Such attributed long-term changes could pertain to the mean state of the climate, or to extremes over a larger area, or to a variable that demonstrably contributes to the extreme event, such as higher water availability for extreme rainfall (e.g., Pall et al., 2011). The less direct the relationship is between an attributed human contribution to change in a climate variable and a type of extreme event, the more results hinge on climate models reliably replicating the effect of human influence, and the less the result is grounded on observations.

Studies often rely on a scientific understanding of the causes of change in a related aspect of temperature (such as the observed long-term warming of the regional or global climate) where there is little doubt (Bindoff et al., 2013) that there has been significant change due to human activities. These changes in mean conditions then provide a basis for expecting that there also should be related changes in extreme conditions. For instance, a change in extremes at a location may be linked directly to a change in the mean at that same location (see Figures 1.1 and 3.2), and thus, an attributed change in the mean may provide supporting evidence for attribution for the related extremes (e.g., Rahmstorf and Coumou, 2011). Somewhat less directly than is the case with temperature extremes, heavy rainfall is influenced by a moister atmosphere, which has been linked to human influence because it is an expected consequence of a warmer atmosphere (e.g., Bindoff et al., 2013; Santer et al., 2007, 2009). Significant low-frequency natural variability can make it difficult to detect a change due to human influence because the natural variability reduces the signal-to-noise ratio. Similarly, attribution may be complicated by circulation changes that can either strengthen or offset the effects of human influence, and several studies have claimed to find such an effect (Christidis et al., 2015; Herring et al., 2015a; Schaller et al., 2014; Szeto et al., 2015). Tropical cyclone intensity or the probability of severe convective storms are even further removed from temperature, but they have known relationships to large-scale climate parameters whose relationships to climate are somewhat better understood than those of the events themselves.

Event attribution is most reliable when the link to an attributed long-term change is made explicitly and is fairly tightly connected to the event. The attribution of long-term change (e.g., as assessed in Bindoff et al. [2013] and Hegerl et al. [2007]) necessarily involves both observations and models. The link between long-term change and event frequency or intensity may, in some cases, be demonstrated through the use of climate models; in other instances, however, such a link will rely on physical reasoning or conceptual models (e.g., see Hegerl and Zwiers, 2011). The establishment of a strong link may not be possible in all cases, with the result that the link to the observed attributed changes may be fairly indirect in some studies. In principle, the changing probability of a type of event could be evaluated based on climate model simulations in the absence of any trend detection in historical observations, but in most cases confidence would be lower than for attribution of changes that have actually been observed. Also, any positive result from such studies is likely to be challenged, as models are not perfect replications of reality.

ATTRIBUTION OF EXTREME WEATHER EVENTS IN THE CONTEXT OF CLIMATE CHANGE

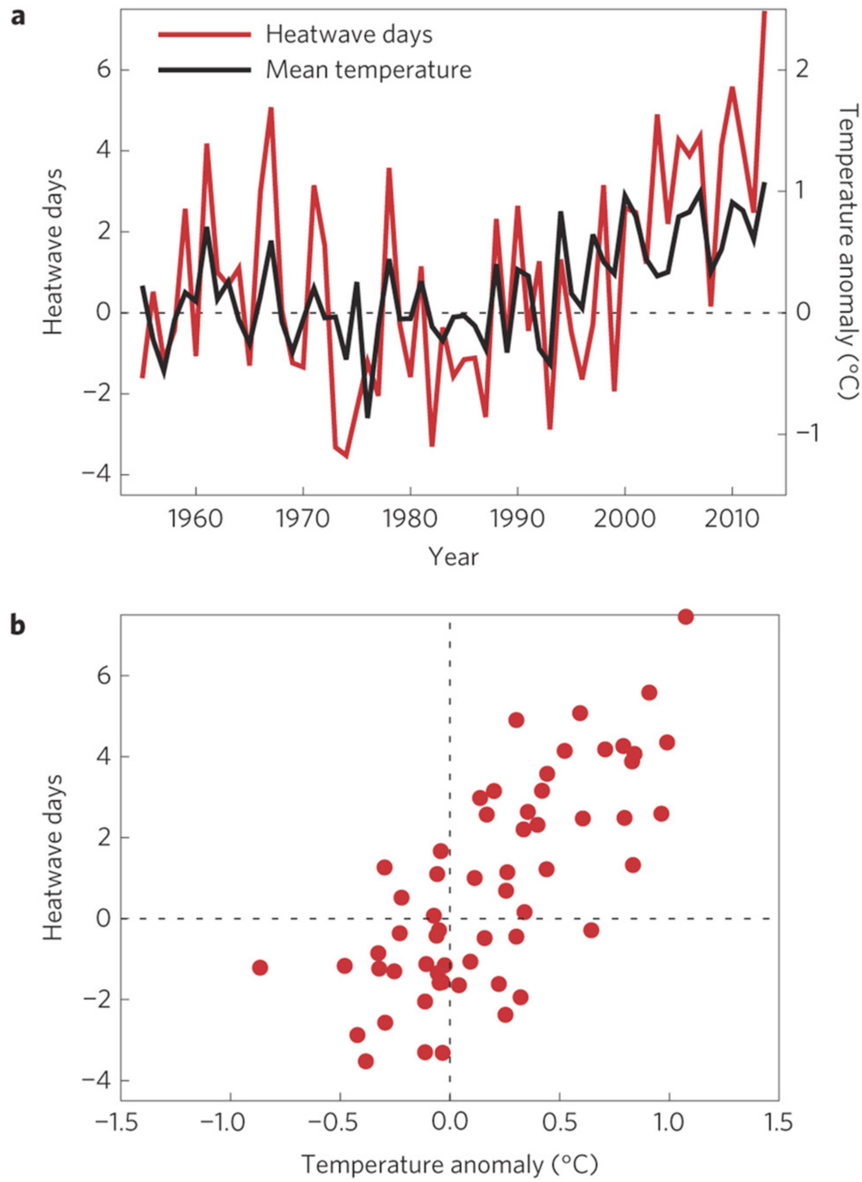

FIGURE 3.2 The five hottest summers in eastern China's observed record over the past six decades have all occurred since 2000—in 2013, 2007, 2000, 2010, and 2011—with 2013 and 2007 summer temperatures being the hottest. This figure shows the relationship between anomalies of the number of heat wave days and of summer mean temperatures in Eastern China: time series of the number of summer season (June-August) heat wave days and mean temperature anomalies relative to the 1955-1984 average (a) and scatter plot of heat wave days and summer temperature anomalies (b). A day is considered a heat wave day if the daily maximum temperature is 35°C or above. SOURCE: Sun et al., 2014.

Statistical Analysis of Observations

Statistical analysis of observations can be used to quantify the changing probability of specific events even in the absence of the use of climate models. Such approaches are attractive because results hinge neither on the reliability of a particular climate model nor on its ability to simulate the event in question. They do, however, hinge on the availability of long-term, high-quality data. In addition, an observation-based analysis requires a statistical analysis that quantifies changes in extremes over time: for example, the kind of changes that might be expected from GHG or aerosol forcing. In particular, such a statistical model for human influence needs to be strongly supported by understanding of the causes of related changes in the climate system (Hegerl et al., 2010). If this is the case, such studies can be complementary to attribution studies based on climate models.

Statistical Analysis of Observed Change in Events

This type of approach uses historical observations to characterize the distribution of a type of event that is similar to a particular observed event (generally excluding the particular event itself to avoid some aspects of selection bias; see Chapter 2). In order to address the human influence, it identifies a trend or covariate in observed data that may be related to human influences. This approach is justifiable only if there is supporting evidence that the covariate indeed has a causal link to human influences. Otherwise, trends caused by other factors or natural variability may be aliased, leading to either an overestimate or an underestimate of the human influence.

An example of such work is King et al. (2015), who analyze the annual recordings in the Central England Temperature (CET) meteorological dataset and rely on an earlier paper (Karoly and Stott, 2006) that attributes at least part of CET warming to human influences . They fit a generalized Pareto distribution[2] (GPD) to the warmest 20% of annual temperatures above a time-varying threshold that increases linearly with CO_2 concentration. This statistical model assumes no change in variability in the upper tail of the annual temperature distribution, and it also assumes that the temperature response to rising CO_2 is linear. When available evidence points to a strong human contribution to the mean temperature change at that location, as in King et al. (2015), this suggests a two-step attribution (Hegerl et al., 2010) of some of the change in extremes to the human forcing. The fraction of attributable risk (FAR) is calculated based

[2] The generalized Pareto distribution is a statistical distribution used to model exceedances above a specified threshold level.

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on the probability of an extreme annual temperature (in particular, exceedance of the second highest annual temperature) for the present compared to the probability for early in the 20th century.

Similarly, van Oldenborgh et al. (2015) apply a generalized extreme value (GEV) distribution[3] to seasonal and daily winter minimum temperature from station data in De Bilt, the Netherlands, and Chicago. The study leaves out the extreme event in question (which occurred in 2013/2014 winter in both locations) and allows the GEV location parameter to shift with climate change (represented by global mean temperature). Such an approach allows comparison of the return time of an extreme event between the climate of the 1950s and the present. Results indicate that very cold events have become significantly more rare, and very warm events more frequent. Again, results hinge on the time evolution of global mean temperature being a good approximation to the time evolution (although not magnitude) of the human influence at that location.

Overall, attribution using statistical analysis of observed time series works best for temperature, or variables that are closely related to temperature, as global and many regional results are available that quantify the human contribution to long-term temperature change. For example, regional temperature scales reasonably well with the global temperature evolution on longer timescales for many, but by far not all regions (see Sutton et al., 2015). Studies that rely on such supporting evidence attributing the trend should point this out clearly. It would be preferable if such studies could explicitly include uncertainty in the fraction of trend that is due to human influences in the analysis as well as additional uncertainty due to the indirect relationship of the variable in question to the larger-scale attributed trend. In the example of temperatures in De Bilt, for instance, the human contribution to global mean temperature is a range, not a single value, and uncertainty increases further when going to the regional scale. Any anthropogenic trend may be enhanced or reduced by decadal climate variability (Box 3.1). For example, multidecadal variability can influence regional precipitation patterns and cause apparent trends (Dai, 2013), such as those found for storminess over Great Britain (Alexandersson et al., 2000).

Observed Circulation Analogues

A second approach is based on analysis of the synoptic situation of a given event and looks for historical analogues with similar circulation states (e.g., Cattiaux et al., 2010;

[3] The generalized extreme value is a statistical distribution used to model the extremes of blocks of data of fixed lengths, such as a season or 1 year.

Yiou et al., 2007) in order to determine how meteorologically similar events have changed (e.g., due to the thermodynamic effects of climate change). As such, this approach conditions on a particular synoptic situation (or sequences of situations), although studies also have diagnosed the frequency of circulation states in order to determine if these may explain or counteract any change in extreme events when conditioned (e.g., Cattiaux et al., 2010; see discussion in Chapter 2).

Cattiaux et al. (2010) analyze the synoptic situation of the winter of 2009/2010 in Europe and find that it was less cold than would have been expected based on temperatures from days in earlier winters with similar synoptic situations, particularly given how extreme some of the daily circulation indices were in the winter of 2009/2010. They used several indicators for circulation (e.g., North Atlantic Oscillation [NAO] index and blocking frequency) and selected atmospheric flow analogues for a period around each winter day from the past 61 years. The composite average temperature for these analogues, which were based on prior years, was significantly colder than the 2009/2010 winter mean temperature for most stations (see Figure 3.4). Subtracting the global warming trend from the 2009/2010 winter temperatures yielded similar temperatures to those of the analogues, and no trend was found in synthetic winter temperatures derived from the analogue situations, suggesting that the observed trend is not explained by changes in circulation.

The uncertainties in observation-based analyses are considerable, but they are different and complementary to the uncertainties in attribution approaches that rely strongly on climate models to estimate the difference between present conditions and those that would have occurred without human influences.

METHODS BASED ON CLIMATE AND WEATHER MODELS

In nearly all attribution studies of extreme events, climate and weather models are an indispensable tool. While the specific type and configuration of the model depends on the type of extreme event being studied, most studies use some version of a global atmospheric model. Some also may use one or more coupled climate models (e.g., from the Coupled Model Intercomparison Project Phase 5 [CMIP5] modeling project) or a model that is constructed specifically to represent a particular type of phenomenon, such as tropical cyclones. Such models represent important atmospheric processes, including, among many more, the transport of heat, moisture, and momentum by winds; the interaction of solar and infrared radiation with atmospheric gases and clouds; and the exchange of heat and moisture between the atmosphere and the land or ocean surface.

ATTRIBUTION OF EXTREME WEATHER EVENTS IN THE CONTEXT OF CLIMATE CHANGE

BOX 3.1
UNFORCED NATURAL VARIABILITY

Natural variability includes both the response to natural external forcings, such as volcanic eruptions, and the unforced, chaotic variability that occurs continually in the climate system (also known as internal variability). We experience some of that variability as weather, but it also occurs on much longer timescales, resulting in extended periods that may be cooler, warmer, dryer, or wetter than average. Such low-frequency internal variations at decadal-to-multidecadal timescales represent a major challenge in the attribution of extreme events to anthropogenic climate change. Over these timescales these variations can dominate externally forced changes (Deser et al., 2014; Hawkins and Sutton, 2009) by producing temporarily large trends in key climate variables. The decadal and multidecadal trends associated with internal variations impact not only the mean values over periods of decades but also their distributions in space and time, including the tails of the distributions and hence the frequencies of extreme events (Sardeshmukh et al., 2015).

The following are examples of the impacts of low-frequency natural variability on extreme events of the type addressed in this report. First, by one definition, the occurrence of heat waves in the United States peaked in the Dust Bowl decade of the 1930s, and the record frequencies of heat waves during that decade have yet to be exceeded (Peterson et al., 2013b; Figure 3.3). These heat waves occurred during a period of rapid global warming over the period 1900 to 1950 that probably had a human component on the global scale (Hegerl et al., 2007) as well as a natural variability component, but it also was a period of anomalous circulation and strong variability (see Bindoff et al., 2013). Second, hurricane activity in the North Atlantic displays multidecadal variability associated with low-frequency variations in Atlantic Ocean sea-surface temperatures (Camargo et al., 2013), although human-caused greenhouse gas increases and particulate pollution also have been implicated in recent hurricane trends in the North Atlantic (Booth et al., 2012). Third, the North Pacific and adjacent land areas are influenced by multidecadal variations in temperature and precipitation associated with the Pacific Decadal Oscillation (Dai, 2013). The latter has a longer timescale than the El Niño–Southern Oscillation, although the connections between these two modes of ocean-atmosphere variability are still being investigated (Wang et al., 2014). Both of these large-scale climate oscillations have been linked to variations in the risk of intense precipitation over North America (e.g., Fuentes-Franco et al., 2015; Zhang et al., 2010). Observationally derived annual probabilities of extreme events (or their inverses, return periods) may be misleading if the available record length is too short to adequately reflect the full range of variation from low-frequency natural variability (e.g., Jain and Lall, 2001) or if the underlying statistical methodology does not account for the presence of such variability.

BOX 3.1 CONTINUED

In model-based attribution studies, the use of large ensembles of simulations can enable averaging that removes much of the unforced natural variability. Thus, externally forced signals may be more prominent in unconditional attribution studies. When attribution of extreme events is conditioned on observed SSTs (for which there is only one historical realization), however, unforced natural variability may impact conclusions about likelihoods. In the case of a counter-factual SST state, for example, the counterfactual climate would have its own natural variability that might or might not be comparable to that of the present climate, with implications for the likelihoods of SST anomalies of a particular magnitude in the two climates. Finally, anticipation of future changes in extreme events over the next decade or two—the timescales of interest for many risk assessments (e.g., by insurers)—must consider the role of natural variability in the likelihood of particular types of events.

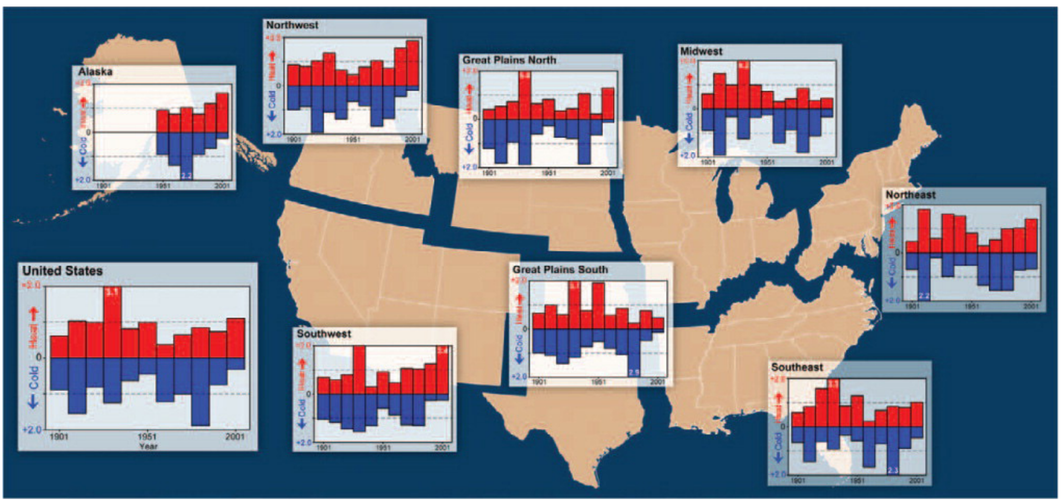

FIGURE 3.3 Time series of decadal average values of heat wave (red bars) and cold wave (blue bars) indices over various regions of the United States; the average for the entire United States is shown at the lower left. These indices are a normalized (to an average value of 1.0) metric of the number of extreme temperature events for spells of 4-day duration. An event is considered extreme if the average temperature exceeds the threshold for a 1-in-5 year recurrence. The horizontal labels give the beginning year of the decade. Recent decades tend to show an increase in the number of heat waves and a decrease in the number of cold waves, but over the long-term, the drought years of the 1930s stand out as having the most heat waves. SOURCE: Peterson et al., 2013b.

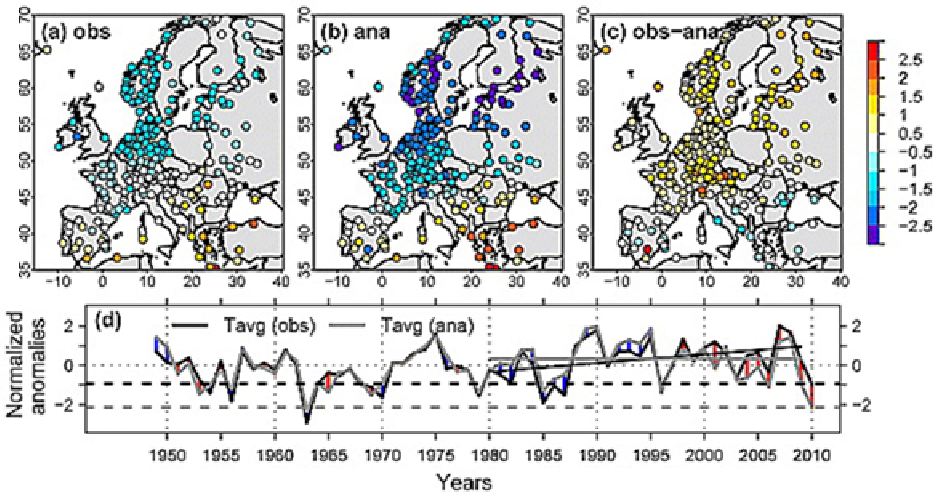

FIGURE 3.4 Example of an analysis using observational circulation analogues, investigating the unusually cold winter conditions in Europe in 2010. In the top figure, panel (a) shows observations of winter 2010 European temperatures; panel (b) shows an average of winters with similar daily circulation over the second half of the 20th century (analogue); and panel (c) shows the difference between both. The time series (bottom figure) analyzes the (averaged over all European stations) winter 2010 anomaly of daily mean temperature of −1.3°C (indicated by a dashed line) in the context of the historical record and analogues. It shows normalized 1949-2010 time series of observed (black line) and analogue mean temperature anomalies (gray line), illustrating the warming of observed winters relative to analogue winters (red segments: positive observed–analogue differences; blue segments: negative observed–analogue differences). SOURCE Cattiaux et al., 2010.

The advantages of using climate and weather models include the ability to utilize specific input conditions (e.g., sea-surface temperature [SST], levels of atmospheric CO_2, or aerosols) and to compare results between simulations using different input conditions, generally for the *factual (currently observable) world as it exists in the context of climate change* and the hypothetical *counterfactual worlds without climate change*, to assess changes in event frequency. It is also necessary and useful to repeat the simulation many times (e.g., by making small random perturbations to the initial conditions) in order to generate a larger sample of simulations and thus obtain better estimates of some of the uncertainties and sensitivities involved in event attribution.

Model simulations are well suited to provide quantitative estimates of the degree to which extreme event frequencies or magnitudes in the factual world differ from what would have happened in a world unperturbed by human emissions of GHGs (and other forcing factors; see Chapter 2 for a discussion of framing). It is essential, however, that any models used for event attribution be able to simulate extreme events reasonably similar to the one that is analyzed. The models also should be carefully evaluated to assess if they correctly reproduce the statistics of extreme events, the specific weather situation leading to events, and local feedbacks that may strengthen events (see Zhang et al., 2014, 2015). It is important to note that evaluating the ability of models to simulate particularly rare events remains a challenge. Reliable simulation of non-extreme events does not necessarily indicate that a model will reliably simulate extreme events. This section describes some specific types or configurations of models and how they have been used in extreme event attribution studies.

Coupled Climate Models

Many studies use coupled climate models, such as the models that participated in CMIP5 (Taylor et al., 2012). Such models incorporate interactive representations of the atmosphere, ocean, sea ice, and the land surface, and often they also include representations of the carbon cycle. CMIP5 and similar earlier experiments are coordinated efforts of modeling groups around the world to provide simulations with global climate models using several scenarios of relevance to extreme event attribution. Some simulations of the recent past (typically 1850-2005) use only estimates of natural forcing such as changes in solar radiation and volcanic eruptions (CMIP5-NAT). Others are run using only anthropogenic forcing (CMIP5-ANT), or only GHG changes (CMIP5-GHG), as distinct from anthropogenic forcing that also includes, for example, changes in sulfate aerosol distributions. The most realistic simulations of historic global climate change are usually those that include all of the above (CMIP5-ALL). For simulations covering periods after 2005, extreme event attribution studies usually draw from one or more of the four scenarios of future GHG concentrations known as Representative Concentration Pathways, or RCPs. (Note that differences between scenarios emerge only later in the 21st century, so the scenario choice has little influence for the period between 2006 and the present.) Some modeling groups have provided as many as 40 simulations of the 21st century. Preindustrial control simulations, many several hundred years long, are sometimes used to define the counterfactual world (e.g., Sun et al., 2014), while in other cases CMIP5-NAT simulations are used for this purpose (e.g., King et al., 2015).

Coupled climate models can be used to assess the changes in the likelihood of breaking current regional average monthly or seasonal temperature or rainfall records. The chances of breaking an existing record are compared in the simulated current climate with the chances in the counterfactual world and used to provide a lookup table of the FAR values for whenever a new record is set (Lewis et al., 2014).

Studies using coupled models would typically be considered unconditional attribution studies[4] (see Chapter 2) unless the study specifically attempted to control for some feature of the state of the climate system. In the CMIP5 models, SSTs from a given year do not correspond to those observed in that year. Therefore, studies that condition on an observed SST anomaly pattern (conditional attribution; see Chapter 2 and discussion below) do not use CMIP5 outputs. They may, however, use the atmospheric components of coupled models that participated in CMIP5, or higher-resolution atmospheric models that are most closely related to weather prediction models.

It also is possible to use coupled models for conditional attribution studies, such as for El Niño years, by selecting specific years that have the same phase of El Niño as observed (Lewis and Karoly, 2013).

CMIP5 is most suitable for studying extremes with large spatial scale (e.g., heat waves, droughts, and cold events), though other types of studies also have used CMIP5. CMIP5 simulations have two key advantages over atmosphere-only simulations: the inclusion of the oceans, and the large number of simulations already available, which can be used to generate more robust statistics. For example, large multi-model ensembles, on the order of 100 simulations or more, have been used for studies detecting human influence on the frequency of record high CETs, such as occurred in 2014 (King et al., 2015), for study of the California drought (Seager et al., 2015), and for studies of the record warm summer in eastern China in 2013 (Sun et al., 2014).

Atmosphere-Only Models Using Observed SSTs

A second type of model simulation uses an atmospheric general circulation model (GCM) in which the observed historical evolution of SSTs and sea ice extent is specified. These are often called "AMIP" runs[5] and are usually coupled to a land model. Specific patterns of SSTs and GHGs (or other boundary conditions) can be imposed, exerting a degree of conditioning on the results that is not present in CMIP simulations. Atmosphere-only model studies are most valuable when the coupling between the ocean and the atmosphere is primarily one-way: that is, when feedbacks of the atmosphere to the ocean can be neglected for the purposes of the phenomenon

[4] Studies using coupled models normally include conditioning on natural external forcing of climate, such as volcanic activity and variations in solar output. This has not been a significant issue since event attribution was proposed simply because we have not seen an explosive volcanic eruption on a scale likely to significantly impact the statistics of weather events. Nevertheless, this will happen eventually, of course.

[5] Originally referring to the Atmospheric Model Intercomparison Project, a specific experiment using observed SSTs from 1979 to 1993 (Gates, 1992).

being studied. The number of ensemble members in such studies can vary from a relatively small number of runs for analysis of large-scale events (order 10s of runs, e.g., Funk et al., 2013; Wilcox et al., 2015) to others using large ensembles with 100 or more simulations (e.g., Christidis and Stott, 2012). In some cases, atmospheric model ensemble simulations may consist of many thousands of model runs (e.g., Otto et al., 2015a; Pall et al., 2011; Schaller et al., 2016). Such studies are often facilitated by the climate*prediction*.net/weather@home infrastructure (see Box 3.4 later in this chapter). Two common features of studies that use very large ensembles is that they are often restricted to a single model, and they use a large number of short simulations (e.g., less than 1 year to perhaps a decade) in contrast to a smaller number of multidecadal or longer simulations.

Three types of perturbations are relevant for generating ensemble members: initial condition, model physics, and SSTs. Initial condition ensembles (the model is run with a variety of slightly different initial conditions at the start) are used in almost all model-based event attribution studies (including unconditional studies using ensembles such as CMIP5) to provide the replication needed to quantify the frequency of events or distribution of event magnitudes. One approach to producing such ensembles is to perturb initial condition using next-day differences from a separate simulation (e.g., see Massey et al., 2014).

Perturbed physics experiments are not generally used in attribution studies—primarily because with a prescribed-SST design, perturbations that do not significantly degrade the model climatology also have been found to have relatively little impact on variables of interest—but they could be. The opportunity for this kind of perturbation arises because processes in the models that occur at scales smaller than the resolved scale are normally approximated using information from resolved-scale fields (e.g., temperature, geopotential, winds). These approximations involve adjustable parameters with values determined from empirical studies and usually are fixed for all model runs. Atmospheric convection, which occurs on spatial scales of a few kilometers, is an example of the type of process that must be parameterized in models that have resolutions that are too coarse to allow convection to be well simulated on the explicit model grid. In perturbed physics experiments, these parameters are varied across a range of plausible values. Simulations using particular parameter combinations are evaluated both to determine the realism of the simulated climate compared with observed (20th-century) climate and to span a range of uncertainty in future climate or climate parameters, such as the climate sensitivity (Stainforth et al., 2005).

For attribution experiments, SST perturbations of the counterfactual world are sometimes used as well. Instead of simply using control simulations as in CMIP5, experiments using fixed SSTs include "counterfactual" SSTs in which an estimate of the anthropogenic contribution to modern SST patterns is subtracted from the observed SSTs (e.g., Pall et al., 2011). Perturbations to the SST patterns are done to assess sensitivity or to quantify uncertainty in event attribution results to the choice of the counterfactual SST. Different climate models generate different patterns of SST changes in response to human influences: for example, because they exhibit different aerosol forcing or cloud feedbacks to warming. The choice of different SST patterns to be removed matters in practice, and this uncertainty is discussed below (e.g., see Figure 3.5). Studies using mul-

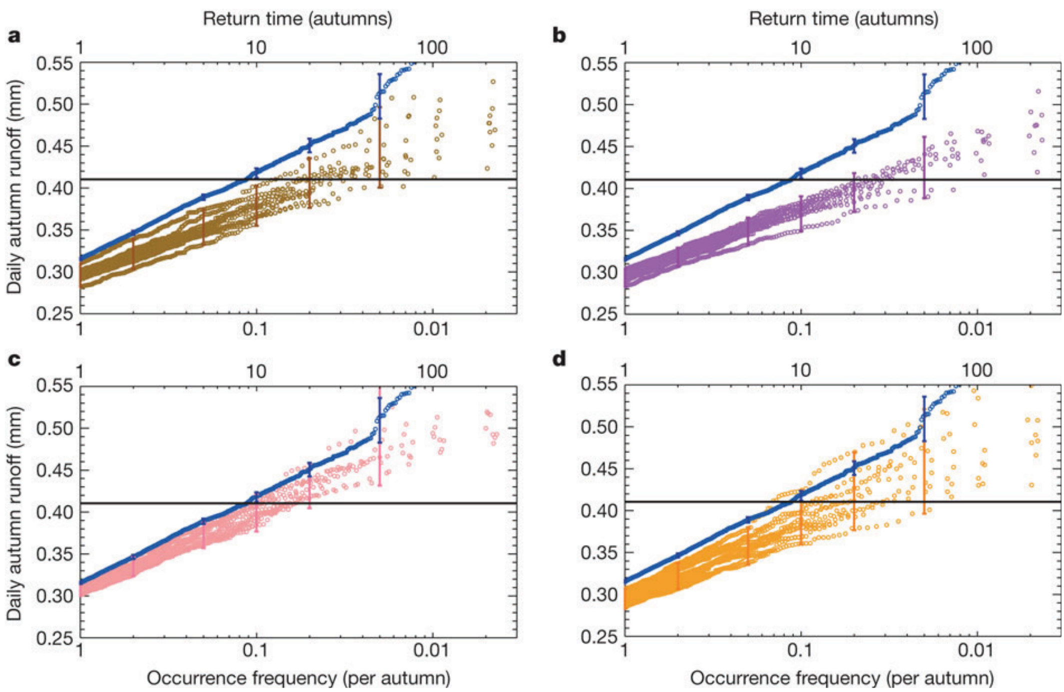

FIGURE 3.5 Sensitivity of change in the occurrence frequency of extremely high river runoff in England and Wales for autumn 2000 using different climate models to characterize and remove the human influence on sea-surface temperature from a counterfactual world. This figure illustrates that while present condition runoff return periods tend to be more frequent than those in any such counterfactual world, the occurrence frequencies in a counterfactual world depend on the model used to create it. Blue is the modeled return time for 2000 runoff (identical in each panel) against occurrence frequency, while colored dots show the return times in a counterfactual world, constructed by removing the pattern of human influence on SSTs from four different climate models: HadCM3 (brown, a), GFDL (purple, b), PCM (pink, c) and MIROC (orange, d). The horizontal black line on each panel corresponds to the highest daily runoff observed during these 2 months. SOURCE: Pall et al., 2011.

tiple estimates of counterfactual SSTs have employed both global atmospheric models (e.g., Feser et al., 2015b; Massey et al., 2014; Pall et al., 2011; Rupp et al., 2012) and a regional climate model (discussed further in the next subsection) that is nested within a global atmospheric model (e.g., Bergaoui et al., 2015; Black et al., 2015; King et al., 2015).

Studies Conditioning on Seasonal Forecasts

On the seasonal timescale, Hoerling and colleagues (2013), studying the 2011 Texas drought, use the National Oceanic and Atmospheric Administration (NOAA) Climate Forecast System (CFS) initialized at six-hourly intervals starting June 1, 2011, with CO_2 concentrations set at either 1988 or modern values, for a total of 240 runs and also additional ensembles of 15 and 24 runs started on the first day of June of each summer between 1981 and 2011. Hence, they explore the impact of the increase in CO_2 concentrations since 1988 conditioned on that component of climate variability that was predictable on a seasonal timescale. The weather@home contribution to the near–real-time attribution studies in the World Weather Attribution project also uses an ensemble of seasonal forecast SSTs (from the UK Met Office GLOSEA5 forecast system) to define present-day conditions prior to subtracting a range of signals of anthropogenic warming. In both of these cases, the definition of "present-day conditions" in the conditioning of attribution statements is restricted to the component of present-day weather that is predictable on a seasonal timescale. In many cases, this may be more consistent with the expectations of stakeholders interpreting attribution statements than is conditioning on SSTs precisely as observed.

Downscaling

Some types of extreme events are not well simulated by global models, either coupled or atmosphere-only, often because these models are not run at sufficiently high spatial resolution. Additional models, embedded within a global model to provide large-scale environmental conditions, may be used to represent these events better. Because these models are meant to represent finer scales than the global models in which they are embedded, such methods can be collectively termed "downscaling." One example is a high-resolution regional atmospheric model that runs on a subset of the global domain and is forced at the lateral boundaries by the global model (e.g., Marthews et al., 2015). Other downscaling models may be designed especially to capture a specific event type. For example, Emanuel (2006) embeds an efficient, idealized tropical cyclone model within large-scale fields obtained from global models. Other downscaling methods are statistical, not involving any dynamic model at all. Examples include environmental indices used to predict the genesis of tropical cyclones (Emanuel and Nolan, 2004; Tippett et al., 2011) or of tornadoes (Brooks et al., 2003; Diffenbaugh et al., 2013; Tippett et al., 2012; Trapp et al., 2007). These indices are derived from statistical analysis, using observations, of spatio-temporal relationships between large-scale variables and the extreme event in question. As with any other kind of model, it is important to test such specialized models—independently, and in combination with the global climate model as used in any attribution study—in order to determine model adequacy.

Highly Conditioned Simulations

The studies just discussed constrain the state by specifying SST anomaly patterns (or the component thereof that is predictable on a seasonal timescale) for factual and counterfactual world simulations. As discussed in Chapter 2, some approaches provide much stronger constraints on the current state of the climate system than conditioning on SST patterns, corresponding to different framings of the attribution question. Such highly conditioned studies, which are fewer and less well developed than the types discussed above, constrain the initial conditions closely to observed, and perform forecast-type simulations.

Some of these highly conditioned studies use ensembles of forecast simulations in order to improve estimates of uncertainty. Two types of forecasts have been undertaken: (1) weather-type forecasts, over a period of a few days; and (2) seasonal forecasts, over a period of a few months. In the first case, the model must be initialized within the predictability window—that is, only a few days in advance of the event—so that the model may actually simulate the development of the event from the beginning. For example, Meredith and colleagues (2015), who studied the floods that affected the Black Sea town of Krymsk in July 2012, use a triply nested configuration of the Weather Research and Forecasting model, initialized at six-hourly intervals over a 30-hour period (hence 6 runs) for two different SST forcings, for a total of 12 runs. Another recent example is Lackmann (2015), who use a nested modeling approach to study Hurricane Sandy.

Closely related to the forecasting approach, Hannart and colleagues (2015b) recently proposed using a data assimilation system for event attribution. The idea is to define events in a highly specific fashion such that the probability of the event is very small in both the factual and the counterfactual world, which implies that the probability of sufficient causation (Hannart et al., 2015a) also is very small. Such definitions are possible for variables that are measured on continuous scales (e.g., temperature, precipitation, and the central pressure of storm systems), and where differentiation between minutely different values is at least possible, in principle. For example, the probability of an event defined in terms of maximum temperature that lies within a narrow range of an observed value, $T_{max,obs} - \varepsilon < T_{max} < T_{max,obs} + \varepsilon$ where $\varepsilon > 0$, converges to zero as ε approaches zero for all values of $T_{max,obs}$ even though the probability density function $f(T_{max,obs}) > 0$ for all physically plausible values of $T_{max,obs}$.[6] Under these conditions the FAR, which Hannart and colleagues (2015b) relate to the probability of necessary causation, converges to one minus the ratio of probability density functions in the two worlds for the variable defining the event. A data assimilation system (such as an Ensemble Kalman Filter–based system of the type used at many weather forecasting centers) can then be used to estimate these probability density functions.

Development of this idea is currently in its very preliminary stages, but it suggests a path toward operational event attribution that exploits current operational weather forecasting capabilities. It would, however, be restricted to sharply focused event definitions based on quantities that are assimilated in numerical weather prediction systems.

UNCERTAINTIES IN MODEL-BASED STUDIES

Many event attribution methods and analyses rely on estimating event probabilities or distributions of event magnitudes from model simulations. As a result, confidence in attribution results necessarily depends on the skill of the model in simulating the event type under analysis in both of the scenarios. This dependence is well known in the event attribution community (e.g., Christidis et al., 2013b), but emphasis on assessing models varies across attribution studies and may be little recognized among stakeholders, policy makers, and the general public.

Model quality with regard to event attribution requires careful thought. Christidis and colleagues (2013b) contrast the ability of a model to accurately represent the climatology (i.e., the distribution of weather over time) in terms of frequency and climatological features of the event of interest with the model's predictive skill. They argue that robust event attribution is possible even when only the climatology is well represented. The quality of the model(s) in representing an event or the climatology of an event class is best assessed using the factual simulations, because these are expected to correspond most closely to the observed climate. Even then, however, only limited information is available from observations for extreme events. For instance,

[6] Note that the relationship between the probability of the event $T_{max,obs} - \varepsilon < T_{max} < T_{max,obs} + \varepsilon$ and the probability density function $f(T_{max})$ is given by $P(T_{max,obs} - \varepsilon < T_{max} < T_{max,obs} + \varepsilon) = \int_{T_{\max,obs}-\varepsilon}^{T_{\max,obs}+\varepsilon} f(t)\,dt$.

Stott and colleagues (2004) considered whether the model's interannual variability corresponded to that of the observations, while Pall and colleagues (2011) considered the model's quality with respect to dynamic features, and Christidis and colleagues (2013b) considered the reliability of hindcasts.

Such evaluations are necessary, but they are not a sufficient demonstration of model quality. The quantitative correspondence of the statistics of such variables as temperature and precipitation between model output and observations does not necessarily imply that the mechanisms that produce variability and extremes are well represented in the model. Thus, assessment of the model needs to go beyond a quantitative comparison that accounts for sampling uncertainty and must assess key processes that lead to or exacerbate the event.

The quality of a model under the counterfactual scenario may be difficult to evaluate. A counterfactual scenario that describes the present-day climate, absent the influence of anthropogenic forcing but accounting for contemporaneous volcanic and solar forcing, does not exist; thus, its quality is not directly assessable by comparison against observations that have been made under exactly those forcing conditions. In this case, quality can be determined only from the evaluation of model performance under other forcing scenarios for which observational data are available.

Such assessment includes the evaluation of model quality for the factual world with anthropogenic forcing over the past several decades, and it may be based on instrumental data for time periods before extensive anthropogenic influence and possibly using paleoclimatic reconstructions of earlier periods. Also, knowledge of fundamental climate science and of model structure can provide an understanding of what kinds of events may or may not be well characterized by models in terms of the variables that are used to define the events, dependence on circulation patterns, dependence on SSTs, spatial scales, and temporal scales.

As discussed in Chapter 2, a key decision in the framing of a model-based event attribution study is the degree of conditioning that is imposed on the model. The optimal choice of both conditioning and model will depend on the question being addressed and the event under consideration.

Unconditional Attribution

At one level, the most comprehensive and most easily interpretable kind of attribution is unconditional. For this, a model must be both global and coupled to a dynamic ocean. It must then be run for sufficiently long periods to reliably determine the statistics of the extreme in question: the rarer the extreme, the longer this needs to be. Those two constraints will limit the spatial resolution and the degree of complexity of the model that can be used. In general, at present, models that can be run in this mode will be something like CMIP5-class models (e.g., King et al., 2015; Knutson et al., 2014). The challenging part of this kind of attribution is supporting the assumption that the model is a reliable mimic of reality. Given the known capabilities (and deficiencies) of this class of model, which have been comprehensively assessed in the Intergovernmental Panel on Climate Change (IPCC) reports, this requirement has implications in terms of which kinds of extreme events can be addressed.

Most coupled models exhibit substantial biases in mean climate and variability relative to observations, especially at the regional scale, so some bias correction will almost certainly be required, and the validity of this must be established. Typically, model output is bias corrected by computing anomalies, either by subtracting or by dividing by some climatological mean and potentially adjusting the variance (e.g., Sippel and Otto, 2014). A further intervention requiring even stronger assumptions entails adjustments to quantiles to make the distribution of the model output correspond better to that of the observations (e.g., Edwards et al., 2014). The argument for such adjustments is that a model may reasonably represent long-term climate change but be offset in terms of the magnitudes of variables of interest (e.g., Bindoff et al., 2013). Such adjustments should ideally be founded in physical arguments, because it is not clear what type of evaluation against observations could be done to give confidence to estimated changes in probability or magnitude in such circumstances. Also, it should be recognized that the bias adjustments rely on observations that may be uncertain for a variety of reasons in and of themselves. Sources of observational bias and uncertainty are multiple and include insufficient or changing instrumental coverage; bias from sources such as poor placement of the instrument; inhomogeneity arising for a variety of reasons, including changes in exposure, instrument, observing protocol, and location in the case of *in situ* observations, and, for example, orbital drift in the case of satellite data; and uncertainty associated with gridding and analysis procedures (see previous section on observational approaches).

Temperature extremes can probably be addressed with some degree of confidence using CMIP5-class models, although there may be challenges for heat extremes where land-atmosphere coupling provides a strong feedback. In contrast, droughts would be somewhat more challenging as they depend on precipitation over land, which models generally find challenging, as well as on the land surface and its feedbacks (Seneviratne et al., 2010). To the extent that both phenomena depend on atmospheric blocking and storm track dynamics, however, these models are unlikely to be fully reliable because they continue to exhibit deficiencies in these phenomena (Flato et al., 2013). Moreover, events such as large intense storms may not be addressable with such models, because most do not adequately simulate such events (e.g., Seiler and Zwiers, 2015a). In general, such models should be used only to address extremes that are under a strong thermodynamic control. If dynamic processes are the dominant feature of the event, as would be the case for an explosive extratropical storm or a tropical cyclone, then model uncertainty needs to be addressed, and this may be extremely challenging. The effects of dynamic and thermodynamic processes also may be difficult to disentangle—for example, as in a flooding event—because dynamic processes may control the circulation that transports and converges the moisture that produced the flood, while thermodynamic processes may determine the amount of moisture that was actually transported to the drainage basin where the flooding occurred.

Multi-model ensembles can be used for event attribution either in a sensitivity analysis framework, repeating the analysis for each model, or by averaging across models in some fashion. While a multi-model ensemble may have less bias than any single model, when representing both the mean state (e.g., Flato et al., 2013; Gleckler et al., 2008) and the indices of moderate extremes (e.g., Sillmann et al., 2013b), even results averaged across models may be biased relative to the true earth system because of shared inadequacies in their representation of the system. An example is the general equatorward bias in the North Atlantic storm track (Zappa et al., 2013b). In addition, because model ensembles are generally ensembles of opportunity, with some models being closely related (see Knutti et al., 2013), the issue is further complicated. In general, as discussed in the section "Uncertainty Quantification" below, model bias is difficult to quantify, particularly for extremes for which large observational uncertainty hinders the ability to compare to the truth (Kharin et al., 2007, 2013) and even more so for the counterfactual scenario.

Conditional Attribution

In conditional attribution analyses, model quality should ideally be assessed conditionally: Does the model accurately represent the climatology given the forcings and the conditioning factors? And, does it produce extremes similar to the observed event for similar reasons?

Conditioning on Patterns of Sea-Surface Temperatures

The first level of conditioning is by SST anomaly pattern. Because the SST pattern is imposed, an atmospheric model can be used. This has two practical benefits: First, model biases associated with the ocean state will be mitigated. Second, because only the atmosphere and land surface are simulated, the model can be run for longer periods of time to quantify more extreme statistics, can be run at higher spatial resolution, or can include more complete representations of the land-surface or key model components.

In general, models that can be run in this mode may be something like seasonal-forecast or previous-generation weather-prediction models, which might have better representations of storm track dynamics and moist processes than CMIP5-class models, although often the atmospheric components of CMIP5-class models also are used. Because biases are usually reduced when specifying the ocean state and with potentially better representations of relevant processes, it might be possible to more confidently address some types of drought. Extratropical cyclones also may be addressable at some level. It is unlikely, however, that it would be possible to perform reliable event attribution on tropical storms and intense convective precipitation with such models, even if resolution and the representation of moist processes are somewhat better than for CMIP5 models. Although dynamically driven extremes may be reasonably well represented in such models, the dynamic response of the atmosphere to climate change remains uncertain. This uncertainty must be addressed in any attribution study, which at a minimum argues for using more than one model, although this is often not sufficient (see the section "Uncertainty Quantification" below).

Additional uncertainties arise in studies that condition on the SST patterns. One issue is the uncertainty associated with estimating the counterfactual ocean state. This uncertainty arises because such studies condition on the ocean state in the factual (i.e., currently observable) world, and therefore, they condition on a feature of that world; but one needs a corresponding ocean state in the counterfactual world. Nevertheless, studies that use atmospheric models often use multiple estimates of the ocean warming due to human influences and results—particularly in studies of precipitation—can be surprisingly sensitive to this (see Otto et al., 2015c; Pall et al., 2011; see Figure 3.4). The uncertainty associated with estimating the counterfactual ocean state is driven by the uncertainty in estimating the anthropogenic component of the factual world SSTs, which is performed using regression-based detection and attribution formalisms (e.g., Hegerl and Zwiers, 2011).

A second issue is that the attribution statement comparing the factual and counterfactual worlds depends on the conditioning in this setting; as discussed in Chapter 2, such a conditional analysis does not account for differences in the likelihood of the conditional SST anomaly pattern in the two worlds. Finally, little work has been done to date to understand how attribution statements vary across different possible ocean states—in particular, different modes of variability (e.g., whether conditional attribution statements would differ markedly under El Niño or La Niña conditions).

One strategy for addressing extremes at smaller scales within this framework is to use regional models embedded within global models (see the section "Downscaling" above). This is a useful strategy for events that are driven by large-scale circulation and can improve the representation of precipitation extremes, particularly when associated with orographic influences. Nevertheless, uncertainties will remain and the gridpoint scale of such a model still cannot be reliably compared to the local scales at which extreme convective events are experienced (Westra et al., 2014).

Other kinds of conditioning on large-scale aspects of the climate state, such as soil-moisture anomalies, sea-ice extent, or stratospheric circulation, would be subject to similar considerations.

Conditioning on the Features of an Event

The options change yet again for conditioning on the space and timescale of a single large storm event, such as one of the named European winter storms or a tropical cyclone, which can be done with data assimilation and/or short-term forecasts. In this case, a high-resolution weather forecast model with a detailed representation of topography—and perhaps even with explicit convection—can be used because the simulations need only be performed for a few days or weeks at most. Thus, tropical storms and severe precipitation events can be studied (see e.g., Lackmann, 2015; Meredith et al., 2015), but tornadoes remain a challenge. Because the factual simulation can now be directly compared with the observed event, in all its relevant details, evaluation of whether the model is fit-for-purpose can be performed at a level that is not possible in frameworks more weakly constrained by observations (i.e., less strongly conditioned). Nevertheless, the description of the counterfactual remains a challenge because it is necessary to determine the anthropogenic component of the thermodynamic conditions relevant for the event; this introduces uncertainties comparable to those of determining the counterfactual ocean state in atmosphere-only model simulations, as discussed above.

In general, uncertainties that result from model skill limitations are difficult to describe precisely and are circumstance specific; these uncertainties are discussed further below.

UNCERTAINTY QUANTIFICATION

Uncertainty arises from many sources; some of this uncertainty is amenable to statistical characterization, while other aspects are difficult to quantify. Sampling uncertainty is the inherent uncertainty from trying to quantify the intensity and frequency of extreme weather or climate events using datasets of limited size from either observations or model ensembles. Additional uncertainties arise from the use of models in event attribution.

Quantifying Sampling Uncertainty

Sampling uncertainty arises from using a dataset of limited size—either an observational dataset or an ensemble of model simulations—to estimate event probabilities or distributions of event magnitudes. In the context of event attribution, the main source of sampling uncertainty is the chaotic unforced variability that is a pervasive feature of the climate system and that is simulated to various extents by climate models, even when run without any type of time-varying natural or anthropogenic external forcing. This can include substantial contributions from the low-frequency natural variability of the climate system (Box 3.1), including the effects of long-term oscillations that may confound the effects of human-induced changes in analyses based on short observational records. Observational uncertainty in the actual state of the climate system caused by datasets of limited size and by errors in measurements can also contribute to sampling uncertainty. Such uncertainty is represented in ensemble observational datasets such as HadCRUT4 (Morice et al., 2012) and ensemble reanalyses such as the 20th Century Reanalysis (Compo et al., 2011).

Quantifying uncertainty because of limited sampling can be addressed using well-established statistical techniques and could be done from either a frequentist or a Bayesian perspective (Box 3.2). The simplest approach is to use the empirical probability, namely, to calculate the proportion of times that the event (often defined based on a given variable exceeding a threshold) occurred. The uncertainty from the difference between this empirical probability and the true underlying probability can be estimated using a variety of standard techniques (Fagerland et al., 2015). With limited data, and when attempting to quantify small probabilities in the tail of a distribution, extreme value methods can be helpful in reducing statistical variability (Coles, 2001; Kharin and Zwiers, 2005). One difficulty that can arise is when the estimated p_1 or p_0 is 0, which can result in difficulty in quantifying sampling uncertainty in estimates of risk ratio (RR) or FAR as well as FAR values that become uninformative because they saturate near 1 (see Chapter 2). Some statistical techniques can estimate a one-sided uncertainty interval in such situations (Hansen et al., 2014b), but these have not been part of common practice in event attribution analyses.

In modeling studies, uncertainty from natural variability is accounted for in analyses that use coupled models. Such model simulations sample over the state of the climate system and, if run for sufficiently long or with sufficiently large ensembles, should, in principle, represent the full distribution of natural variability as a component of sampling uncertainty. For a representative sample, however, very long time series may be needed (Wittenberg et al., 2014), and models may not capture dynamics in response to forcing or teleconnections well.

As discussed earlier, observation-based approaches that avoid the use of models often compare a recent time period intended to represent the world under anthropogenic influence to a historical time period (e.g., the early or mid-20th century) with weaker anthropogenic influences (e.g., Hansen et al., 2014b; King et al., 2015; van Oldenborgh et al., 2014) as proxies for the factual and counterfactual scenarios. Sampling uncertainty considerations discussed above apply to estimating probabilities for both time periods. For extreme events, one generally needs adequate replication over time—thus, requiring a long time period—to reduce uncertainty, and uncertainty is often high because of a paucity of data. A statistical bias may arise, however, when using data from long time periods because the climate is not stationary over that period, though some statistical techniques are able to account for some aspects of non-stationarity (King et al., 2015; van Oldenborgh et al., 2015). In addition, uncertainty can be high because the length of the time period under consideration may not represent the full range of natural variability. In the face of natural variability that includes decadal-scale variability that will not be well sampled in most observational samples, it will be difficult even to adequately quantify the uncertainty.

A technical concern with the statistical analyses in the event attribution literature is that studies often mix frequentist and Bayesian perspectives (Box 3.2) and methodologies without a clearly defined probabilistic framework. In particular, analyses often use the well-established bootstrap technique to quantify uncertainty in quantities such as FAR and RR (Christidis et al., 2013b; Pall et al., 2011; Stone and Allen, 2005). The bootstrap is a technique that estimates the sampling distribution of a statistic (Davison and Hinkley, 1997), such as an empirical probability, $\hat{p}$. In other words, it quantifies the variability of $\hat{p}$ (around the true p) that would occur in repeated analyses with statistically equivalent samples of data; this is the "repeated sampling" discussed in Box 3.2. In the most straightforward approach to the bootstrap, this involves resampling with replacement from the data: for example, resampling from the ensemble members in a model-based attribution analysis. This sampling distribution can then be used to es-

BOX 3.2
FREQUENTIST VERSUS BAYESIAN APPROACHES TO STATISTICS[a]

Both the frequentist and the Bayesian approaches to statistics attempt to use data to estimate quantities of interest and to quantify our uncertainty in making such estimates, but the approaches differ in how probability is used. Frequentists use probability only to model certain processes that relate to how data are collected and are broadly described as "sampling." Bayesians use probability more widely to model sampling as well as other kinds of uncertainty and variability. Both approaches then use well-established principles to calculate estimates of the quantity of interest and uncertainty bounds on those estimates.

The easiest way to appreciate the differences between the two approaches is to first consider a simple example that is unrelated to climate science. Thus, imagine that we are interested in the average height *h*, in inches, of all adult males in the United States.

A Bayesian statistician would begin with a "prior distribution," meaning a probability distribution that describes what we know about *h* before collecting any data. Some prior information is available: *h* is certainly between 60 and 84 inches, and is more likely near the middle of this range. A reasonable way to describe this knowledge might be to use a bell-shaped curve that gradually rises from a value of zero for values of *h* greater than 60, reaches a peak at 72 inches, and then gradually declines again until again becoming zero at 84 inches. The curve is drawn so that the area under the curve is one, indicating that the true value of *h* has to be somewhere between 60 and 84, and the peak at 72 indicates our prior belief that this is the most likely value of *h*. After collecting some data (e.g., the heights of a random sample of U.S. adult males), the Bayesian would use established techniques to update this prior distribution in light of the data to get a new probability distribution for *h* called the "posterior distribution." The posterior distribution reflects our state of knowledge about *h* after collecting data. Using the posterior distribution, the Bayesian can make a statement such as $P(70 \le h \le 74) = 0.95$—that is, there is a 95% chance that the average height of all males in the United States lies between 70 and 74 inches.

Frequentists do not allow themselves to make such statements. For a frequentist, *h* is simply an unknown constant that could in principle be known (such as by measuring the heights of all adult males at a given time). To frequentists, the probability statement above is meaningless because *h* is a fixed value, and they make probability statements that only describe what happens with repeated sampling. An example of an acceptable probability statement for a frequentist would be $P(70 \le H \le 74) = 0.65$, where *H* is the height of a randomly drawn individual from the population of adult males in the United States. Such a statement would tell us that 65% of U.S. males have heights between 70 and 74 inches. We might judge from this that the average height *h* also lies in this range, but a frequentist would not assign a probability to that judgment. But, he or she might give a confidence interval for *h*. In this case, the end points of such an interval are constructed from the heights of a random sample of males in such a way that, if the sampling process were repeated, the interval would cover *h* with a specified probability, such as 90%. That is, if the sampling process were repeated 100 times, and if a 90% confidence interval were calculated each time, then we would expect approximately 90 out of the 100 of the confidence intervals to include the unknown constant *h*. The confidence level and the length of this interval together give an indication of the precision of the estimate of *h* that is obtained from the available sample.

continued

BOX 3.2 CONTINUED

The sampling variability that is described by frequentists can arise in a number of ways. In the example above, it originates from the process of randomly selecting individuals from the U.S. population of adult males. In climate science, it can arise from observing different periods in the evolution of a weather or climate process that exhibits chaotic variability (e.g., 30-year temperature trends calculated from different 30-year periods would almost surely be different even if there were no external influences on the climate), by selecting different periods from a single climate or weather model simulation, or using different simulations from the same climate or weather model that have been started from different initial conditions. In all cases, a frequentist describes the uncertainty that arises from using different samples drawn in statistically equivalent ways, whereas a Bayesian also will use additional knowledge that is described in the form of probability distributions that quantify what is known or judged to be more or less likely given the available understanding before gathering further data. This can include descriptions of uncertainties, such as model and parametric uncertainty, that may rely on expert judgment (to greater or lesser extents in different situations) to describe the relative likelihoods of different possibilities.

[a] Adapted from https://www.quora.com/What-is-the-difference-between-Bayesian-and-frequentist-statisticians (accessed June 1, 2016).

timate a standard error or confidence interval. This is a frequentist approach because the sampling distribution is the probability density function (PDF) of the statistic, $\hat{p}$, not the PDF of the true value, p. In the frequentist approach, p is not random and therefore cannot have a distribution. Necessarily, only a Bayesian approach can provide a PDF for the true value of the quantity of interest, such as p, FAR, or RR, based on the available observational or modeling data.

Event attribution analyses, however, generally plot the sampling distribution and carry out calculations with it that are presented and interpreted in a Bayesian framework. An early example of this is Stott and colleagues (2004), who report PDFs (they also call these "normalized likelihoods") for return probability and FAR, where these PDFs are based on the bootstrap and are actually sampling distributions. This interpretation of a sampling distribution as a PDF for the quantity of interest (i.e., as a Bayesian posterior distribution) is akin to the common statistical misinterpretation that a hypothesis test provides a probability that the null hypothesis is true. In certain simple circumstances, the numerical results from interpreting the sampling distribution as a Bayesian posterior coincide with the Bayesian posterior distribution that would have been computed from implementing a Bayesian approach to the problem (Gelman et al., 2013). However, no statistical result shows that this is, in general, the case, so use of the bootstrap to compute results that are then interpreted in a Bayesian fashion is not, in general, justified by statistical theory. Rather than carrying out a frequentist analysis and giving it a Bayesian interpretation, an analysis that seeks to provide a PDF for a quantity such as FAR or RR should use the Bayesian framework with a stated prior distribution and determine the resulting posterior distribution rather than using the bootstrap. This would require the analyst to specify a prior distribution, which can be difficult to decide on and may be subjective. A frequentist alternative that will often be straightforward to implement is to report a confidence interval calculated using standard statistical methods, such as the bootstrap.

Quantifying Uncertainty in Model-Based Analyses

In studies based on model output, one can quantify sampling uncertainty as described in the previous section, and one can reduce sampling uncertainty as much as desired by using larger ensembles, limited only by computational time and resources. Uncertainty from using a model (or models) to approximate the climate system is difficult to quantify or to reduce, however, although there is a large body of literature on uncertainty quantification for deterministic models (Santer et al., 2003; see also some of the discussion in the section "Uncertainties in Model-Based Studies"). In particular, all models have biases in representing the climate system that carry over into a bias in estimated event probabilities, even for events for which a model is carefully evaluated before its use for event attribution. As discussed further below, bias may be reduced but will not be avoided entirely by using multiple models.

The following sources of uncertainty affect estimates of event probabilities and magnitudes in model-based analyses (Hawkins and Sutton, 2009):

- *Boundary condition uncertainty* (sometimes called "scenario uncertainty"): This includes aspects of the system that are fixed in the model and therefore not simulated by the model. For example, depending on the model details, this can include some aspects of land-surface characteristics.
- *Model uncertainty*: This is the uncertainty from the inability of any model to fully represent the system, including uncertainty that arises from the need to parameterize (approximate) the representation of sub-grid scale processes. The nature of this uncertainty will vary with the type of model that is used for event attribution (e.g., ranging from global coupled models, to nested regional climate models, to very-high-resolution convection permitting models).
- *Parametric uncertainty*: This represents uncertainty in the appropriate values for parameters in the climate model. Parametric uncertainty could be considered to be one component of model uncertainty.

ATTRIBUTION OF EXTREME WEATHER EVENTS IN THE CONTEXT OF CLIMATE CHANGE

The following are additional sources of uncertainty in conditional analyses:

- *Counterfactual boundary condition uncertainty*: For the counterfactual scenario, there is uncertainty in boundary conditions such as the SSTs in atmosphere-only model simulations.
- *Conditioning uncertainty*: This is the uncertainty that arises because conditional results pertain directly only to the state of the system that is conditioned on, such as the SST state in atmosphere-only models. As discussed in Chapter 2, conditional attribution inherently ignores changes in the likelihood of the conditioning state and whether the attribution result would differ when conditioning on other possible states of the system.

Standard statistical analysis is not well suited to deal with these sources of uncertainty, and these uncertainties have not been broadly addressed in the large majority of studies, although some studies have addressed limited aspects of model uncertainty. One approach that can help to characterize the parametric uncertainty component of model uncertainty is the use of perturbed physics ensembles (PPEs) to sample from parameter distributions (e.g., Christidis et al., 2013b). The use of multi-model ensembles can help to characterize model uncertainty, as done in studies using the CMIP5 archive. In addition, some studies have done event attribution with atmosphere-only models using multiple SST patterns meant to quantify the uncertainty related to the state of the system under natural forcings (Christidis et al., 2013a; Pall et al., 2011).

Some studies account for these types of uncertainties by using methods that involve drawing samples. For example, in a PPE, one draws multiple parameter samples and runs a model simulation for each draw of the parameters. In a multi-model ensemble, the simulations available can be viewed as drawing a sample from the space of models. Interpretation, however, of such a sample based on an ensemble of opportunity of climate models—for example, those that participated in CMIP3 or CMIP5—remains a challenging topic (Annan and Hargreaves, 2010; Rougier et al., 2013). Estimation of event probabilities (and derived quantities such as FAR or RR) and uncertainties then proceeds by treating the variability induced by varying the parameters or using multiple models as sampling variability from a frequentist perspective.

While implementation of such a procedure is straightforward computationally, the statistical framework for the interpretation of the results remains underdeveloped and requires careful thought and further research. Such analyses are not easily interpreted from a frequentist statistical perspective because they combine uncertainty from conceptually different sources (e.g., chaotic variability generated spontaneously by the climate system versus deliberate investigator imposed variations of parameter values versus the sequence of difficult to characterize decisions that are made in construct-ing a given CMIP5 climate model). They might be considered as Bayesian analyses, however, that sample from prior distributions over parameters and/or models (Tebaldi et al., 2005), although this interpretation may require some alteration to the details of the statistical analysis. Finally, it is important to recognize that while a Bayesian analysis quantifies the uncertainty for the given prior distribution (e.g., over parameters or models), results depend on that prior distribution, and the prior distribution may be difficult to characterize.

Such analyses, either frequentist or Bayesian, do not eliminate or quantify statistical bias from systematic differences between model results and the real climate system (see Box 3.3). Because observations are not available to assess the quality of model-based estimates of p_0, and they will often be inadequate to assess estimates of p_1, it is not possible to determine whether estimates of p_1, p_0, FAR, and RR are unbiased estimates of their real-world counterparts. Viewed from a Bayesian perspective, the prior distribution over parameters or models is not updated based on observed data as in a standard Bayesian analysis.

This concern about statistical bias can be stated in another way in the context of multi-model analyses. Agreement among models in estimates of p_1, p_0, FAR, and RR may be considered a necessary, but not sufficient, condition for confidence in an attribution statement because agreement does not limit the possibility of inadequacies and unknown errors that are common among models.

BOX 3.3
BIAS VERSUS VARIANCE

In considering the frequentist statistical properties of a statistical procedure, statisticians distinguish bias from variance. *Bias* is the systematic difference between the true quantity and data-based estimates of that quantity that is present across repeated studies with statistically equivalent samples of data. *Variance* is the variability of the estimates across repeated studies. In principle, it is straightforward (though not necessarily practical) to reduce variance by increasing the sample size. In contrast, bias is hard to quantify and to reduce in either frequentist or Bayesian analyses, particularly if it is fundamentally related to the manner in which the data are collected. For example, if there is no limit on computing resources, then the variance of a model-based estimate of risk ratio (RR) can be reduced to any specified small level by generating sufficiently large ensembles of the factual and counterfactual simulations from that model. But because the estimate is from a model that inherently has limitations, it will nevertheless be biased relative to the true RR. Because one cannot carry out a controlled experiment by drawing samples of real Earth systems, it will be difficult to avoid bias.

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In light of the difficulties that arise in trying to quantify overall uncertainty in model-based analyses, one alternative to formal uncertainty quantification is simple sensitivity analysis that assesses how sensitive the results are to such choices as model or parameter values. For example, certain work in the statistics literature attempts to quantify the extent to which a potential source of bias could change the conclusions of an analysis (e.g., VanderWeele and Arah, 2011). Alternatively, analyses could make use of observations to weight parameter values and models based on a comparison of factual world simulations to observations. Choosing the metric on which to judge the skill of different models remains difficult, however, and rankings of models can vary widely depending on the metric and outcome under consideration (e.g., Flato et al., 2013; Gleckler et al., 2008). Furthermore, such a weighting assumes that it also holds in the counterfactual world. As yet, there has been limited success in identifying "emergent constraints" (e.g., Bracegirdle and Stephenson, 2012; Hall and Qu, 2006) that use observations to identify models that will perform similarly under future forcing, and similar difficulties can be expected when considering model performance in the counterfactual world.

In summary, given the complicated nature of the various sources of uncertainty in model-based analyses, efforts at uncertainty quantification in event attribution analyses mix frequentist and Bayesian ideas and may not carefully define the statistical framework being used. The lack of a defined statistical framework makes it difficult to evaluate the uncertainty statements, yet such evaluation is a critical component of the overall evaluation of event attribution methods. As with operational weather forecasting, it is important to evaluate not just the best estimate in the attribution statement but also the uncertainty stated for that estimate.

THE USE OF MULTIPLE METHODS

Any study on event attribution will be influenced by the way the event is selected and framed, the way uncertainties are estimated and communicated, and the extent to which the model is suitable for purpose. It is clear, however, that satisfyingly addressing uncertainties in all of these aspects is difficult if not impossible. In the absence of being able to do so, some studies have started using multiple, different methods to estimate human influences on a given event. King and colleagues (2015) use an observations-only detection method to estimate changes in return period of an unusually warm year in Central England Temperature (CET), in comparison with a CMIP5 modeling-based approach. The latter approach uses climate model simulations, selecting models that reasonably simulate the variability of CET, and it compares the probability of an anomalously hot year between simulations with natural forcings only and those that include anthropogenic forcings. Results were not identical but were comparable, and the authors chose to communicate the conservative result. Nevertheless, while unusually hot years are an interesting test bed, they pose greatly reduced difficulties compared to other types of extremes. Hence, multi-approach papers for non-temperature extremes in particular are recommended.

There also are a variety of papers analyzing similar events in the *Bulletin of the American Meteorological Society* (BAMS) reports (Herring et al., 2014, 2015b), such as multiple analyses of the California drought (Funk et al., 2014; Swain et al., 2014; Wang and Schubert, 2014). The case of the California drought illustrates that careful analysis of contradictory results in particular is required and that using a single study may provide incomplete information: Swain and colleagues (2014) show that the atmospheric conditions, such as the anomalous ridge that contributed to the drought, may have been made more likely due to global warming (at least in CMIP5 models). Thermodynamic changes such as more available water vapor may counteract human influences on circulation (Wang and Schubert, 2014), which means human influences on California precipitation are unclear (all three papers).

Bringing multiple studies together, when there is robust scientific understanding, helps separate results that are reasonably robust from those that are more sensitive to framing and approach.

RAPID ATTRIBUTION AND OPERATIONALIZATION

The media, the public, and decision makers increasingly ask for results from event attribution studies during or directly following an extreme event. To meet this need, some groups are developing rapid and/or operational event attribution systems to provide attribution assessments on faster timescales than the typical research mode timescale, which can often take years (Box 3.4).

Efforts to develop rapid event attribution (hours to days) are often being developed in a research setting by university-based groups because they tend to operate in a reactionary mode and to analyze events that draw interest and that fall within their capabilities.

While some groups are working to provide attribution statements on rapid timescales, a key focus of operational attribution is to provide attribution assessments on seasonal timescales. Operational attribution is defined as a regular activity with well-established protocols to systematically evaluate the causes of extreme events based on predefined and tested methods. It would provide results on a range of timescales:

BOX 3.4
EXAMPLES OF RAPID AND/OR NEAR-OPERATIONAL EVENT ATTRIBUTION EFFORTS

A brief summary of the main groups engaging in the development of operational and/or rapid attribution systems is included below.

EUCLEIA

The EUropean CLimate and weather Events: Interpretation and Attribution project, or EUCLEIA, is a 3-year project funded by the European Union that studies the attribution of weather and climate risks, primarily for Europe. The project aims to "provide well-verified assessments of the extent to which weather-related risks have changed due to human influences on climate" and to "identify those types of weather events where the science is still too uncertain to make a robust assessment of attributable risk."[a] A key deliverable of this project is an operational attribution system based on HadGEM-A,[b] which will run on a seasonal cycle, delivering attribution assessments for each season together with estimated uncertainty. A component of the project in its preoperational phase is to test developing capability to assess specific weather and climate events, using test cases of heat waves, cold spells, droughts, floods, and storm surges that are being conducted. An early example is the exploration of the role of atmospheric circulation and climate change in the extreme rainfall in the United Kingdom during the winter of 2013-2014 (Christidis and Stott, 2015). EUCLEIA is working closely with stakeholders to derive the requirements for this operational system and involves social scientists as well as natural scientists in order to better obtain insights from the stakeholder perspective.

EUCLEIA also collaborates with weather@home and World Weather Attribution, whose efforts are described below.

World Weather Attribution[c]

World Weather Attribution, or WWA, is an international effort coordinated by Climate Central[d] designed to sharpen and accelerate the ability of the scientific community to not only analyze but also communicate the possible influence of climate change on extreme weather events. The project relies on a range of approaches described in this chapter, including observationally based approaches, the use of existing ensembles of climate change simulations such as those produced for CMIP5, and the generation of very large ensembles with the weather@home infrastructure. In the latter case, WWA uses the weather@home experimental design, but it replaces the observed sea surface temperatures (SSTs) with seasonal forecasts in order to predict the probability of extreme events under current climate conditions 1 month ahead. The counterfactual world is simulated as in other weather@home experiments. The intent is both to shorten the response time of attribution studies following an event, to an almost real-time response, and to restrict the conditioning of attribution statements to that component of observed natural variability that is predictable on these timescales, because this is more consistent with the level of conditioning of these statements expected by stakeholders (see discussion of the role of conditioning in attribution statements). WWA is also coordinating with the international disaster response community through its partnership with the Red Cross/Red Crescent Climate Centre.[e]

BOX 3.4 CONTINUED

Weather@home[f]

Weather@home is a project within climate*prediction*.net, a climate-modeling project that uses the computing capacity available in desktop computers of volunteers in the general public. Climate*prediction*.net is based at the University of Oxford in the Environmental Change Institute and the Oxford e-Research Centre. Using the computing resources provided by volunteers through the climate*prediction*.net distributed computing network, weather@home runs very large ensembles of simulations with the UK Met Office's HadAM3P global atmosphere-only model to investigate how the odds of extreme weather events change due to anthropogenic climate change, other external forcings, and natural variability. Depending on the problem that is being investigated, the system can also be configured to dynamically downscale the output from HadAM3P by nesting the HadRM3P[g] regional model nested in the output from the global model.

For example, to investigate the 2013 heat waves and drought in Australia and New Zealand, weather@home is using their distributed computing power to run two experiments: representing 2013 as observed using SST observations from December 2012 through November 2013 and present-day atmospheric gas concentrations, and the counterfactual world of 2013 obtained by removing the modeled SST patterns of anthropogenic forcing from the observed 2012/2013 SSTs.[h]

While weather@home is not aiming to do its own rapid attribution system, they are nonetheless a crucial partner in WWA and, as such, provide real-time attribution.

Weather Risk Attribution Forecast

The Weather Risk Attribution Forecast (WRAF) is a collaboration of the University of Cape Town, the Lawrence Berkeley National Laboratory, and the University of Botswana, which provides the first real-time product to examine whether and how greenhouse gas emissions have contributed to our weather. The WRAF is a product, based on HadAM3-N48[i] and HadAM3P- N96[j] models, run in parallel with the seasonal forecast produced by the Climate Systems Analysis Group (CSAG) at the University of Cape Town. The attribution forecasts are issued monthly. Preliminary forecasts are generated 1 month in advance; the final (hindcast) version is issued 2-3 months later when observed SSTs become available and are integrated into the model simulations.

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[a] See http://eucleia.eu (accessed June 1, 2016).

[b] HadGEM-A is a coupled Earth System Model that was used by the Met Office Hadley Centre for the CMIP5 centennial simulations.

[c] See http://www.climatecentral.org/wwa (accessed June 1, 2016).

[d] See http://www.climatecentral.org (accessed June 1, 2016).

[e] See http://www.ifrc.org (accessed June 1, 2016).

[f] See http://www.climateprediction.net/weatherathome (accessed June 1, 2016).

[g] HadRM3P is a high-resolution, regional configuration of HadAM3 (atmosphere-only model) with improved physics.

continued

BOX 3.4 CONTINUED

[h] See http://www.climateprediction.net/weatherathome/australia-new-zealand-heat-waves/experiment-setup (accessed June 1, 2016).

[i] HadAM3-N48 is a dynamic model of the atmosphere produced by the UK Met Office Hadley Centre. It solves equations describing the evolution of the atmospheric state on a polar grid with a spatial resolution of 3.75 degrees in longitude and 2.5 degrees latitude with 19 vertical levels.

[j] HadAM3P-N96 is a dynamic model of the atmosphere produced by the UK Met Office Hadley Centre. It is a modified version of HadAM3 that runs at a higher spatial resolution (1.875 × 1.25 degrees) and uses different methods of estimating the effects of small-scale processes.

during and immediately following an event, monthly or seasonally, and for publication in annual assessments (Stott et al., 2015). Such results would be supported by subsequent in-depth study of key events and regular updates on the performance of the event attribution system. By utilizing predetermined, objective event selection criteria, selection bias (see Chapter 2) would be minimized, helping stakeholders understand how individual events fit into the broader picture of climate change (Stott et al., 2015). The nascent efforts to operationalize event attribution employ many of the methods discussed in this chapter.

Objective approaches to compare and contrast the analyses among multiple different research groups based on agreed event selection criteria are yet to be developed, although the annual BAMS special issues on event attribution (Herring et al., 2014, 2015b; Peterson et al., 2012, 2013a) could be considered an initial step in the ongoing operationalization of event attribution.

Groups engaging in various near-operational and rapid event attribution efforts acknowledge that careful consideration must be given to the assessment of uncertainties and communication of the results. As discussed in Chapter 2, the ways in which the research questions are framed can influence the outcomes and results of event attribution analyses. The time constraints associated with rapid attribution may affect framing and methodological choices by limiting analyses to approaches that can be undertaken quickly. Examples of possible limitations are: reliance on a primarily observationally based approach and possibly on station data that have not yet been quality controlled; inability to assess the robustness of model-based results through reliance on single models with specified SSTs or "off-the-shelf" global model runs from an ensemble of opportunity; and insufficient time either to investigate causal mechanisms or to evaluate the model for the particular extreme events. Providing robust attribution statements on very short timelines is therefore difficult and results are likely to be less robust. This has to be balanced against the need for timely information. Hence, it is important to follow up on any rapid attribution with studies that are not subject to such limitations in order to evaluate and improve the reliability.

Clearly communicating key messages to stakeholders about the methods and framing choices as well as the associated uncertainties and probabilities is critical to ensuring successful operational services. Furthermore, an important component of an operational system would be the use of methods to routinely evaluate the reliability of the event attribution assessments in much the same way that objective skill scores are an important aspect of the monitoring and evaluation of the performance of seasonal forecasting systems. Additionally, such systems should have rigorous approaches to managing and implementing system improvements, again akin to the methods used to continually improve models and data assimilation systems in operational weather prediction centers.

GUIDANCE FOR INCREASING THE ROBUSTNESS OF EVENT ATTRIBUTION

There is no single best method or set of assumptions for event attribution because these depend heavily on the framing of the question and the amount of time available to respond to the question. Time constraints may themselves affect framing and methodological choices by limiting analyses to approaches that can be undertaken quickly (e.g., van Oldenborgh et al., 2015). This could mean relying primarily on observations, or using conditioned or highly conditioned modeling approaches that can be undertaken with computationally fast dynamic models, or using unconditional approaches based only on available simulations, such as the CMIP5 ensemble of historical climate change simulations.

Assessment of model quality in relation to the event or event class of interest is critical for enhancing confidence in event attribution studies. Different event types pose different requirements for model fidelity. In general, larger-scale and longer-timescale events should be representable in global models, although representation of land-surface processes may be important for drought and heat waves and may lead to biases in event amplitude—for example, in some models (e.g., Hanlon et al., 2013). Smaller-scale and shorter-timescale events may require high-resolution models, which generally will be regional and could be either embedded within a global model or run in weather-forecast mode; they also could be based on a well-performing downscaling tool. Community-developed standards could help to encourage careful assessment.

For extremely rare meteorological events (e.g., Hurricane Sandy), the combination of rarity and spatial scale makes an unconditional attribution approach challenging from a modeling perspective. In this case, following the event itself in a highly conditional manner, either through short-term forecasts or through data assimilation, allows the use of high-resolution modeling tools capable of representing the event with great fidelity. When discussing results of such studies, however, this conditioning needs to be clearly communicated because it strongly constrains the types of statements that can be made. In particular, the change in probability of event occurrence—measured, for example, by FAR or RR—cannot be assessed by this method, and this could serve either to counteract or to amplify the changes in event magnitude or other properties that are attributed.

In almost all cases, event attribution questions relate to differences in the probability of a given event class or in the distribution of event magnitudes, and questions should be answered in the context of explanations about sources of uncertainty. Different approaches and levels of conditioning may help to control the sources of uncertainty, with greater amounts of conditioning being expected to improve signal-to-noise ratios. Nevertheless, uncertainty can never be fully eliminated. Thus, statistical methods are required in all cases, including those when the analysis is highly conditioned on specific features of the circumstances surrounding an event, to properly account for uncontrolled variability and uncertainty. Statistics plays a key role in framing, designing, and interpreting event attribution studies.

Uncertainty in event attribution results needs to be estimated as much as possible and clearly communicated. Uncertainty emerges from a number of different sources. In the context of event attribution, the main source of sampling uncertainty is the chaotic unforced variability that is a pervasive feature of the climate system and that is simulated to various extents by climate models, even when run without any type of time-varying natural or anthropogenic external forcing. This can include substantial contributions from the low-frequency natural variability of the climate system, including the effects of long-term oscillations that may confound the diagnosis of the effects of human-induced changes in analyses based on short observational records. There are well-established statistical procedures for accounting for sampling uncertainty induced by limited sample sizes in observations and in initial condition model ensembles. In contrast, quantifying uncertainty from using models to represent the climate system is difficult, and well-established statistical procedures are not available for use in the event attribution context. In some cases, results from methods that are designed explicitly to account for sampling variability have been given a Bayesian interpretation without establishing the framework within which such an interpretation would have meaning. In contrast, standard frequentist analysis or explicit implementation of Bayesian methods stands on firm statistical footing. The statistical framework for the interpretation of analyses that sample from parameter, model, and initial/boundary condition distributions is not yet well-defined and needs further development. While a full quantification of uncertainty is desirable, it may be difficult to quantify the effect of many sources of uncertainty in a falsifiable way. Thus, sensitivity analyses may offer the best practical path forward.

Event attribution results, particularly for local events or such events that are strongly influenced by climate dynamics and its changes, are subject to substantial uncertainty and hinge on assumptions made when selecting a modeling setup and using statistical tools to quantify uncertainty. Given that these choices and the representation of uncertainties can be highly technical, communicating results of event attribution to the broader public in a way that does not overstate the result or fails to sufficiently highlight the assumptions involved in the analysis is difficult.

CHAPTER FOUR

Attribution of Particular Types of Extreme Events

The scientific issues and challenges associated with extreme event attribution vary greatly from one event type to another. This chapter considers event types one at a time, focusing first on issues associated with event definition. Such issues may be conceptual or associated with limitations of the available observations. As background to attribution studies of single events of each type, prior knowledge also is reviewed. This includes research on patterns or trends in historical observations as well as projections of future change using climate models. Though not strictly attribution, this broader context is relevant to the statement of task in that any scientifically responsible attribution statements are informed, necessarily, not just by formal attribution studies but by all aspects of existing scientific understanding of the relationship between the extreme event type in question and climate change. Existing attribution studies on single extreme events also are reviewed as part of this background. The number of studies varies widely; for some event types there are few or even no such studies. For each category, advances that might be possible in the near future are considered.

The event types considered here do not represent all possible event types influenced by climate factors; moreover, some examples are of events defined not solely by atmospheric or meteorological quantities like temperature. The section on extreme precipitation, a meteorological event, considers only precipitation itself, not flooding, as the defining characteristic. The section on drought focuses on meteorological drought (primarily precipitation deficit) and hydrological drought, which are consequences of atmospheric factors. Wildfires are not, strictly speaking, meteorological events at all, but they—like other extreme events discussed here—are of great societal concern, and the likelihood and extent of wildfires can be influenced by climatic factors. These choices about how and whether to include non-meteorological factors in our assessment of attribution are subjective and reflect committee judgment, available literature, and expertise. The committee recognizes that many additional events and other natural hazards may be impacted by climate change (e.g., sea level rise, landslides, coral bleaching, etc.) that could be discussed in the context of event attribution.

EXTREME COLD EVENTS

Event Type Definition

Extreme cold events are generally described in terms of temperature, although wind, snow, and ice can compound the impacts of an extreme cold event (Figure 4.1). The actual temperatures that characterize a cold event vary regionally and seasonally, but the temperatures during such an event will be in the cold tail of the probability distribution of temperatures for a location or region and time of year. The event definitions most often are based on daily temperatures, although multiday or longer averages also have been used. The criteria can be either an absolute temperature threshold (e.g., 0ºC, 0ºF, –20ºC), often arbitrarily chosen, or a percentile value such as the 1-percentile or the 10-percentile criterion used in the Expert Team on Climate Change Detection and Indices (ETCCDI) ClimDEX database (Sillmann et al., 2013a,b). Duration and inten-

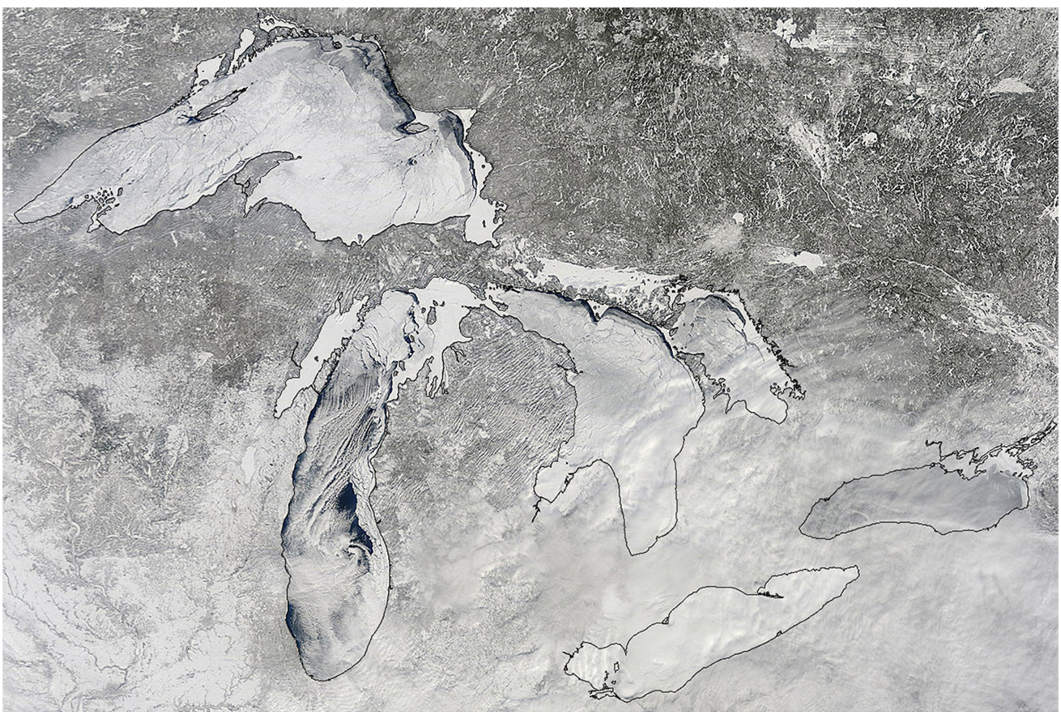

FIGURE 4.1 The frozen Great Lakes during February 2014 (National Aeronautics and Space Administration image). Cold outbreaks ranging from days to seasons still occur, but their frequencies and magnitudes are decreasing.

sity are other metrics of an extreme cold event. Metrics of duration can be the length of time (e.g., number of days) that a certain minimum threshold of temperature is exceeded or the time for which the multiday average temperature is below a prescribed threshold; intensity, on the other hand, is often measured by the lowest temperature attained. In some instances, the severity of a cold event has been quantified as the product of the event duration and intensity.

Prior Knowledge and Overview of Attribution Studies

Extreme cold events are driven by a combination of thermodynamics (cold air mass formation) and dynamics (the large-scale circulation, advection). Horton and colleagues (2015) have used self-organizing maps derived from atmospheric reanalyses to show that both factors have played roles in recent changes in extreme cold events. In particular, increasing trends in northerly flow have led to an increasing trend in winter cold extremes over central Asia.

The research to date indicates that extreme cold events are less frequent and less severe than in previous decades, although interannual variability is still large enough to allow extreme cold events such as occurred in North America in 2014 and Europe in 2012. Even over 60-year periods, trends in the coldest temperature of the year are not compellingly positive over Europe and the United States (van Oldenborgh et al., 2015, Figure 4b). The increases in cold extreme daily minimum temperatures (i.e., warming) are generally greater than are the increases in extreme daily maximum temperatures, and there is no indication of increased variability of daily or monthly winter temperatures over the United States (Kunkel et al., 2015; Screen et al., 2015). A similar warming of the coldest temperatures over other land areas of the world emerged from Sillmann and colleagues'analysis (2013a,b) of the ETCCDI indices for 1948-2005 in 4 different atmospheric reanalyses and 31 Coupled Model Intercomparison Project Phase 5 (CMIP5) models. The tendency for cold extremes to warm by more than hot extremes also is apparent in Collins and colleagues' (2013) Figures 12.13 and 12.14 as well as the U.S. National Climate Assessment's Figure 2.20 (Melillo et al., 2014).

The general expectation is that cold events defined relative to fixed temperature thresholds should become less frequent and less severe as the climate warms on the global scale. But, it is nonetheless possible for them to increase in frequency or intensity regionally for periods of time (e.g., due to increases in the intensity of cold air advection from polar to lower-latitude regions).

Extreme cold events in eastern North America have characterized a few recent winters (2014, 2012), but such events are less frequent and their actual temperatures

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less extreme in the past few decades than in earlier decades of the 20th century (van Oldenborgh et al., 2015; Wolter et al., 2015). In an analysis of observational data, van Oldenborgh and colleagues (2015) find that the return times of the lowest minimum temperatures of 2014 in the midwestern United States ranged from 6 to 44 years in the present climate, but only from 3 to 7 years in the climate of the 1950s; likewise, return times of the cold winter-averaged temperatures were greater in the present climate than in the 1950s. Decreases in cold wave events of 4-day duration had the lowest frequency during the 2001-2010 decade in all eight subregions of the United States examined by Peterson and colleagues (2013b), although the decade of the 1980s had the highest frequencies nationally. But, 20-year return values of the daily minimum temperatures warmed over the entire contiguous United States during the 1950-2007 period, by as much as 3° and 4ºC in much of the West (Peterson et al., 2013b).

There is a notable absence of conditional attribution studies pertaining to extreme cold events. Nevertheless, observational studies do provide evidence of a general decrease in the frequency of occurrence of extreme cold temperatures over the past few decades in most land areas of the world (Hartmann et al., 2013; Kharin et al., 2013). Kharin and colleagues show that the trends of extreme cold ETCCDI indices are comparable in atmospheric reanalyses and CMIP5 historical simulations in which external forcing was historical. In this respect, external forcing (including its anthropogenic component) is implicated in the decreasing frequency of observed cold extremes. The reduction of cold extremes has been detected and attributed in extreme seasonal and annual temperatures (Christidis et al., 2012; Stott et al., 2013) as well as in the ETCCDI metrics of cold daily extremes (Morak et al., 2013; Zwiers et al., 2011). Attribution studies by Kharin and colleagues (2013) and others have drawn on comparisons of observational data with climate model simulations driven by natural and anthropogenic forcing.

More recently, Wolter and colleagues (2015) also find decreasing frequencies of extreme cold events: in this case, events affecting the Upper Midwest of the United States, in CMIP5 models and in an ensemble of Community Earth System Model (CESM) simulations driven by historical forcing. The decreased frequency of cold extreme arises primarily from the underlying increase of the mean temperature, not from the decreased variability (Screen et al., 2015; Trenary et al., 2015; Wolter et al., 2015). Gao and colleagues (2015) show that decreases in temperature variance account for generally less than 20% of the projected 21st-century decreases in extreme cold temperatures over North America; the mean warming accounts for most of the remainder. The fact that underlying warming has moderated cold extremes also has been shown using daily circulation analogs for the European cold events of 2010 (Cattiaux et al., 2010).

Several recent attribution studies have examined extreme cold events in the context of retreating Arctic sea ice. By prescribing reduced Arctic sea ice cover but historically observed ocean temperatures outside of the Arctic in two different global climate models, Screen and colleagues (2015) find that ice loss is associated with decreased likelihood of extreme cold events (as well as decreased variability of temperature) over nearly the entire Northern Hemisphere land areas. The exception is the central Asian region, where the probability of extreme cold events increases with ice loss, in agreement with earlier studies (Inoue et al., 2012; Kim et al., 2014; Mori et al., 2014). For the rest of the hemisphere, the underlying warming dominates the trend of extreme cold events, implying that thermodynamically induced changes dominate dynamically induced variations, such as the jet stream. While some studies do point to influences of sea-ice change on large-scale dynamics (Francis and Vavrus, 2015; Jaiser et al., 2013; Kim et al., 2014; Peings and Magnusdottir, 2014), the signals remain embedded in the noise of natural variability (Barnes et al., 2014) and, from the perspective of extreme cold events, are overwhelmed by the underlying warming. Additional attempts to link Arctic warming with an amplified jet stream and cold winters in middle latitudes have been made by Francis and Vavrus (2012, 2015).

On the Horizon

While the observational network is sufficiently dense to capture extreme cold events over most land areas (except possibly Antarctica), there have been few evaluations of the ability of models to simulate the frequency and the intensity of these events. Sillmann and colleagues (2011) and Whan and colleagues (2016) show that some climate models are able to capture the linkage between atmospheric blocking and cold events over Europe and North America, respectively. More comprehensive assessments are needed, however, of models' ability to simulate cold temperatures for the right reasons. The lowest temperatures are often reached under clear-sky, calm conditions characterized by strong near-surface temperature inversions. Limited vertical resolution is likely to impact model simulation of temperatures in such situations. It also is apparent from the studies cited above that atmospheric blocking events must be well simulated if models are to simulate extreme cold events realistically. Finally, decadal and even longer trends in cold extremes can be impacted by multidecadal variability in the climate system (e.g., the Atlantic Multidecadal Oscillation [AMO] and the Pacific Decadal Oscillation [PDO]), which models must simulate in order to capture the temporal spectrum of extreme cold events.

With regard to a possible role of sea-ice loss and Arctic amplification, mechanistic linkages are still an active area of research. Such linkages may contribute to cold events in some areas, particularly central Asia, but the dynamic mechanisms underlying such linkages need to be established. Hypothesis-driven model experiments are needed to identify any dynamic mechanisms linking Arctic changes with midlatitude extreme events.

Finally, impact-relevant metrics of extreme cold events need to be developed for use in attribution studies. In a climate with polar amplified warming, increased equatorward flow will likely be required if cold air advection is to cause any hypothetical increase of extreme cold events in middle latitudes. In such cases, the extreme cold temperatures will be associated with winds to a greater extent than in the past, which, in turn, will contribute to more extreme windchill values. Metrics such as the windchill index are just starting to be used in cold event attribution studies (Gao et al., 2015).

EXTREME HEAT EVENTS

Event Type Definition

Heat events have been defined over a variety of timescales in the literature, from as little as 1 day to at least 1 year. This report distinguishes between temperature anomalies of short duration (days, heat events) and those of longer duration (weeks and longer, warm anomalies). Because temperature is a continuous variable, the spatial extent of a given heat event or warm anomaly is somewhat subjectively defined and can change through time as the event unfolds. Typically, a latitude-longitude box is used, but sometimes single stations (e.g., King et al., 2015) or political boundaries (e.g., Texas or Korea) are used. While a large majority of studies focus on heat events over land, some (e.g., Funk et al., 2013; Kam et al., 2015) have looked at warm sea surface temperatures (SSTs) anomalies over periods of seasons to years.

The impacts of heat events and warm anomalies (e.g., on human health) can be exacerbated by high dew points, and also by high nighttime temperatures (which, in turn, are more likely if dew points are high; e.g., Gershunov and Guirguis, 2012). Conversely, the amplitudes of the warm anomalies themselves can be increased by land-atmosphere feedbacks if moisture is low; this connection between drought and warm anomalies is covered below in the section on drought. In addition to their direct impacts, warm anomalies over both land and ocean can contribute to other types of extreme events (e.g., droughts or wildfires).

Prior Knowledge and Overview of Attribution Studies

The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (Hartmann et al., 2013) noted that "a large amount of evidence continues to support the conclusion that most global land areas analyzed have experienced significant warming of both maximum and minimum temperature extremes since about 1950" and concludes that "it is . . . *very likely* that human influence has contributed to observed global scale changes in the frequency and intensity of daily temperature extremes since the mid-20th century, and *likely* that human influence has more than doubled the probability of occurrence of heat waves in some locations" (Figure 4.2). They also note that minimum temperatures have increased more than maximum temperatures, and maps of changes show statistically significant increases in two indices of extreme temperatures in almost every land area since 1950: the 90th percentile of daily minimum temperatures and the 90th percentile of daily maximum temperatures. For the region of North and Central America (lumped for purposes of simplicity in a table), they assess changes in heat waves and warm events as "*medium confidence*: increases in more regions than decreases but 1930s dominates longer-term trends in the USA." The U.S. National Climate Assessment corroborates and provides additional details: "Heat waves have generally become more frequent across the U.S. in recent decades, with western regions (including Alaska) setting records for numbers of these

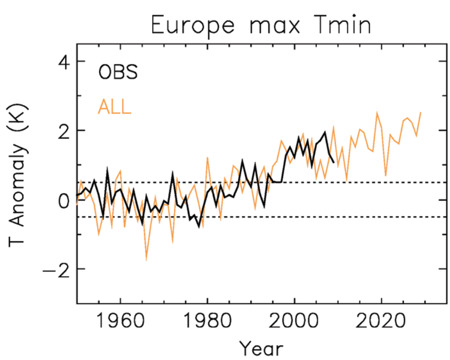

FIGURE 4.2 This figure shows a time series of the annual maximum nighttime temperature averaged over the European Region. Temperatures are plotted as anomalies, or deviations from normal (in this case, 1961-1990), in degree Kelvin (K). Observed temperatures are represented by the black lines and are based on Caesar et al. (2006; updated). The orange lines come from model simulation (Martin et al., 2006). Both observations and model output show an increasing trend in nighttime temperature anomalies over time. The horizontal dotted lines denote the uncertainty range (5-95%) due to natural climate variability. SOURCE: Stott et al., 2011.

events in the 2000s. . . . Most other regions in the country had their highest number of short-duration heat waves in the 1930s" (Walsh et al., 2014). Regarding future projections, in the IPCC Fifth Assessment Report, Collins and colleagues (2013) stated that "It is also *very likely* that heat waves, defined as spells of days with temperature above a threshold determined from historical climatology, will occur with a higher frequency and duration."

For northern hemisphere land areas, numerous studies have examined different aspects of trends in extreme temperatures. Horton and colleagues (2015), for example, relate trends in extreme temperatures to atmospheric circulation changes over the 1979-2013 period, and Abatzoglou and Redmond (2007) explain the asymmetry in seasonal warming (1958-2006) between the eastern and western United States as a consequence of changes in atmospheric circulation. Peterson and colleagues (2013b) note the decadal changes in heat waves in nine U.S. regions, defined as collections of states, for each decade since the 1900s, where a heat event is defined as a 4-day period exceeding the 5-year return period value for the period 1895-2010 (Figure 3.5). The 1930s remains the decade with the most heat waves, a curious fact that may be partly explained by the types of circulation changes noted by Horton and colleagues (2015) and Abatzoglou and Redmond (2007) for more recent periods. They note that even on these spatial scales, natural variability can dominate over anthropogenic warming to date.

Heat events are arguably the extreme weather events for which attribution studies are most straightforward and have the longest history. Public and scientific interest in extreme event attribution increased rapidly after the 2003 European heat wave, which was associated with tens of thousands of excess deaths and prompted the seminal paper by Stott and colleagues (2004), whose methods form the groundwork for much subsequent work in this field (e.g., fraction of attributable risk). Of the events covered in the annual Explaining Extreme Events special issue of BAMS, heat events or warm anomalies are the largest share (e.g., 8 out of 32 for 2014). This may reflect the greater likelihood of successful attribution of heat waves, compared to other event types, to human-induced climate change using existing models and data (see the discussion of selection bias in Chapter 2).

Most attribution studies of heat events and warm anomalies include an assessment of the trend in the temperature statistic used to define the event and an indication of how extreme the event was in the context of the observed record. Many studies also compare the magnitude with a distribution from long CMIP5 runs: in some cases, from long simulations with constant 19th-century radiative forcing; in some cases, from simulations using observed radiative forcing (i.e., CMIP5-ALL). For example, the European annual mean temperature in 2014 was shown to be far outside the distribution of CMIP5 20th-century simulations even with observed forcing (Kam et al., 2015).

Most recent studies calculate fraction of attributable risk (FAR), and some also estimate the uncertainty in FAR—for instance, by bootstrapping subsets from natural ensembles using 10 general circulation models (GCMs) (King et al., 2015). Some studies also explore how the results depend on event definition: for example, Black and colleagues (2015) examine the January 2014 heat events in Adelaide and Melbourne, Australia, using definitions of heat wave with durations ranging from 1 to 5 days. Some studies also compute return periods for different thresholds (e.g., Christidis et al., 2015) or the risk ratio (RR) (e.g., Hannart et al., 2015a).

A number of studies used very large ensembles (i.e., bigger than available from CMIP5) from either a global (e.g., Massey et al. 2014; Rupp et al., 2012) or a regional (Black et al., 2015; King et al., 2015; Figure 4.3) atmospheric model. In these studies, changes in FAR, RR, and/or return period are calculated using an approach (see Chapter 3) that estimates the anthropogenic contribution to modern SSTs and subtracts that from the observed SSTs, typically with SST patterns from at least a few global coupled climate models used to estimate the anthropogenic contribution. Other approaches to estimating the counterfactual include using early 20th-century or preindustrial control (e.g., Black et al., 2015).

On the Horizon

Simulations of heat events and warm anomalies may benefit from improvements in land-surface schemes in global and regional models. Few studies include an evaluation of the models' ability to simulate the important statistical properties of the event of interest. While Trenberth and colleagues (2015) do not include heat events among their examples of a highly conditioned approach, this approach clearly could be applied to heat events, starting perhaps with one of the most impactful events, like the Russian heat wave of 2010. Heat events and warm anomalies may be the best candidates for assessing the reliability and robustness of attribution methods because the direct thermodynamic effects on this type of extreme event are generally more straightforward than, for example, heavy rainfall.

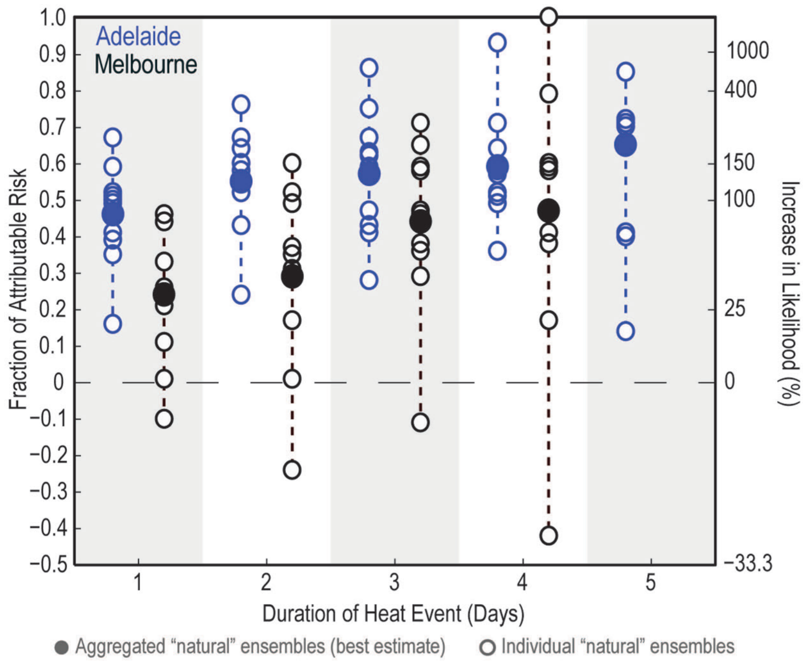

FIGURE 4.3 The single very hot days in Melbourne still show a large spread in FAR values despite the higher frequency of such events under both the "natural" and the "all forcings" climate scenario, compared with the counterfactual. This figure shows FAR and the corresponding increase in likelihood calculated for Adelaide (blue) and Melbourne (black) heat waves of different durations. The temperature threshold used to define heat waves was 42°C for Adelaide and 41°C for Melbourne. Ten "natural" ensembles are aggregated (black symbols) in order to calculate a best estimate of FAR, while each of the "natural" ensembles is considered separately (white symbols) in order to better sample the possible range of FAR values and estimate uncertainties. SOURCE: Black et al., 2015.

DROUGHTS

Event Type Definition

Droughts are complex phenomena involving various combinations of atmospheric inputs (chiefly precipitation, but also temperature), storage terms like soil moisture and snowpack, and responses of the human and natural system on a variety of timescales. In addition, there are several types of drought (Wilhite and Glantz, 1985); these include meteorological drought (lower than expected precipitation over an extended period); hydrological drought (depletion of surface or subsurface water supply); agricultural drought (aspects of meteorological drought or hydrological drought that have impacts on agriculture, like reduced crop yield); and socioeconomic drought (effects on the supply of economic goods like hydroelectric power). In this report, we focus on meteorological drought and hydrologic drought.

Droughts are driven by multiple factors, including precipitation deficits, feedbacks associated with soil moisture and evapotranspiration, and large-scale dynamics associated with ocean, land, and air temperatures. Droughts can occur across broad regions up to continental scale, but they also can have dramatically different implications for communities that are in close proximity to each other. The same drought can change in location and intensity from month to month in dramatic ways, as can be seen in the maps produced by the National Integrated Drought Information System (NIDIS) and the U.S. Drought Monitor. Furthermore, anthropogenic climate change has been shown to affect drought differently in different seasons and in different regions, particularly in the varied ways that reduced snowpack affects surface flows.

As Redmond (2002) points out, drought may be better defined as "insufficient water to meet needs." Thus, a holistic view of droughts encompasses both meteorological and hydrologic factors, on the "supply" side, and terrestrial ecosystems, human consumption, and losses, on the "demand" side, as well as infrastructure for water delivery, policies that affect water use, flexibility in addressing local shortfalls, etc. Because event selection for extreme event attribution is often driven by the magnitude of the impacts rather than the magnitude of the atmospheric driver, such considerations can be important in framing a drought attribution study. Similar holistic considerations apply to other extreme event types, to varying degrees.

One reason that attributing both extreme flooding and extreme droughts to anthropogenic climate change is particularly difficult is that changes in the hydrologic cycle are both causes of the event (a climatic driver) and consequences of the event (with water supply availability and flooding being literally "downstream" from the changes in precipitation). Another is that land use decisions and investments in water-related infrastructure for hydroelectric power generation, flood control, and water supply have dramatically changed the natural hydrology within watersheds and have usually decreased—but sometimes increased—the risks associated with extreme events. It is therefore often quite challenging to attribute the impacts of droughts and floods to extreme events in the same way that it is possible to attribute changes in the intensity of precipitation (which is "upstream" from the drought or flood).

As an illustration of the complexity of defining and assessing drought, consider some of the hydrologic contributing factors to drought. Redmond (2002) refers to a "snow drought"—that is, for locations like much of the western United States that receive a majority of precipitation as snowfall and where summer precipitation is typically

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quite low, a deficit in winter snow can lead to summer drought. Bumbaco and Mote (2010) take the concept further, providing specific examples of when low winter precipitation or, in some cases, high winter or spring temperature ends up producing unusually low snowmelt for the dry summer period. Because there are so few observations, especially long records, of soil moisture, many studies use an index of drought computed from monthly observations of precipitation and/or temperature, like soil moisture computed in a hydrologic model, the Standardized Precipitation Index, or the Palmer Drought Severity Index (Funk et al., 2013). The simplicity of the latter makes it attractive to use in large-scale drought assessments, but that also may bias results—especially in the context of climate change. Thus, assessment of change in drought characteristics should consider including several indices, with specific consideration of their particular limitations (Seneviratne et al., 2012; Sheffield et al., 2012).

Prior Knowledge and Overview of Attribution Studies

The IPCC Special Report on Extremes (Seneviratne et al., 2012) noted that on a global scale, and owing in part to the variety of ways to define drought, there were not enough direct observations of drought-like conditions to conclude that there were robust global trends, but some regions of the world have experienced more intense and longer droughts. The IPCC Fifth Assessment Report (Hartmann et al., 2013) notes that some studies find an increase in the percentage of global land area in drought since 1950, but interannual and decadal-scale variability is high, and the results depend on datasets and methods used. The attribution section assigns low confidence to attributing changes in drought over global land areas since the mid-20th century due to observational uncertainties and, again, high variability (Bindoff et al., 2013). Also, results differ depending on whether drought is defined as a rainfall deficit or by using hydrological variables like evaporation, many of which are affected by warming (see, e.g., Seneviratne et al., 2010). Nevertheless, some regional attribution studies are available. For example, Barnett and Pierce (2009) suggest that human influence has affected the hydrology of the western United States when snowpack and seasonal streamflow are considered. Because temperature plays a role in determining evaporation, snowpack, soil moisture, and—indirectly—streamflow, attribution of hydrological drought may be more robust than is strictly meteorological drought, which is more strongly influenced by precipitation. It also may be the case that attribution for some specific droughts may be more straightforward than reaching broad conclusions about the role of anthropogenic climate change in droughts globally because some of the specific regional factors that cause varying responses of drought to climate may be better understood in particular locations and times than others.

Regarding projections of future drought over the 21st century due to human influence, the IPCC Special Report on Extremes expressed "*medium confidence* that droughts will intensify in the 21st century in some seasons and areas, due to reduced precipitation and/or increased evapotranspiration. This applies to regions including southern Europe and the Mediterranean region, central Europe, central North America, Central America and Mexico, northeast Brazil, and southern Africa" (Seneviratne et al., 2012). Low confidence was expressed elsewhere due to disagreement between different projections, resulting both from different models and from different indices of drought. Additional uncertainties result from soil moisture limitations on evapotranspiration, the impact of CO_2 concentrations on plant transpiration, observational uncertainties relevant to interpretation of historical trends, and process representation in current land models (e.g., Greve et al., 2014; Sheffield et al., 2012; Trenberth et al., 2014).

Many drought-related attribution studies (e.g., Funk et al., 2015; Hoerling et al., 2013; Wilcox et al., 2015) use a similar approach to those for heat: comparing CMIP5 runs from the preindustrial control, natural-only 20th century, and anthropogenic forcings. Some (e.g., Barlow and Hoell, 2015; Hoerling et al., 2013) use SST-conditioned runs: that is, atmosphere-only model simulations using observed SSTs, often compared with a counterfactual to compute FAR. A few also use an approach closer to seasonal forecasting, which somewhat resembles a highly conditioned approach: Hoerling and colleagues (2013) use an 80-member ensemble with the operational Global Forecast System (GFS) model for October 2009-September 2011 to study the Texas drought of 2011, and Funk and colleagues (2015) also use GFS to study the east African drought of 2012.

With both global and regional models, numerous papers have used very large ensembles of simulations generated on the climate*prediction*.net platform. For example, Bergaoui and colleagues (2015) looked at drought in the Southern Levant (approximately Israel) using the Hadley HadAM3P global model and counterfactual SSTs generated from 11 GCMs; Marthews and colleagues (2015) use the regional model HadRM3P to study drought in east Africa; Rupp and colleagues (2012) use the HadAM3P global model to study heat and drought over Texas.

Other studies using large ensembles do not use climate*prediction*.net, however. Seager and colleagues (2015) draw on simulations with observed SSTs to April 2014 made by 7 research groups, with a total of 150 GCM simulations. Their focus is more on diagnosing teleconnections to specific SST anomalies, however, than on attribution to human-induced climate change. Shiogama and colleagues (2013b) use a 100-member ensemble of MIROC5 to study drought in the south Amazon region.

As might be expected given the ambiguity of results concerning the trends in fraction of global area affected by drought (Hartmann et al., 2013), attribution studies do not always find strong influence of anthropogenic climate change. Some recent studies of the Colorado River anticipate dramatic impacts on river flows associated with changes in temperature (Vano et al., 2012, 2014). Meanwhile, no anthropogenic contribution was specifically identified in a recent study of eastern Brazil's recent drought; rather, it was linked to a natural but unusual excursion of the South Atlantic Convergence Zone (Otto et al., 2015c). Several other studies (namely, Barlow and Hoell, 2015; McBride et al., 2015; Wilcox et al., 2015) found uncertain changes in likelihood and strength (see also Herring et al., 2015a, for summary tables). Shiogama and colleagues (2013a) note that their results were sensitive to bias correction.

While most attribution studies of drought focus on precipitation deficits, others have taken a more expansive approach. Funk and colleagues (2015) run a hydrologic model over eastern Africa and discuss changes in soil moisture and evapotranspiration, though they do not conduct attribution on those variables. Marthews and colleagues (2015), also studying east African drought, compute return periods for precipitation, specific humidity, and both shortwave and longwave radiative fluxes.

While drought is acknowledged to be a complex phenomenon due to the many physical processes involved and the broad range of societal factors that influence its occurrence and intensity, some aspects of drought are influenced by temperature in ways that are better understood, and thus more amenable to attribution, than others. In particular, temperature exacerbates hydrological drought in some regions by increasing surface evaporation, so that increasing temperature causes an increasing risk of hydrological drought even if precipitation does not change (e.g., Diffenbaugh et al., 2015; Williams et al., 2015).

On the Horizon

Because drought is caused by multiple factors at different scales and contexts, an area that needs further work is understanding the dominant factors that have historically been causes of drought in specific regions and watersheds. For example, for much of the United States, the drought of record is still the 1930s Dust Bowl era, which, in turn, might have been exceeded by droughts early in the last millennium (e.g., Herweijer et al., 2007). Though there are anthropogenic links to changes in atmospheric circulation patterns (and associated anomalies in precipitation and temperature) in different seasons of the year and in different regions of the globe, the multiple interacting causes of individual droughts are not well understood. It may be possible to disentangle some of these components of drought and perform attribution studies in this context. Other possible future efforts that remain largely unexplored include using a combination of large ensemble and full hydrologic model simulations for attribution, decomposing droughts into circulation components and thermodynamic components (as suggested by Trenberth et al., 2015). Another challenge in the attribution of drought relates to its linkage to climate variability (e.g., SST anomalies in different basins) on seasonal-to-decadal timescales. Given that understanding is lacking on how different climate modes change as a result of anthropogenic climate change, our ability to understand drought response related to changes in climate variability is limited. Because droughts (like many other extremes) can lead to shifts in water management and policy, water managers and policy makers alike often ask the attribution question, alongside more immediate questions like predicting the end of a current drought, and these demands are likely to continue.

The ongoing California drought has been the subject of a large and rapidly growing number of studies, often reaching apparently contradictory conclusions. For example, Cheng and colleagues (2016) distinguish between the response of shallow (<10cm) and deep (>1m) soil moisture and estimate little effect of anthropogenic warming on drought risk because of competing influences of rising precipitation and rising temperature. By contrast, Diffenbaugh and colleagues (2015) find that warming alone increases drought risk in California, using a modified drought severity index. It will be an important challenge for future workers to develop a systematic approach to synthesizing all of these different studies.

EXTREME RAINFALL

Event Type Definition

An extreme rainfall event is defined as one in which precipitation over some specified time period exceeds some threshold, either at a point (i.e., as measured by a single rain gauge) or in an average over some spatial region.

In practice, the definition of an extreme rainfall event varies widely. Time periods of interest can vary from hourly to monthly. The choice of threshold also is quite variable. Some studies use fixed absolute thresholds (e.g., 25.4 mm or 1 inch/day), while others use a fixed percentile based on the distribution at a given location in order to capture variations in what "extreme" means in practice in different regions. Some studies do not use thresholds at all. For example, some studies use annual or seasonal maxima (e.g., 24-hour precipitation accumulation). This approach also is used to develop the

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intensity duration frequency (IDF) curves for extreme precipitation that are used in engineering practice.

Extreme precipitation can typically be traced to forcing associated with strong vertical motion and significant water vapor (Westra et al., 2014). Extreme precipitation is associated with an array of meteorological processes, including tropical cyclones, extratropical cyclones, monsoons, atmospheric rivers, and localized convection (Kunkel et al., 2013).

Changes in extreme rainfall can be quantified using such empirically defined metrics as trends in the frequency with which some specified threshold is exceeded. Alternatively, statistical methods rooted in extreme value theory (Coles, 2001) can be used, allowing return levels for the most extreme events to be quantified (Kunkel et al., 2013).

Attribution of regional precipitation extremes is more challenging than that of temperature extremes (Bhend and Whetton, 2013; van Oldenborgh et al., 2013). Numerical models, as a rule, do not simulate precipitation as well as they do temperature because of the smaller space and timescales of the precipitation field and the strong reliance on parameterizations of convection and other physical processes in all but the highest-resolution models. Kendon and colleagues (2014) argue that convection-permitting models on the order of 1.5 km horizontal resolution are necessary to resolve convective processes associated with certain types of events. The salient lesson is that caution is required with extreme rainfall analysis of lower resolution models.

Prior Knowledge and Overview of Attribution Studies

More intense and more frequent extreme precipitation events have long been projected in a warming climate (Hartmann et al., 2013; Hirsch and Archfield, 2015). An array of studies continues to provide strong support for upward trends in the intensity and frequency of extreme precipitation events (Kunkel et al., 2013; Seneviratne et al., 2012). Wuebbles and colleagues (2014) project that such trends will continue and that heavy precipitation in simulations in CMIP5 may be underestimates relative to observed trends. Regarding the recent historical record, Hartmann and colleagues (2013) state: "It is *likely* that since about 1950 the number of heavy precipitation events over land has increased in more regions than it has decreased. *Confidence* is *highest* for North America and Europe where there have been *likely* increases in either the frequency or intensity of heavy precipitation with some seasonal and/or regional variation. It is *very likely* that there have been trends towards heavier precipitation events in central North America." With respect to future projections, Kirtman and colleagues (2013) state: "The frequency and intensity of heavy precipitation events over land will *likely* increase on average in the near term. However, this trend will not be apparent in all regions because of natural variability and possible influences of anthropogenic aerosols."

Global atmospheric water vapor concentrations are robustly expected to increase with temperature at a rate of around 6-7% per degree Celsius, approximately consistent with the saturation value as determined by the Clausius-Clapeyron relationship, because observed and projected changes in relative humidity are small (e.g., Held and Soden, 2006; Wright et al., 2010). Global mean rainfall values cannot increase at this rate because of global energy budget constraints (e.g., Held and Soden, 2006). Extreme rainfall events are not subject to these constraints, and a simple hypothesis is that the intensity of such events should increase at the rate that water vapor does (Allen and Ingram, 2002). This would be the case if the atmospheric circulation (including the strength of convective updrafts) were to remain constant in amplitude and structure. Dean and colleagues (2013) conclude that moisture availability was 1 to 5% higher for an extreme precipitation event in New Zealand because of anthropogenic greenhouse gases (GHGs). They also conclude that the number of synoptic events with ample moisture for extreme rain events increased. Integrated Water Vapor (IWV) Transport associated with Atmospheric Rivers (ARs) also has been shown to increase using CMIP-5 models under RCP8.5 (Warner et al., 2015). This led to increased mean and extreme winter precipitation along the West Coast of the United States.

Thus, analysis of trends in extremes sometimes focuses on whether trends in either models or observations are less than, equal to, or greater than that expected from the Clausius-Clapeyron relationship (e.g., Lenderink and Van Meijgaard, 2008; O'Gorman and Schneider, 2009; Singleton and Toumi, 2013). This is useful in that it separates the relatively well-understood role of increasing specific humidity from the much less well-understood role of changes in updraft strength or vertical structure, focusing attention on possible physics behind the latter to the extent it is found to be important.

Consistent with this expectation, Kunkel and colleagues (2013) note that trends in the mean are less than those in the extreme values. Wuebbles and colleagues (2014) summarize key findings using the extreme precipitation index (EPI) and note an upward trend in both the intensity and the frequency of extreme precipitation events in the United States. A number of other studies have noted statistically significant increases in the frequency of occurrence or intensity of extreme precipitation events with durations ranging from hours to several days in various parts of the world (Donat et al., 2013; Krishnamurthy et al., 2009; Mann and Emanuel, 2006; Westra et al., 2013).

Westra and colleagues (2013), using land-based data, find that annual maxima of 1-day precipitation have increased significantly, with a central estimate of roughly 7% per

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1-degree C temperature rise. Herring and colleagues (2014) cite a number closer to 5.3% per 1-degree C temperature rise, though within the uncertainty range of Westra and colleagues (2013). Janssen and colleagues (2014) update previous EPI-based studies and evaluated climate model simulations using Representative Concentration Pathways. Their results find increasing trends in extreme precipitation over the continental United States. Zhang and colleagues (2013) conclude that increases in Northern Hemisphere precipitation extremes since 1951 can be partially attributed to human influence on the climate, estimating a sensitivity of 5% per degree C in intensity. Their findings suggest that 1-in-20 year events in the 1950s are trending toward becoming 1-in-15 year events, which translates to a FAR of 25% and a RR of 1.33.

Most approaches to attribution of regional precipitation extremes have utilized ensembles of global models, a specific model in conjunction with a long historical record, or non-parametric statistical analyses of observational climate datasets.

Hoerling and colleagues (2014), using the National Aeronautics and Space Administration's (NASA's) Goddard Earth Observing System Model, Version 5 (GEOS-5) simulations, conclude that the extreme 5-day rainfall in northeast Colorado in 2013 could not be conclusively linked to anthropogenic climate change. In fact, they argue that such events may have become less frequent in that region. By contrast, they did note that Sillmann and colleagues (2013a,b) show increases in 5-day rainfall intensities for the globe and in the overall averages by the end of the 21st century. The strength of Hoerling and colleagues' (2014) simulations lies in the 1-degree model simulations available over a significant period of the record (1871-2013), which allow for robust statistical analysis and characterization of the tails of the distribution. Model uncertainty itself is not addressed, however, nor is the dynamic mechanism for the simulated weakening of precipitation extremes in northeast Colorado identified or its robustness assessed.

Knutson and colleagues (2014) analyze seasonal precipitation extremes in the regions of the United States in 2013, using Global Historical Climate Network data in combination with CMIP5 output to perform attribution to external forcing (natural and anthropogenic combined). They find a role for external forcing in some of the observed extremes and "some suggestion of increased risk attributable to anthropogenic forcing," but they are not able to clearly distinguish anthropogenic from natural forcing because their study design did not separate these. Otto and colleagues (2015a) use very large ensemble or regional-scale models in a probabilistic event attribution study in the United Kingdom. Their results are somewhat conflicting in terms of whether anthropogenic forcing contributed to extreme summer precipitation events. They find that the risk of an extreme rainfall event doubled in July because of anthropogenic forcing but not in the other summer months. The authors suggest that the Clausius-Clapeyron relationship governs the July results but that unresolved dynamic processes are likely playing some role as well.

On the Horizon

Most of the attribution studies related to precipitation extremes have been conducted with a limited number of models or limited simulation samples. Larger multi-model ensembles would increase confidence. Heterogeneity issues in surface observations need to continue to be addressed also. Though convective parameterization continues to be a challenge of modeling studies addressing precipitation, increasing computer power and model spatial resolution should mitigate this limitation.

As the data record of satellite-based precipitation estimates lengthens, they may become viable for trend detection and attribution studies for extreme precipitation. Satellite-based studies are emerging as particularly useful for assessing regional and global extremes, particularly over the oceans and poorly instrumented regions (Lockhoff et al., 2014, Pombo et al., 2015). The Global Precipitation Measurement (GPM) mission and other capabilities will be beneficial in the coming years to decades (Hou et al., 2014).

As stated by Otto and colleagues (2015a), it will be critical that future studies better understand and resolve the multiple meteorological causes of heavy precipitation in order to better grasp causality and attribution. This statement will be relevant to any future attribution studies on extreme rainfall events.

EXTREME SNOW AND ICE STORMS

Event Type Definition

Severe winter weather includes snow and ice (freezing rain) storms, often accompanied by wind. While there are no universal criteria for defining extreme snow or ice storms, the National Weather Service typically issues heavy snow warnings for expected accumulations of 6 inches in 12 hours (or 8 inches in 24 hours) and ice storm warnings for expected ice accumulations of 0.25 inches or more. Impacts of a snow or an ice storm are compounded by wind as well as by the population of the area impacted by the storm. Region-specific impact indices have been developed: for example, the Northeast (U.S.) Snowfall Impact Scale (NESIS), which combines snowfall amounts and the number of people residing in the affected area. The absence of universal metrics for assessing heavy snow and ice events complicates the analysis of trends and attribution studies. In addition, snowfall measurements are known to suffer from heterogeneities, such as gauge undercatch, and data on snow depth are of limited value for determining the snowfall from a single storm, as compaction and drifting are common with winter snow events. Lack of *in situ* measurements hinders the analysis of extreme snow and ice events in sparsely populated areas.

Prior Knowledge and Overview of Attribution Studies

Overall snow cover has decreased in the Northern Hemisphere, due in part to higher temperatures that shorten the time snow is on the ground (Derksen and Brown, 2012). Few studies have addressed trends in heavy snow and ice events, however, especially over regional and larger spatial scales. For the entire Northern Hemisphere, the summary in the preceding section ("Extratropical Cyclones") showed that there is mixed evidence for trends in the frequency and intensity of cold-season storms, regardless of whether they produce snow and/or freezing rain. Several studies of overall storm frequencies also indicate a northward shift in the primary tracks during winter (Seiler and Zwiers, 2015a,b; Wang et al., 2013). Theory suggests that for the coldest climates, the occurrence of extreme snowfalls should increase with warming due to increasing atmospheric water vapor, while for warmer climates it should decrease due to decreased frequency of subfreezing temperatures, though by less than mean snowfall decreases (O'Gorman, 2014).

Over the century timescale, data from 1900 to the early 2000s show no significant trend in the percentage of the United States experiencing seasonal snowfall totals in the upper (or lower) 10 percentiles defined from the record as a whole (Kunkel et al., 2009). But when the top 100 snowstorms (defined on the basis of snowfall amount and areal coverage) are evaluated for various regions of the United States, there are substantial increases in the frequencies of occurrence from 1901-1960 to 1961-2013 in the northern regions (Northern Plains, Upper Midwest, Ohio Valley, and Northeast) but not in the southern regions of the United States (Figure 4.4).

To the committee's knowledge, recent analyses of the frequencies of ice storms in the United States are lacking. Earlier studies of the number of freezing rain days (regardless of amount or intensity) showed no evidence of systematic trends in freezing rain occurrences over the United States during the latter half of the 20th century (Changnon and Karl, 2003; Houston and Changnon, 2006). There are indications of increases in ice storms in the North Atlantic subarctic (Hansen et al., 2014a), however.

In view of the data limitations and the ambiguities in event definition, it is not surprising that there have been few attribution studies of global or regional trends in

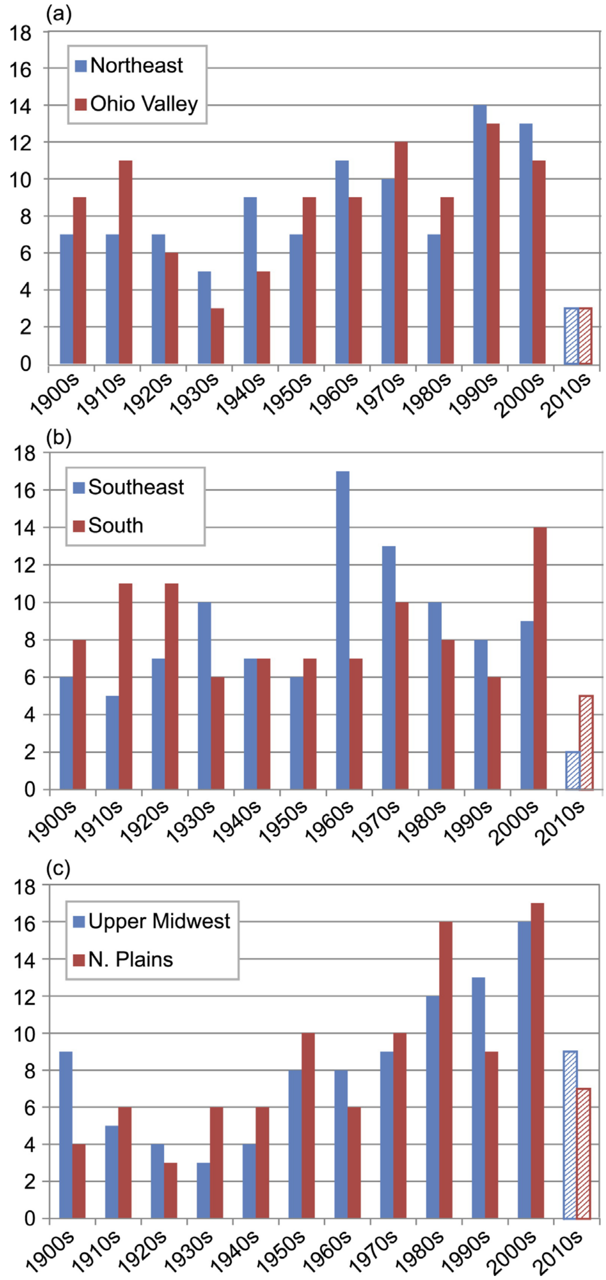

FIGURE 4.4 Decadal frequency of top 100 snowstorms in subregions of the United States from 1901 to 2013: (a) Ohio Valley and the Northeast, (b) Southeast and South, (c) Upper Midwest and Northern Plains. Shaded bars in the 2010s represent snowstorms occurring from October 2010 through April 2013, when the paper was submitted. SOURCE: Lawrimore et al., 2014.

observations of extreme snow and ice events. Yet, there have been several attribution studies of particular events, conditioned on initial conditions in the atmosphere. Edwards and colleagues (2014) simulate the western South Dakota blizzard of October 2013, finding no difference in accumulated snowfall (snow water equivalent) between preindustrial counterfactual runs and modern-day simulations. Anel and colleagues (2014) use an ensemble of model simulations of recent winters to conclude that heavier-than-normal snowfall seasons in the Spanish Pyrenees are not directly attributable to anthropogenic forcing. Wang and colleagues (2015b) show that Himalayan blizzards such as the October 2014 event have an increased likelihood of occurrence when tropical cyclones from the Bay of Bengal interact with stronger extratropical systems, and they inferred an "increased possibility" of such circumstances in the future. In an earlier study conditioned on SSTs, Barsugli and colleagues (1999) find that the major ice storm of 1998 in the northeastern United States and eastern Canada was simulated more accurately when observed El Niño ocean temperature anomalies in the tropical Pacific were prescribed. With the possible exception of a tropical cyclone connection in the study by Wang and colleagues (2015b), none of the event attribution studies point to anthropogenic climate change as a major factor in the heavy snow events. The sample of case studies of extreme snow events examined to date, however, is too small to rule out possible anthropogenic warming effects. While trends in freezing rain events in the northern middle latitudes are prime candidates for effects of anthropogenic warming (Cheng et al., 2011; Klima and Morgan, 2015), systematic analyses of observed trends in freezing rain events have yet to be performed.

On the Horizon

Attribution of extreme snow and ice events suffers from a similar challenge as do some other extreme event types in that the events are strongly governed by the atmospheric circulation, for which externally forced changes are uncertain. For this reason, attribution of extreme snow and ice storm events may benefit from an emphasis on the thermodynamic state during particular events, as argued by Trenberth and colleagues (2015). Conditional attribution studies of snow and ice storms have lagged behind similar studies for other event types.

The databases underlying assessments of heavy snow and icing events have major deficiencies that hinder trend detection as well as attribution studies. It is likely that events are missed and/or their severity is underestimated. The construction of databases suitable for attribution studies merits consideration and action in the observing community.

Finally, recent cold winters and heavy snow events in the northern United States have raised public awareness of this type of event. The number of high-impact events in the northeastern United States, as measured by the population-weighted NESIS index, increased abruptly in the 2006-2015 period. This apparent abrupt increase, as well as the need to distinguish changes in drivers from changes in impacts, makes clarification of the role of anthropogenic climate change in snowstorms affecting the northern United States a high priority.

TROPICAL CYCLONES

Event Type Definition

The National Oceanic and Atmospheric Administration (NOAA) defines a tropical cyclone as "a warm-core non-frontal synoptic-scale cyclone, originating over tropical or subtropical waters, with organized deep convection and a closed surface wind circulation about a well-defined center." In each region of the globe that is prone to tropical cyclones, a Regional Specialized Meteorological Center, under the World Meteorological Organization (WMO), determines when a given system is a tropical cyclone and determines its intensity from available observations.

The intensity of a tropical cyclone is conventionally understood to indicate its maximum sustained wind. This is only a loose guide to the potential severity of a given storm's impacts, however, as hazards associated with cyclones include both coastal and freshwater flooding as well as winds. A specific tropical cyclone event also might be defined for attribution purposes by storm surge, precipitation, storm size, economic damage, or other variables. For some of these quantities, observations are inadequate.

Maximum sustained wind speed itself is determined largely from satellite images, with *in situ* observations used where available. Uncertainties are significant (e.g., Knaff et al., 2010; Landsea and Franklin, 2013; Velden et al., 2006; see Figure 4.5) and may be greater for other variables, such as storm surge in regions where automated tide gauges are not available.

Even with good observations, the severity of an event may be very different in different variables. A storm may have weak winds, for example, but still cause a major disaster due to precipitation, storm surge, or high vulnerability. Similarly, attribution studies may reach different conclusions depending on which variable is considered, without necessarily implying any contradiction.

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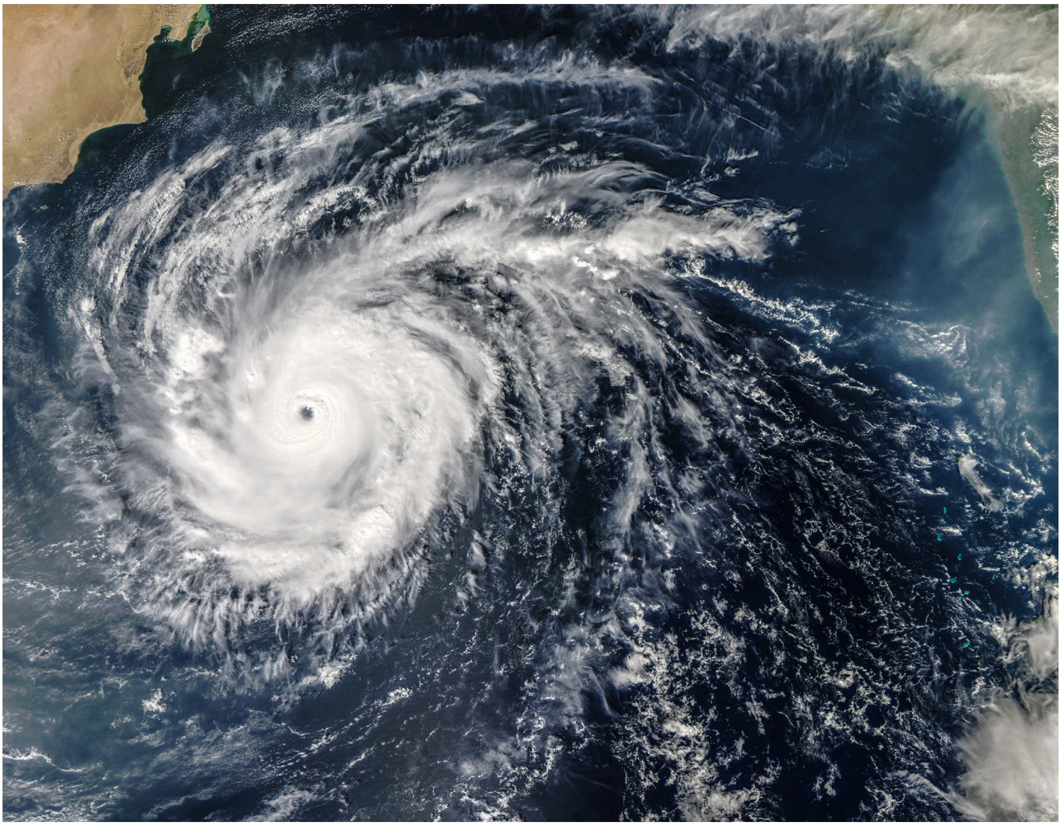

FIGURE 4.5 The Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Aqua satellite acquired this image of Cyclone Chapala (04A) approaching the Arabian Peninsula on October 30, 2015 (it made landfall in early November 2015). Only two tropical cyclones have hit the Peninsula since reliable records started in 1979. At the time of this image, the tropical cyclone had sustained winds between 130 and 135 knots (150-155 miles or 240-250 kilometers per hour) and significant wave heights of 38 feet. SOURCE: NASA. http://earthobservatory.nasa.gov/NaturalHazards/view.php?id=86899 (accessed June 1, 2016).

To the committee's knowledge, purely observation-based methods have not been used to perform event attribution studies on tropical cyclones. Methods that rely on extreme value theory (e.g., van Oldenborgh et al., 2015) are not practical for tropical cyclones. These methods rely on the existence of a continuous time series for the variable of interest, while tropical cyclones are rare events that do not provide such time series. Many studies (as discussed below) look for trends in tropical cyclone statistics, but for the most part these have been inconclusive even on regional or global scales.

Prior Knowledge and Overview of Attribution Studies

Many studies have examined whether long-term trends exist in tropical cyclone statistics. Assessment of these trends is difficult due to the shortness of observational records in many basins; large natural variability, including at low frequencies, which may obscure any longer-term trends; and changes in observing systems and practices over time, which introduce heterogeneities into the observations even in those basins that do have relatively long-term records. Synthesis studies, using specified thresholds of statistical significance against a null hypothesis of zero trend, typically find that long-term trends cannot be clearly detected in tropical cyclone numbers, intensities, or integrated measures of activity (e.g., IPCC, 2014; Knutson et al., 2010; Walsh et al., 2015). An exception may be the frequency of the most intense storms.

Some studies find marginally significant increases in the frequency of category 4 and 5 storms (e.g., Elsner et al., 2008; Emanuel, 2006; Kossin et al., 2013), while others find yet greater significance by, for example, detecting a temporal pattern of increase that more closely matches estimates of GHG-driven change rather than a pure linear trend (Holland and Bruyere, 2014). In some regions, there are clear trends in recent decades; the Atlantic, where data are of highest quality, stands out (e.g., Emanuel, 2006). The attribution of these trends to specific causes remains debated, however, with some attributing them to natural variability and others to reductions in anthropogenic aerosol forcing (Mann and Emanuel, 2006). Kossin and colleagues (2014) find a robust increase—both in the global and hemispheric means and in most individual basins—in the average latitude at which storms reach their maximum intensities.

Little model-based research addresses the question of whether an anthropogenic influence is already present in long-term tropical cyclone statistics. There is, however, a large literature that addresses how tropical cyclones may change in future climates. Some of these studies use the same global climate models as used for overall climate change assessment (e.g., Camargo, 2013), but these are generally viewed as inadequate because their spatial resolutions are too low to produce good simulations of tropical cyclones. The field has advanced greatly in recent years due to the existence of higher-resolution global atmospheric models (e.g., Yoshimura and Sugi, 2005; Zhao et al., 2009) as well as innovative downscaling techniques that combine higher-resolution regional or idealized models of tropical cyclones with global models of climate change (Emanuel, 2006), or statistical refinement techniques to address the limitations on cyclone intensity posed by limited resolution (Zhao and Held, 2010).

Based in large part on these new models, broad consensus has emerged as to the expected future trends and their levels of certainty (e.g., IPCC, 2013; Knutson et al., 2010; Walsh et al., 2015). Tropical cyclones are projected to become more intense as the climate warms. There is considerable confidence in this conclusion, as it is found in a wide range of numerical models and also justified by theoretical understanding, particularly because there is a well-established body of theory for the maximum potential intensity of tropical cyclones (e.g., Bryan and Rotunno, 2009; Emanuel, 1986, 1988; Holland, 1997). The rate of intensification per degree of global mean surface warming remains quantitatively uncertain; however, because maximum potential intensities are projected to rise (e.g., Camargo, 2013), future observations of tropical cyclones with intensities significantly higher than those observed in the past would be consistent with expectations in a warming climate, and attribution studies for such storms would have a firm basis in physical understanding.

The global frequency of tropical cyclone formation is projected to decrease (Camargo et al., 2014; Knutson et al., 2008, 2010; Seneviratne et al., 2012; Walsh et al., 2015), but there is less confidence in this conclusion than in the increase in intensity; some credible models produce increases in frequency (Emanuel, 2013). The uncertainty is still greater in projections of tropical cyclone frequency in individual basins. Changes in the frequency of the most intense storms are related to changes in both the frequency of all storms and the average storm intensity. Thus, they are less certain than the intensity changes alone because reduced frequency and increased intensity have opposing effects; Christensen and colleagues (2013) state that the frequency of the most intense storms "will more likely than not increase substantially in some basins under projected 21st century warming." Precipitation in tropical cyclones is expected to increase because of the increased water vapor content of the atmosphere, similarly to other extreme precipitation events; Christensen and colleagues (2013) express *medium confidence* in this projection. While there are only a few projections of changes in storm surge itself, total coastal flood depths, relative to fixed elevations, are confidently projected to increase as a consequence of sea level rise (e.g., Hoffman et al., 2010; Woodruff et al., 2013). Coastal flood risk due to storm surge is projected to increase due to both sea level rise and tropical cyclone intensity change, though the influence of the latter is more model-dependent (e.g., Emanuel, 2008; Lin et al., 2012).

To the committee's knowledge, attribution studies of single tropical cyclones using large ensemble simulations (without conditioning on event occurrence), for example, as needed to calculate a FAR, have not been performed. Murakami and colleagues (2015), however, executed a study of this kind with a global high-resolution model to perform attribution on a single tropical cyclone season as a whole.

The highly-conditioned method has been used in a few recent studies of individual tropical cyclones. Trenberth and Fasullo (2007) and Wang and colleagues (2015a) estimate the role of climate change in the rainfall produced by pairs of individual storms in the United States and Taiwan. Lackmann (2015) simulates Hurricane Sandy (2012) in a high-resolution regional model nested into large-scale climate fields obtained from coupled simulations representing conditions in 1900, 2012, and 2100. Irish and colleagues (2014) consider the influence of anthropogenic climate change on the flooding due to Hurricane Katrina in 2005, including an estimate of the potential anthropogenic influence on the hurricane's intensity as well as the role of sea level rise in increasing the total water depth relative to a fixed benchmark. All of these studies find modest increases in their respective measures of event intensity due to warming. The highly conditioned approach may be particularly attractive for tropical cyclone studies because large-ensemble approaches have not yet been practical, while a range of tools exists for modeling individual storms and their impacts.

On the Horizon

Though not practical in the past, large-ensemble attribution studies of individual tropical cyclones are becoming technically possible. High-resolution global models now exist that simulate tropical cyclones reasonably well (e.g., Shaevitz et al., 2014) and could be used for this purpose; the challenge is the high computational cost per simulation year as well as the large number of years required for statistical significance. Downscaling methods, whether statistical, dynamic, or hybrid (e.g., Emanuel, 2006), can be much less computationally expensive and could be used today for such studies (e.g., Takayabu et al., 2015). These methods typically require specified SST and so would be conditional on a given SST scenario as well as GHG increases. In addition to these two conditions to model quality requirements, the lack of consensus on the significance of observed trends in tropical cyclone statistics would pose a challenge to the interpretation of such studies for tropical cyclones. Because one of the difficulties in trend detection studies is the sample size in the presence of large low-frequency natural variability, however, model-based attribution studies would have an advantage to the extent that they could generate larger sample sizes than those available from observations.

EXTRATROPICAL CYCLONES

Event Type Definition

The term "extratropical cyclone" refers to the migratory frontal cyclones of middle and high latitudes, which are embedded within the large-scale westerly flow and thus move from west to east. There is no unique operational definition for the term, though a number of features are commonly agreed to be important. Extratropical cyclones derive their energy from the horizontal temperature contrasts in the extratropical atmosphere, through the process of baroclinic instability, and often contain fronts, though they also may be strengthened by latent heat release. Extratropical cyclones likewise can arise as tropical cyclones lose their axisymmetry and other tropical features in the process of extratropical transition. Studies generally define extratropical cyclone intensities either by minimum surface pressure (converted to sea level) or by maximum lower-tropospheric vorticity.

The impacts of extratropical cyclones are generally felt through frontal precipitation, storm surges, or windstorms; the latter are often concentrated in so-called sting jets embedded within the synoptic system. Storm surges warrant special treatment because they also depend on tidal variations and on sea-level rise, not just on the storm itself.

Prior Knowledge and Overview of Attribution Studies

Statistics of observed events exhibit pronounced multidecadal variability, often linked with large-scale circulation patterns such as the North Atlantic Oscillation (NAO). Although trends are sometimes reported in the literature, they are highly sensitive to the period chosen and to how the storms are defined. Assessments of historical centennial timescale changes have to be based largely on reanalyses, which may contain long-term heterogeneities (Krueger et al., 2013). As a result, there is no consensus on attributed trends in observations, at least in the Northern Hemisphere. A recent comprehensive review for the North Atlantic and northwest Europe is provided by Feser and colleagues (2015a), and for the U.S. East Coast by Colle and colleagues (2015).

The expected effect of human-induced climate change on extratropical cyclones is unclear because there are competing factors: The reduction in pole-to-equator temperature gradient expected from polar amplification would tend to weaken cyclones, but the increase in moisture would tend to strengthen them, as would the increase in upper tropospheric temperature gradient (O'Gorman, 2010). Although the IPCC Fourth Assessment Report concluded that cyclones would be expected to strengthen, this was based on a study (Lambert and Fyfe, 2006) that used minimum surface pressure as the index; the overall expected decrease in surface pressure at higher latitudes thus induced a trend which was not actually related to cyclone intensity. In the IPCC Fifth Assessment Report, future projections of extratropical cyclones were found to be uncertain (Christensen et al., 2013).

Moreover, the storm track positions could change location in the future. Zappa and colleagues (2013b) find an overall intensification of the wintertime storm track over northern Europe in the CMIP5 models and a weakening of the Mediterranean storm track, but the confidence in this projection remains uncertain because the relevant physical processes are not yet understood. Seiler and Zwiers (2015a,b) find that explosive cyclones "rapidly intensifying low pressure systems with severe wind speeds and heavy precipitation" tend to shift poleward in the Northern Hemisphere, decrease in frequency due to weakening baroclinicity, and increase slightly in intensity. Hoskins and Woollings (2015) discuss the various physical mechanisms that have been proposed for driving anthropogenic circulation changes at midlatitudes and their link to weather extremes, and they conclude that there is substantial uncertainty concerning what can be expected in the future.

Human influence appears to be stronger in the Southern Hemisphere, where it has been exerted through stratospheric ozone depletion. Model-based attribution studies have found an ozone depletion influence on Southern Hemispheric extratropical cyclones and associated extreme precipitation, evident most clearly in a poleward shift in the storm track (Grise et al., 2014; Kang et al., 2013).

Yang and colleagues (2015) use a seasonal prediction system to assess the drivers of the extreme storminess over the central United States and Canada in winter 2013/2014; they found no evidence of a human influence, but they did find a FAR in the range of 33-75% due to the multiyear anomalous tropical Pacific winds.

Marciano and colleagues (2015) run a weather model to simulate observed individual wintertime extratropical cyclone events along the U.S. East Coast in present-day and project future thermodynamic environments. They find increases in precipitation, cyclone intensity, and low-level jet strength resulting from the increased latent heating. This was for the future, however; there was no assessment of the human influence so far. For storm surges, the contribution from sea-level rise has been estimated under the highly conditioned assumption of no change in storminess; Lopeman and colleagues (2015) perform such a study for Hurricane Sandy in 2012; technically an extratropical cyclone at landfall), while Colle and colleagues (2015) discuss longer-term changes in New York City. In both cases, the anthropogenic contribution to past storm surges was estimated to be small but predicted to become a substantial factor (in terms of decreases in return periods) over the course of this century.

Because extratropical cyclones are defined as discrete events rather than extreme values of continuous time series, observation-based methods for attribution using extreme value theory may not apply as straightforwardly to extratropical cyclones as to some other event types. Nevertheless, both van Oldenborgh and colleagues (2015) and Wild and colleagues (2015) use observational analysis to challenge the suggestion (e.g., Huntingford et al., 2014) that the intense storminess over the United Kingdom in winter 2013/2014 was driven by anomalously warm Pacific SSTs, which might have an anthropogenic component.

On the Horizon

Trzeciak and colleagues (2014) suggest that although current global climate models generally underrepresent the intensity of extratropical cyclones due to insufficient latent heat release, once the horizontal resolution is finer than about 100 km they should be adequate, and that the systematic biases will then mainly involve storm track location. Seiler and Zwiers (2015a) found that resolution is not correlated with explosive storm intensity across the CMIP5 ensemble, but they note that competing effects of vertical resolution and model physics inhibit strong interpretation of that result. Horizontal resolution has been found to be important in sensitivity studies with single models (e.g., Jung et al., 2006), and idealized simulations of extratropical cyclones have been shown to be limited by resolution and dissipation at typical climate model resolutions (Polvani et al., 2004). Thus, it may still be the case that resolution is a factor limiting analyses of storm intensity, and that improvements in resolution will be beneficial to future attribution studies. Zappa and colleagues (2013a) showed that the location biases (features simulated with some fidelity but occurring in the wrong location) in CMIP5 models are generally very severe in the North Atlantic. As a result, typically the model biases in storm count at specific locations are several times larger than the change expected under RCP8.5 at the end of the century. Experience with medium-range and seasonal prediction systems has shown that these biases tend to be alleviated with higher spatial resolution, however. Thus, it is currently feasible to run global models with a reasonable representation of extratropical cyclones. The main issue for event attribution, then, is to assess whether simulated anthropogenic changes in the large-scale circulation that affect the storm tracks are credible. Without a robust physical understanding of the processes controlling such changes, or a clear signature in observations, this will be a challenge (Hoskins and Woollings, 2015).

Any attribution of the impacts of extratropical cyclones—frontal precipitation, storm surges, or windstorms—would likely have to downscale the synoptic situation in some credible manner, which for the foreseeable future will require a highly conditioned framework.

WILDFIRES

Event Type Definition

Although wildfires are not meteorological events, their likelihood and extent can be influenced by climatic factors. Wildfires are often large and rapidly spreading fires affecting forests, shrub areas, and/or grasslands. Wildfires occur in many areas of the world, especially those with extensive forests and grasslands (Romero-Lankao et al., 2014). While most wildfires are started by lightning, a substantial number are started by humans, especially near populated areas. The most common metric of wildfires is the area burned, either by a single wildfire or by all wildfires during a fire season in a particular region.

Attribution of wildfire trends and extreme events is complicated by (1) the role of humans in ignitions, fire suppression, and management of forests and other biomes (Gauthier et al., 2015; Lin et al., 2014); (2) the importance of lightning, hence small-scale thunderstorms, in igniting large fire outbreaks; (3) the importance of larger-scale weather in the wildfire spread and growth into major events (specifically, winds and humidity for fire spread, and rain for extinguishing a fire outbreak; Abatzoglou and Kolden, 2011); and (4) the health of the forest (e.g., a white pine bark beetle infestation). Thus, attribution studies need to consider three time/space scales: (1) individual large fires, which are controlled primarily by short-term weather patterns; (2) regional-scale within-season extreme fire periods, which are driven by seasonal weather patterns; and (3) large fire seasons, which are regional-scale events resulting from climate teleconnections associated with persistent blocking ridges that cause extended fire seasons (with delayed season-ending rains). Preseason preconditioning of soils and vegetation can play a role on all three timescales.

Prior Knowledge and Overview of Attribution Studies

Analysis of wildfire trends and extremes is limited by the availability of consistent data records. For example, fire surveillance methods have improved in recent decades; the area actually burned by a fire can be less than the area within the fire perimeter; and some metrics of fire activity include only large fires. There has been an overall increase in the area burned in the United States over the past several decades (Figure 4.6). The increase is especially apparent in the West. Trends are less apparent in Canada, where the area burned by large fires increased from the 1960s to the 1980s and 1990s, after which there has not been an increase (Krezek-Hanes et al., 2011). Globally, however, fire weather season lengths showed significant increases during 1979-2013 across more

ATTRIBUTION OF EXTREME WEATHER EVENTS IN THE CONTEXT OF CLIMATE CHANGE

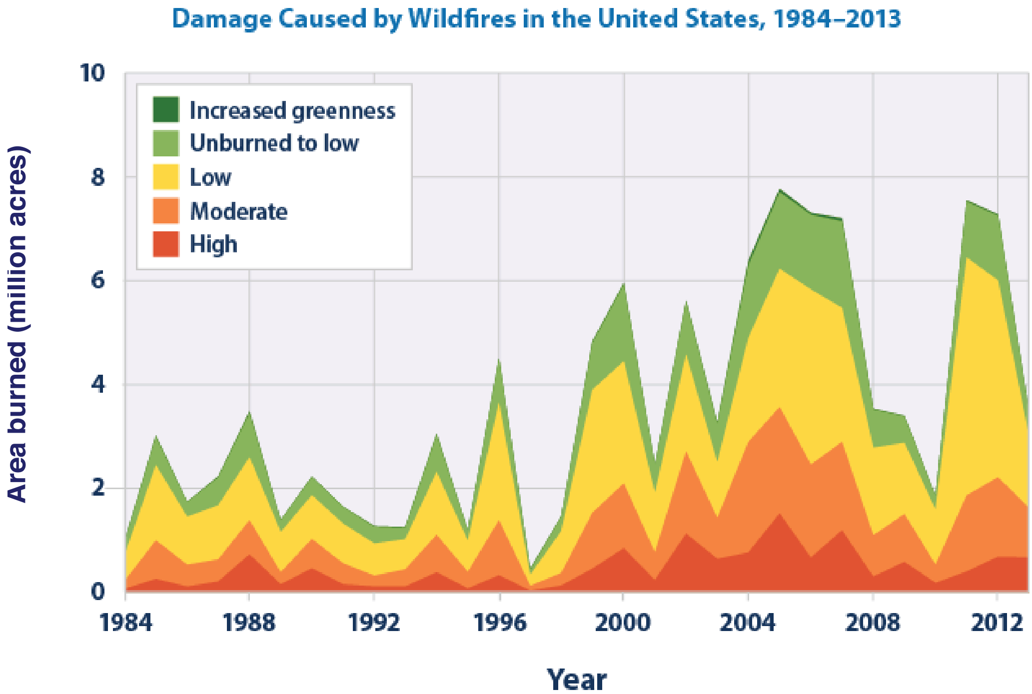

FIGURE 4.6 Yearly area burned by large wildfires in the United States, 1984-2013, color-coded by level of damage caused to the landscape—a measure of wildfire severity. SOURCE: U.S. Environmental Protection Agency's "Climate Change Indicators in the United States." Data source: MTBS (Monitoring Trends in Burn Severity), a multiagency partnership, http://www.mtbs.gov/index.html (accessed June 1, 2016).

than 25% of the Earth's vegetated surface, resulting in a 19% increase in the global mean fire weather season length (Jolly et al., 2015).

Periods of unstable atmospheric conditions result in high winds, rapid fire growth, extreme fire behavior, and convective storms that provide lightning for ignitions. Because climate models do not explicitly include lightning (or explicit formulations of convective storms), atmospheric stability and rain rate have been used to construct indices of lightning activity derived from model output. In an application of this approach to the output of a set of global climate models, Romps and colleagues (2014) project an increase in lightning strikes over the contiguous United States by 12% (+/–5%) per °C of global warming, or about 50% over this century.

Wildfires are closely associated with heat and drought, so some of the attribution issues pertaining to extreme wildfires and their likelihoods are covered in the preceding subsections on heat and drought. One of the earliest attribution studies showed that the increase of wildfire burn areas in Canada during 1959-1999 was consistent with anthropogenic summer warming (Gillett et al., 2004).

In addition to the controls by climate and weather (highlighted above), the availability of fuels and hence the state of the vegetation affects individual fires, as well as overall fire season severity. Attribution studies have generally used climate model output in conjunction with vegetation models or with metrics of fire risk derived from model-simulated precipitation and temperature. An example of the latter is a recent study by Yoon and colleagues (2015), who use ensembles of historical and future RCP8.5 simulations by the CESM model to show that an increase in fire risk in California is attributable to climate change. Beginning in the 1990s, the latter part of the historical simulation, a clear separation emerges between fire risks driven by only natural variability (the counterfactual climate, a long preindustrial simulation) and those driven by anthropogenic climate forcing (Yoon et al., 2015; see Figure 2.2). These results indicate that an increase in fire risk in California is attributable to climate change, consistent with the occurrence since 2010 of several of the most severe fire years on record in California.

Similar model-derived results have been obtained for the broader western United States (Luo et al., 2013; Yue et al., 2013), for Alaska (Mann et al., 2012), and for Canada (Flannigan et al., 2015). In the latter study, each degree of warming was found to require a precipitation increase of 15% to offset the temperature-driven decrease of the moisture content of fine surface fuels.

On the Horizon

Climate warming has resulted in longer fire seasons, consistent with the recent observed increase in severe fire years in the western United States and Alaska, as well as Brazil, eastern Africa, and parts of Eurasia (Jolly et al., 2015). What is less clear is how climate warming is driving changes in the atmospheric circulation and its teleconnections, resulting in persistent areas of high pressure that lead to large fire years on regional scales. Similarly, it is unclear how climate warming is regulating the shorter-term weather patterns that control extreme fire periods during which fires expand rapidly. Counterfactual model experiments are needed to address the role of climate warming in severe fire years regionally and in shorter episodes of rapid fire expansion.

Finally, there is a lack of compelling evidence of an influence of climate warming on the formation of convective storms that result in lightning ignitions. While climate

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and weather conditions (temperature, wind, humidity) determine the rate of wildfire growth, ignitions—primarily by lightning in some areas, but predominantly by humans in others—are a prerequisite for wildfires. In view of the model-based projections of increases in lightning activity and fire season length, there is a need for attribution studies of severe fire years on a regional basis using the large ensemble methods and conditional methods discussed earlier. Such studies could use climate model output in conjunction with vegetation-fire modules that are being developed for inclusion in earth system models. Large fires are almost always smaller than the grid cells of today's earth system models, however, so sub-grid cell variability will need to be represented in land-surface modules that are either run offline or coupled to coarser-resolution atmospheric models.

SEVERE CONVECTIVE STORMS

Event Type Definition

Severe convective storms (SCSs) are those that produce strong winds, hail, tornadoes, extensive lightning, or heavy precipitation. Usually these storms occur over land. The term "convection" in meteorology refers to strong vertical motion—updrafts and downdrafts—driven by buoyancy in the atmosphere. In practice, the term "severe" is typically applied when some variables exceed specified thresholds—for example, wind speeds greater than 25 m/s or hailstones larger than 2 cm (Doswell, 2001). The term "hazardous convective weather" also has been used (e.g., Tippett et al., 2015).

SCSs are small in both spatial extent and temporal duration compared to many other extreme weather events. The most extreme hazards, such as tornadoes and large hail, are particularly localized and not well resolved by conventional meteorological observations. As a consequence, reports by amateur observers on the ground form the longest and most direct observational datasets, at least in the United States. In much of the world, good long-term report data do not exist, and where they do, their formats are generally not uniform from country to country. Even within the United States there are considerable heterogeneities in space and time. The intensities of tornadoes are generally assessed not by direct observation but by surveys of damage on the ground after the fact. This also requires human judgment, introducing additional inhomogeneity. It is possible to assess some aspects of SCS weather from radar and other remote sensing observations, and new datasets are being developed that may allow these observations to be used for climate purposes, but these do not yet have records comparable in length to observer reports.

Based on both physical understanding and empiricism, there is some knowledge of which large-scale environmental conditions are favorable to the formation of SCSs. Vertical instability to buoyant ascent—associated with unusually warm humid near-surface air and cool air aloft (e.g., as measured by convective available potential energy [CAPE])—is required to form strong updrafts and downdrafts, while vertical wind shear enables those to organize into the larger convective storms that generate hail, tornadoes, and other hazards (e.g., Brooks, 2013; Brooks et al., 2003). CAPE, shear, and other relevant environmental variables are better observed and have more homogeneous long-term records (both in direct observations and in observation-based assimilation datasets such as reanalysis) than do SCSs themselves, so many climate studies focus on these large-scale variables. One limitation of this approach is that the associations between these variables and the storms are partly empirical and thus might change as climate does. Also, the occurrence of severe weather is by no means guaranteed by a favorable large-scale environment; rather, it requires initiation by a preexisting disturbance of some kind, a process which appears less predictable and whose dependence on climate is not well understood.

Prior Knowledge and Overview of Attribution Studies

Detection of trends is difficult due to data heterogeneities. In the United States, observations of both tornadoes and hail show significant increases over the latter half of the 20th century, but these are widely understood to be artifacts of increased frequency of reporting rather than actual meteorological trends (e.g., Brooks and Dotzek, 2007). Environmental variables predictive of tornado formation, for example, do not show the trends that tornadoes themselves do (Tippett et al., 2015). Studies of trends in the United States find different results depending on the time period and spatial region chosen, but there is no broad agreement on the detection of long-term trends in overall SCS activity such as might be related to anthropogenic climate change. In the literature, there are some consistent indications of increased year-to-year variability, as well as concentration of activity in fewer outbreaks of larger magnitude (Sander et al., 2013; Tippett, 2014), but there is no clear connection between this and climate change.

Several studies have used climate model projections to estimate the effect of GHG increases on future SCS activity in the United States. Due to the impossibility of adequately simulating severe convection in low-resolution climate models, these studies all focus on changes in large-scale environmental variables associated with SCS activity (e.g., CAPE and vertical wind shear) rather than in the storms themselves, a form of statistical downscaling.

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These studies show that the climate models project conflicting signals for the two primary predictors of SCS activity over the U.S. plains, where storm activity is greatest in the current climate (e.g., Trapp et al., 2007). Convective instability increases in a warming climate, but wind shear decreases. Changes in storms will depend on which of these dominates the other. Studies to date suggest that instability wins, such that SCS activity will increase (Diffenbaugh et al., 2013; Trapp et al., 2009). This conclusion could be sensitive to the details of the environmental index chosen, given that the two effects are competing. The limited number of such studies is presumably the reason why recent reports do not include detailed assessments of future projections of SCS activity. The IPCC Special Report on Extremes (Seneviratne et al., 2012) did consider hail distinctly from other precipitation extremes, finding that "confidence is still low for hail projections particularly due to a lack of hail-specific modelling studies, and a lack of agreement among the few available studies."

Highly conditioned approaches are feasible for SCS today, using either environmental indices or small-domain, high-resolution models forced by environmental conditions derived from larger-scale ones, as has been done earlier for tropical cyclones (Knutson and Tuleya, 2004); a small number of studies have already been done using this methodology for future scenarios (Gensini and Mote, 2015; Trapp and Hoogewind, 2016).

The committee is not aware of any attribution studies of any kind for individual SCS events, whether single storms or outbreaks consisting of multiple storms.

On the Horizon

Attribution studies of SCS events are technically feasible, but they require steps beyond those necessary for some other types of events due to their fine spatial and timescales. A large ensemble approach to attribution can probably be done only for environmental indices predictive of SCS activity, rather than the SCS activity itself. This additional statistical downscaling step would add another layer of uncertainty to the interpretation. As computing power increases, convection-permitting models can be used, allowing some degree of direct representation of SCS activity. For the most severe manifestations, such as tornadoes, explicit simulation in global or regional model attribution studies is probably not feasible in the near future.

CHALLENGES AND OPPORTUNITIES FOR ATTRIBUTION OF PARTICULAR TYPES OF EXTREME EVENTS

Attribution is much more feasible for some events than for others. The existing literature largely reflects this variability, with the most straightforwardly attributable event types having significant numbers of studies and the least having few or none. The difficulty of performing attribution on a given event type is a function of the space and timescales of the event type; the adequacy of observations to resolve the event (and the availability of those observations over a long-term historical record); the ability of climate models to simulate the event; and the simplicity of that event type's physical relationship to anthropogenic climate change.

Extreme heat and cold events are the simplest events on which to perform attribution, and the ones for which the most mature literature exists. They are well resolved by available observations, relatively well simulated in models; and their relationship to global warming—though not without its complexities—is straightforward compared to that of some other event types. Tornadoes (and, more broadly, SCSs) are arguably the most difficult events to attribute, and accordingly, no studies have been performed. These events are poorly observed, cannot be simulated in climate models at present, and have a complex and subtle relation to climate change, with competing factors tending to drive the response in opposite directions. The other event types lie in between. Droughts are more complex than heat and cold events, and thus more challenging targets for attribution. As large-scale events, however, droughts are still more straightforward in their meteorological aspects (i.e., leaving aside non-meteorological components of drought such as land use, water management decisions, etc.) than some other event types. While the non-meteorological aspects of droughts can render them complex, the role of increasing temperature in exacerbating hydrological drought through increased evaporation is more straightforward, and this increases confidence in attribution results that hinge on that mechanism. Tropical cyclones are among the more challenging event types, though they are somewhat more tractable than tornadoes due to their larger scales and better observations. Extratropical cyclones, extreme precipitation events, and snow and ice storms are in between these extremes. Wildfires present unique challenges due to the fact that they are not fundamentally meteorological events and are difficult to classify on this spectrum. The committee assessed their confidence in event attribution capabilities for different classes of extremes, as illustrated in Figure 4.7 and Table 4.1. Figure 4.7 schematically depicts the committee's assessment of the state of attribution science for specific event types along two axes.

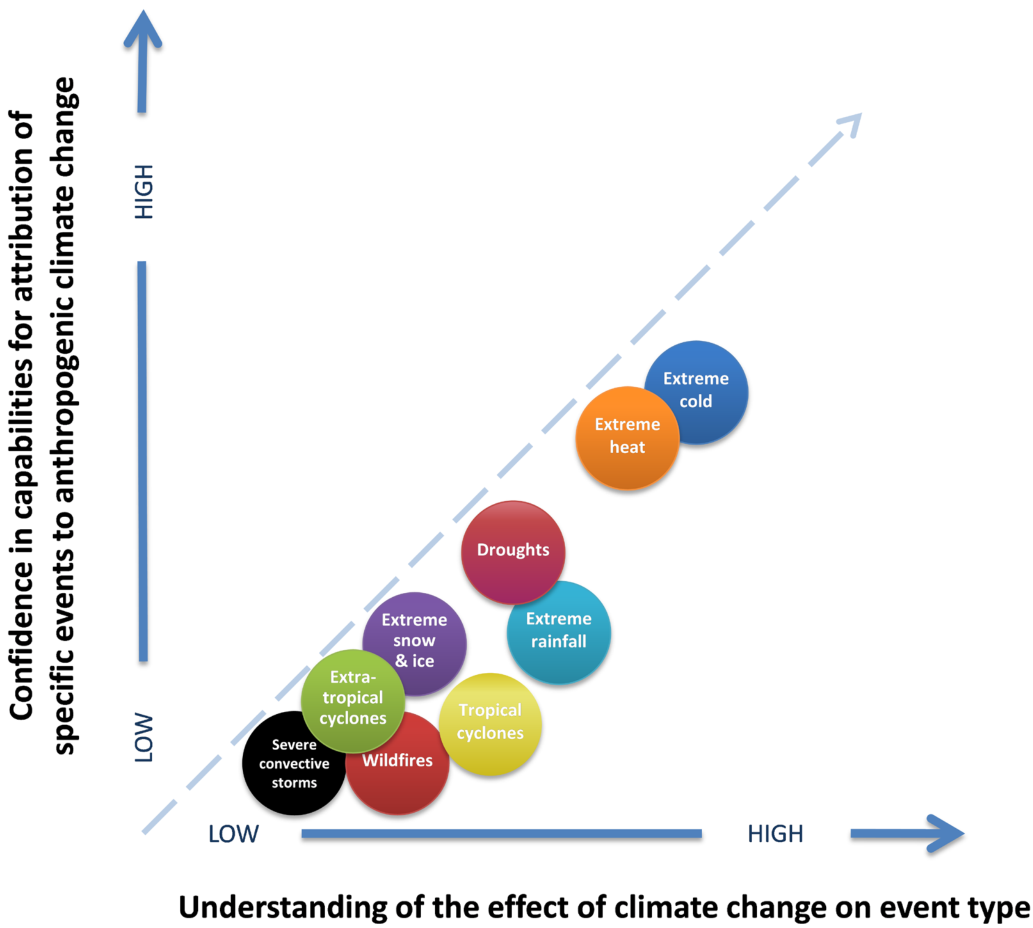

FIGURE 4.7 Schematic depiction of this report's assessment of the state of attribution science for different event types. The horizontal position of each event type reflects an assessment of the level of understanding of the effect of climate change on the event type, which corresponds to the right-most column of Table 4.1. The vertical position of each event type indicates an assessment of scientific confidence in current capabilities for attribution of specific events to anthropogenic climate change for that event type (assuming the attribution is carried out following the recommendations in this report), which draws on all three columns of Table 4.1. A position below the 1:1 line indicates an assessment that there is potential for improvement in attribution capability through technical progress alone (such as improved modeling, or the recovery of additional historical data), which would move the symbol upward. A position above the 1:1 line is not possible because this would indicate confident attribution in the absence of adequate understanding. In all cases, there is the potential to increase event attribution confidence by overcoming remaining challenges that limit the current level of understanding. See Box 4.1 for further details and caveats about this figure.

TABLE 4.1 This table, along with Figure 4.7, provides an overall assessment of the state of event attribution science for different event types. In each category of extreme event, the committee has provided an estimate of confidence (high, medium, and low) in the capabilities of climate models to simulate an event class, the quality and length of the observational record from a climate perspective, and an understanding of the physical mechanisms that lead to changes in extremes as a result of climate change. The entries in the table, which are presented in approximate order of overall confidence as displayed in Figure 4.7, are based on the available literature and are the product of committee deliberation and judgment. Additional supporting information for each category can be found in the text of this chapter, summarized in Box 4.1. The assessments of the capabilities of climate models apply to those models with spatial resolutions (100 km or coarser) that are representative of the large majority of models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5). Individual global and regional models operating at higher resolutions may have better capabilities for some event types, but in these cases, confidence may still be limited due to an inability to assess model-related uncertainty. The assessments of the observational record apply only to those parts of the world for which data are available and are freely exchanged for research. Most long records rely on *in situ* observations, and these are not globally complete for any of the event types listed in this table, although coverage is generally reasonable for the more densely populated parts of North America and its adjacent ocean regions.

● = high ◉ = medium ○ = low	Capabilities of Climate Models to Simulate Event Type	Quality/Length of the Observational Record	Understanding of Physical Mechanisms That Lead to Changes in Extremes as a Result of Climate Change
Extreme cold events	●	●	●
Extreme heat events	●	●	●
Droughts	◉	◉	◉
Extreme rainfall	◉	◉	◉
Extreme snow and ice storms	◉	○	◉
Tropical cyclones	○	○	◉
Extratropical cyclones	◉	○	○
Wildfires	○	◉	○
Severe convective storms	○	○	○

BOX 4.1
ADDITIONAL DETAIL FOR FIGURE 4.7 AND TABLE 4.1

Figure 4.7 and Table 4.1 should be interpreted qualitatively rather than quantitatively. The position of each event type in this space is the result of committee judgment, and therefore, each is subjective. The relative positions of event types that are close to each other, in particular, can all be debated. Below is a brief justification for each event type's position.

Extreme cold events: These are broadly similar to heat events with some differences. There is perhaps even greater confidence in the attribution of long-term change in cold extremes to human influence than for hot extremes. Land-surface feedbacks may be less important, and observed trends in minimum temperatures are stronger than those in maxima, and there are theoretical reasons for expecting a decrease in variance as the pole-to-equator temperature gradient weakens. The impact of selection bias is particularly important here as warming reduces the number of events likely to be targeted for attribution.

Extreme heat events: Climate models represent heat events well, compared to many other event types, and observations characterize events and trends similarly well. Long-term change in hot extremes has been attributed to human influence on the climate system. Some challenges remain due to land-surface feedbacks and understanding of low-frequency variability.

Droughts: Observations and global models capture precipitation deficits better than some other extreme event types. Difficulties stem from land-surface feedbacks, lack of soil moisture observations, the role of low-frequency variability, the complexity of defining drought for the purpose of attribution, and the role of non-meteorological factors in causing drought. The relatively high placement of drought along both axes in the figure reflects the well-understood role of warming in hydrological drought via increased surface evaporation, reduced snow accumulation, and increased snowmelt.

Extreme rainfall: Climate models have some capability, though model physics and resolution are limiting. There is a strong physical basis for expecting a climate change influence, and observed trends are broadly consistent with that expectation. Because extreme rainfall events are small-scale and occur on weather timescales, the overall climate change signal includes many such events, increasing the robustness of the signal.

In all cases of event attribution, observations are critical, and at the same time, improvement depends to some extent on improvement in numerical models. This need is most acute for those event types with the smallest space and timescales. To some extent, increasing computer power, thus allowing higher resolution, will facilitate progress.

BOX 4.1 CONTINUED

Extreme snow and ice storms: Few attribution studies have been performed. Physical bases of climate change influences are well understood individually, but event attribution is made difficult due to the complexity of influences in combination (increasing water vapor increases potential snow and freezing rain amounts, but increasing temperature decreases likelihood of freezing). Observations also are inadequate for extreme snow and ice storms.

Tropical cyclones: Most climate models have inadequate resolution for attribution studies, though specialized higher-resolution models are better and improving quickly. Few attribution studies of individual storms have yet been performed. There is considerable physical understanding of some aspects; tropical cyclone intensity and precipitation are confidently expected to increase with warming. Detection of trends in observations is challenging due to low-frequency variability as well as inhomogeneity and shortness of records.

Extratropical cyclones: Climate models can simulate the events to some extent, though resolution and physics may still be limiting in many models, particularly in their ability to resolve the most extreme local manifestations of the storms, such as strong winds and heavy precipitation. Detection of trends in observations, robustness of projections, and physical understanding of climate change influences are all weak. Few attribution studies have been performed.

Wildfires: Few attribution studies have been performed. Observations are problematic, and typical climate models do not include all the physical processes, especially variations in fuel properties. Wildfire process understanding also remains limited, particularly on the macro scale that is relevant to assessing the influence of climate on fire. While it is very likely that warming increases the risk of fire, the important role of non-meteorological factors and limitations of both observations and models nonetheless pose challenges for attribution.

Severe convective storms: The committee is not aware of any attribution studies. Observations of both individual events and trends are problematic. Climate models do not resolve the events, and some phenomena (e.g., tornadoes) are not resolved even by the highest-resolution models in use for operational weather forecasting. Physical understanding of the events' relationship to climate change is limited. Statistical or dynamic downscaling offers promise of improvement.

CHAPTER FIVE

Conclusions

In the past decade, the field of extreme event attribution has made great strides in understanding and explaining extreme events in the context of climate change. This is still an emerging science, however; thus, continued research is required to increase the reliability of event attribution results, particularly for event types that are presently poorly understood. The need for improved understanding is coming at a time when there is increasing inquiry by the public, policy makers, and practitioners about the relationship between specific weather events and climate change (e.g., the question, "Is it caused or affected by climate change?"). Advances in the field will depend not only on addressing scientific problems specific to attribution but also on advances in the basic underlying science, including observations, weather and climate modeling, statistical methodology, and theoretical understanding of extreme events and their relation to climate.

This chapter builds on the information presented in the preceding chapters to provide guidance for framing questions about event attribution and approaches to ensuring the robustness and reliability of event attribution studies and information. The committee also recommends future research that would improve extreme event attribution capabilities and discusses the future of event attribution in an operational context.

ASSESSMENT OF CURRENT CAPABILITIES

Event attribution is more reliable when based on sound physical principles, consistent evidence from observations, and numerical models that can replicate the event. The ability to attribute the causes of some extreme event types has advanced rapidly since the emergence of event attribution science a little over a decade ago, while attribution of other event types remains challenging. In general, confidence in attribution results is strongest for extreme event types that

- have a long-term historical record of observations to place the event in an appropriate historical context;
- are simulated adequately in climate models; and
- are either purely meteorological in nature (i.e., the nature of the event is not strongly influenced by the built infrastructure, resource management actions,

etc.) or occur in circumstances where these confounding factors can be carefully and reliably considered.

Non-meteorological factors confound observational records and can limit the accuracy of model simulations of extreme events. Drought and wildfire are examples of events for which non-meteorological factors can be especially challenging in attribution studies.

Furthermore, confidence in attribution results that indicate an influence from anthropogenic climate change is strongest when

- there is an understood and robustly simulated physical mechanism that relates a given class of extreme events to long-term anthropogenic climate changes such as global-scale temperature increase or increases in water content of a warmer atmosphere.

Confidence in attribution findings of anthropogenic influence is greatest for those extreme events that are related to an aspect of temperature, such as the observed long-term warming of the regional or global climate, where there is little doubt that human activities have caused an observed change. For example, a warmer atmosphere is associated with higher evapotranspiration rates and heavier precipitation events through changes in the air's capacity to absorb moisture. Atmospheric circulation and dynamics play some role, however, which is different for different event types. Changes in atmospheric circulation and dynamics are generally less directly controlled by temperature, less robustly simulated by climate models, and less well understood. Event attribution can be further complicated by the existence of other factors that contribute to the severity of impacts.

Confidence in attribution analyses of specific extreme events is highest for extreme heat and cold events, followed by hydrological drought and heavy precipitation. There is little or no confidence in the attribution of severe convective storms and extratropical cyclones. Confidence in the attribution of specific events generally increases with our understanding of the effect of climate change in the event type. Nevertheless, the gap between this understanding and confidence in attribution of specific events varies among event types.

Attribution of events to anthropogenic climate change may be complicated by low-frequency natural variability, which influences the frequencies of extreme events on decadal to multidecadal timescales. The Pacific Decadal Oscillation and Atlantic Multidecadal Oscillation are examples of such variability. Characterization of these influences is uncertain because the observed record is too short to do so reliably, and it also is too short to assess whether climate models simulate these modes of variability correctly.

PRESENTING AND INTERPRETING EXTREME EVENT ATTRIBUTION STUDIES

There is no single best method or set of assumptions for event attribution because these depend heavily on the framing of the question and the amount of time available to answer it. Time constraints may themselves affect framing and methodological choices by limiting analyses to approaches that can be undertaken quickly.

A definitive answer to the commonly asked question of whether climate change "caused" a particular event to occur cannot usually be provided in a deterministic sense because natural variability almost always plays a role. Many conditions must align to set up a particular event. Extreme events are generally influenced by a specific weather situation, and all events occur in a climate system that has been changed by human influences. Event attribution studies generally estimate how the intensity or frequency of an event or class of events has been altered by climate change (or by another factor, such as low-frequency natural variability).

Statements about attribution are sensitive to the way the questions are posed and the context within which they are posed. For example, when defining an event, choices must be made about defining the duration of the event (when did it begin and when did it end) and the geographic area it impacted, but this may not be straightforward for some events (e.g., heat waves). Furthermore, different physical variables may be studied (e.g., drought might be characterized by a period with insufficient precipitation, excessively dry soil, or reduced stream flow), and different metrics can be used to determine how extreme an event was (e.g., frequency, magnitude). Whether an observation- or model-based approach is used, and the sorts of observations and/or models available for studying the event, also will constrain the sorts of questions that can be posed.

Attribution studies of individual events should not be used to draw general conclusions about the impact of climate change on extreme events as a whole. Events that have been selected for attribution studies to date are not a representative sample (e.g., events affecting areas with high population and extensive infrastructure will attract the greatest demand for information from stakeholders). In addition, events that are becoming less likely because of climate change (e.g., cold extremes) will be studied less often because they occur less often than events whose frequency is increasing because of climate change. Furthermore, attribution of individual events is generally more difficult than characterizing the statistical distribution of an event of a given type and its dependence on climate. For all of these reasons, counts of available attribution studies with either positive or negative or neutral results are not expected to give a reliable indication of the overall importance of human influence on extreme events.

ATTRIBUTION OF EXTREME WEATHER EVENTS IN THE CONTEXT OF CLIMATE CHANGE

Unambiguous interpretation of an event attribution study is possible only when the assumptions and choices that were made in conducting the study are clearly stated and the uncertainties are carefully estimated. The framing of event attribution questions, which may depend strongly on the intended application of the study results, determines how the event will be studied and can lead to large differences in the interpretation of the results. Event attribution studies presented in the following manner are less likely to be misinterpreted:

- Assumptions about the state of one or more aspects of the climate system at the time of the event (e.g., sea-surface temperature [SST] anomalies, atmospheric circulation regimes, specific synoptic situations) are clearly communicated.
- Estimates of changes in both magnitude and frequency are provided, with accompanying estimates of uncertainty, so users can understand the estimated degree of change from the different perspectives.
- Estimates of changes in frequency are presented as a risk ratio: that is, in terms of the ratio of the probability of the event in a world with human-caused climate change to its probability in a world without human-caused climate change. Equivalently, one can compare the return periods of the event (i.e., how rarely an event occurs) in the world without climate change to that in the world with climate change.
- The impact of assumptions (e.g., of how estimates of changes in magnitude and frequency depend on SST anomalies or atmospheric circulation regimes) is discussed.
- Statements of confidence accompany results so users understand the strength of the evidence.

Bringing multiple scientifically appropriate approaches together, including multiple models and multiple studies, helps distinguish results that are robust from those that are much more sensitive to how the question is posed and the approach taken. Utilizing multiple methods to estimate human influences on a given event also partially addresses the challenge of characterizing the many sources of uncertainty in event attribution.

Examples of multiple components that can lead to more robust conclusions include:

- Estimates of event probabilities or effect magnitudes based on an appropriate modeling tool that has been shown to reasonably reproduce the event and its circumstances, such as the dynamic situation leading to the event.
- Reliable observations against which the model has been evaluated and that give an indication of whether the event in question has changed over time in a manner that is consistent with the model-based attribution.

- Assessment of the extent to which the result is consistent with the physical understanding of climate change's influence on the class of events in question.
- Clear communication of remaining uncertainties and assumptions made or conditions imposed on the analysis.

THE PATH FORWARD

Improving Extreme Event Attribution Capabilities

A focused effort to improve understanding of specific aspects of weather and climate extremes could improve the ability to perform extreme event attribution. The World Climate Research Programme (WCRP) has identified climate extremes as one of its grand challenges, suggesting major areas of scientific research, modeling, analysis, and observations for WCRP in the next decade. Because extreme event attribution relies on all aspects of the understanding of extremes and their challenges, the committee endorses the recommendations from the white paper "WCRP Grand Challenge: Understanding and Predicting Weather and Climate Extremes" (Box 5.1; Zhang et al., 2014) as necessary to make advances in event attribution. Advances made in understanding the physical mechanisms and in improving the realism of extreme events in weather and climate models will benefit event attribution studies.

The committee recommends that research that specifically aims to improve event attribution capabilities include increasing the understanding of

- the role of dynamics and thermodynamics in the development of extreme events;

BOX 5.1
KEY RECOMMENDATIONS FROM THE WHITE PAPER "WCRP GRAND CHALLENGE: UNDERSTANDING AND PREDICTING WEATHER AND CLIMATE EXTREMES"

- substantial advances in modelling (including but not limited to model resolution)
- advances in the understanding of the physical mechanisms leading to extremes
- increased effort to extend the historical observational record, including planned climate quality reanalyses over longer historical periods
- improvements in remote sensing products that extend long enough to document trends and sample extremes

SOURCE: Zhang et al., 2014.

ATTRIBUTION OF EXTREME WEATHER EVENTS IN THE CONTEXT OF CLIMATE CHANGE

- the model characteristics that are required to reliably reproduce extreme events of different types and scales;
- changes in natural variability, including the interplay between a changing climate and natural variability, and improved characterization of the skill of models to represent low-frequency natural variability in regional climate phenomena and circulation;
- the various sources of uncertainty that arise from the use of models in event attribution;
- how different levels of conditioning (i.e., the process of limiting an attribution analysis to particular types of weather or climate situations) lead to apparently different results when studying the same event;
- the statistical methods used for event attribution, objective criteria for event selection, and development of event attribution evaluation methods;
- the effects of non-climate causes—such as changes in the built environment (e.g., increasing area of urban impervious surfaces and heat island effects), land cover changes, natural resource management practices (e.g., fire suppression), coastal and river management (e.g., dredging, seawalls), agricultural practices (e.g., tile drainage), and other human activities—in determining the impacts of an extreme event;
- expected trends in future extreme events to help inform adaptation or mitigation strategies (e.g., calculating changes in return periods to show how the risk from extreme events may change in the future); and
- the representation of a counterfactual world that reliably characterizes the probability, magnitude, and circumstances of events in the absence of human influence on climate.

Research that is targeted specifically at extreme events, including event attribution, could rapidly improve capabilities and lead to more reliable results. In particular, there are opportunities to better coordinate existing research efforts to further accelerate the development of the science and to improve and quantify event attribution reliability. Examples of event attribution research coordination include EUropean CLimate and weather Events: Interpretation and Attribution (EUCLEIA), weather@home, World Weather Attribution (see Box 3.4 for additional information on these), and the International Detection and Attribution Group (IDAG), all of which also coordinate with one another. Furthermore, given that event attribution spans climate and weather, the field would benefit from interdisciplinary research at the interface between the climate, weather, and statistical sciences to improve analysis methods. Event attribution capabilities would be improved with better observational records, both near–real time and for historical context. Long, homogeneous observed records are essential for placing events into a historical context and for evaluating to what extent climate models reliably simulate the effect of decadal climate variability on extremes.

Event attribution could be improved by the development of transparent community standards for attributing classes of extreme events. Such standards could include an assessment of model quality in relation to the event/event class. Community agreement is needed on when a model represents a given event type well enough for attribution studies to be possible. At present, such standards do not clearly exist, and some model-based attribution studies do not even attempt to assess model adequacy. Such standards are critical for enhancing confidence in event attribution studies. Other examples of necessary community standards include use of multiple lines of evidence, development of a transparent link to a detected change that influences events in question, and clear communication of sensitivities of the result to framing of the event attribution question.

Systematic criteria for selecting events to be analyzed would minimize selection bias and permit systematic evaluation of event attribution performance, which is important for enhancing confidence in attribution results. Studies of a representative sample of extreme events would allow stakeholders to use such studies as a tool for understanding how individual events fit into the broader picture of climate change. Irrespective of the method or related choices, it would be useful to develop a set of objective criteria to guide event selection. A simple example of an objective approach might be to select events based on their rarity in the historical record using a fixed threshold, such as 24-hour precipitation events throughout a given domain that exceed the local 99th percentile of historical precipitation events. It should be noted, however, that even in this case, subtleties associated with historical quantile definition would need to be considered. The development of objective criteria for event selection would help both to reduce selection bias and to lead to methodological improvements. A path forward to avoiding selection bias is to perform event attribution on a predefined set of events of several different types that could reasonably be expected to occur in the current climate. This could involve systematic definition of events or consideration of events based on the full historical record and not just current events. Christidis and colleagues (2014) describe one example of such an approach: namely, a method for precomputing estimates of how human influence has changed the odds of extremely warm regional seasonal mean temperatures based on a formal detection and attribution methodology (see Chapter 3). Another example is the approach of trying to identify "grey swan tropical cyclones" (events not seen before, but theoretically possible) before they occur (Lin and Emanuel, 2015).

Event selection criteria also is a prerequisite for the development of a formalized approach to evaluating event attribution results and uncertainty estimates. Such evaluation is important for establishing confidence in event attribution statements. Development of such an approach could be modeled after existing approaches used to evaluate weather forecasts. One possible approach to evaluation would be to use a large sample of objectively selected events on a global scale to evaluate if, on average, model predictions or simulations of extreme events are on target. This could involve seasonal and decadal predictions of the number of events of a certain type based on simulations with external drivers only. Events that become more frequent with global warming, as well as events that become less frequent, such as cold spells, would be included in such an approach.

Event Attribution in an Operational Context

As more researchers begin to attempt event attribution, their efforts can benefit from coordination to improve analysis methods and work toward exploring uncertainties across methods and framing. Event attribution can benefit from links to operational numerical weather prediction where available. As discussed in Chapter 3 (see also Box 3.4), some groups are moving toward the development of operational extreme event attribution systems to systematically evaluate the causes of extreme events based on predefined and tested methods. Objective approaches to compare and contrast the analyses among multiple different research groups based on agreed event selection criteria are yet to be developed.

In the committee's view, a successful operational event attribution system would have several key characteristics. First is the development and use of objective event selection criteria to reduce selection bias so stakeholders understand how individual events fit into the broader picture of climate change. Second is the provision of stakeholder information about causal factors within days of an event, followed by updates as more data and analysis results become available. This is analogous to such other fields as public health and economics, where it is acceptable to revise initial forecasts and analyses as more data become available (e.g., Gross Domestic Product estimates, recession start and stop dates, etc.). A third characteristic of a successful event attribution system is clear communication of key messages to stakeholders about the methods and framing choices as well as the associated uncertainties and probabilities. Finally, reliable assessments of performance of the event attribution system are needed. Such assessments could be developed through processes utilizing regular forecasts of event probability and intensity, observations, and skill scores similar to those used routinely in weather forecasting for evaluation. Rigorous approaches to managing and implementing system improvements also are a critical element of these assessments.

Some future event attribution activities could benefit from being linked to an integrated weather-to-climate forecasting effort on a range of timescales. The development of such an activity could be modeled from concepts and practices within the Numerical Weather Prediction (NWP) and seasonal forecasting community. NWP, which dates back to the 1950s, is focused on taking current observations of weather and processing these data with computer models to forecast the future state of weather. A project linking attribution and weather-to-climate forecasting likewise could build on recent efforts to increase national and international capacity to forecast the likelihood of extreme events at subseasonal-to-seasonal timescales[1] (WMO, 2013).

Ultimately the goal would be to provide predictive (probabilistic) forecasts of future extreme events at lead times of days to seasons, or longer, accounting for natural variability and anthropogenic influences. These forecasts would be verified and evaluated utilizing observations, and their routine production would enable the development and application of appropriate skill scores (using appropriate metrics to define and track the skill). The activity would involve rigorous approaches to managing and implementing system enhancements to continually improve models, physical understanding, and observations focused on extreme events.

Correctly done, attribution of extreme weather events can provide an additional line of evidence that demonstrates the changing climate as well as its impacts and consequences. An accurate scientific understanding of extreme weather event attribution can be an additional piece of evidence needed to inform decisions on climate change–related actions.

The committee also encourages continued research in event attribution outside of an operational context to ensure further innovation in the field. This would facilitate better understanding of a breadth of approaches, framings, modeling systems, and the performance of event attribution methods across past events, including in the longer historical context.

[1] Another National Academies of Sciences, Engineering, and Medicine committee is studying this topic and will produce a report in the spring of 2016: http://dels.nas.edu/Study-In-Progress/Developing-Research-Agenda/DELS-BASCPR-13-05.

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APPENDIX A

Statement of Task

An ad hoc National Academies of Sciences, Engineering, and Medicine committee will examine the science of attribution of specific extreme weather events to human-caused climate change and natural variability. Specifically, the committee will:

- Provide an assessment of current scientific understanding and capabilities for attribution of specific extreme weather events to climate change.
- Provide guidance about the robustness of extreme event attribution science. The guidance should discriminate among different attribution approaches and different classes of extreme events, and should consider various characteristics of the analysis (e.g., data coverage and quality, model performance, etc.).
- Identify research priorities for further development of the approaches.

APPENDIX B

Workshop Agenda

Extreme Weather Events and Climate Change Attribution
Workshop Agenda
October 21-22, 2015
Keck Center
500 Fifth Street, NW, Washington, DC

WORKSHOP GOALS

Inform the committee as they write their report on the science of attribution of specific extreme weather events to human-caused climate change and natural variability.

Specifically, the committee will:

- Provide an assessment of current scientific understanding and capabilities for attribution of specific extreme weather events to climate change.
- Provide guidance about the robustness of extreme event attribution science. The guidance should discriminate among different attribution approaches and different classes of extreme events, and it should consider various characteristics of the analysis (e.g., data coverage and quality, model performance, etc.).
- Identify research priorities for further development of the approaches.

WEDNESDAY, OCTOBER 21, 2015

OPEN SESSION–Keck 103

12:00 P.M. *Lunch available to all participants*

OPEN SESSION–Keck 100

1:00 P.M. Welcoming remarks and introduction

David Titley, Pennsylvania State University

1:30 P.M. Framing of event attribution questions and risk-based perspective for decision making

Alexis Hannart, National Center for Scientific Research (France)

2:00 P.M. Background and overview on climate attribution of extreme events

Friederike Otto, University of Oxford

2:30 P.M. *Break*

3:00 P.M. Panel on Methods and Uncertainties

Moderated by: Ted Shepherd, University of Reading

Panelists will have 5 min for a brief presentation; remaining time to be used for discussion.

- Observed climate change, Geert Jan van Oldenborgh, Royal Netherlands Meteorological Institute (*WebEx*)
- Coupled ocean/atmosphere climate models, David Karoly, University of Melbourne (*WebEx*)
- Large ensembles, Myles Allen, University of Oxford
- SSTs and sea ice, Judith Perlwitz, National Oceanic and Atmospheric Administration Earth System Research Laboratory
- Circulation analogs, Pascal Yiou, Alternative Energies and Atomic Energy Commission (France)
- Building confidence, Leonard Smith, University of Oxford

5:00 P.M. General Discussion

(includes questions/comments from Webinar participants)

Moderated by: John Walsh, University of Alaska, Fairbanks

5:45 P.M. *Adjourn*

6:15 P.M. Reception *[Keck Atrium]*

THURSDAY, OCTOBER 22, 2015

OPEN SESSION–Keck 100

9:30 A.M Panel on Attribution of Specific Weather Phenomena

Moderated by: Phil Mote, Oregon State University

Panelists will have 5 min for a brief presentation; remaining time to be used for discussion.

- Extreme heat and cold events, Ken Kunkel, National Oceanic and Atmospheric Administration National Centers for Environmental Information/North Carolina State University
- Drought events, Marty Hoerling, National Oceanic and Atmospheric Administration Earth System Research Laboratory
- Wildfires, Eric Kasischke, National Aeronautics and Space Administration/University of Maryland
- Extreme rain events/flooding, Michael Wehner, Lawrence Berkeley National Laboratory
- Extreme snow/freezing rain events, Jay Lawrimore, National Oceanic and Atmospheric Administration National Centers for Environmental Information
- Hurricanes, Tom Knutson, National Oceanic and Atmospheric Administration Geophysical Fluid Dynamics Laboratory
- Tornadoes, Jeff Trapp, University of Illinois
- Extreme sea level rise events, William Sweet, National Oceanic and Atmospheric Administration National Ocean Service

10:45 A.M. *Break*

11:15 A.M. Panel discussion continues

12:15 P.M. *Working lunch*

1:15 P.M. Break out group session to identify opportunities and challenges on the following topics:

1. Uncertainty quantification:
    a. assessing model quality
    b. uncertainty quantification given a reasonable model
    c. how can event attribution be evaluated
2. Framing of event attribution questions (Are we asking the right questions?) and how to describe and quantify a potential anthropogenic component to the meteorological causes of an extreme event, given that natural variability is generally playing a dominant role.
3. Timescale/operational event attribution (e.g., How does the timescale of an event impact our ability to attribute the event? On what timelines can event attribution studies be conducted? How does the timescale of an event affect the timeline on which attribution studies can be conducted?).

3:15 P.M Break (Time for Rapporteurs to collect their thoughts)

3:45 P.M. Rapporteurs report back in plenary

4:15 P.M. Invited responses to the workshop discussions

Kathy Jacobs, University of Arizona

5:00 P.M Wrap up

David Titley, Pennsylvania State University

5:30 P.M. *Adjourn*

APPENDIX C

Committee Mini Biographies

Dr. David Titley (*Chair*) is a Professor of Practice in Meteorology and the Founding Director of the Center for Solutions to Weather and Climate Risk at Pennsylvania State University and a Senior Adjunct Fellow at the Center for New American Security. Dr. Titley's 32-year Naval career included duties as Oceanographer and Navigator of the Navy and Assistant Deputy Chief of Naval Operations for Information Dominance. Dr. Titley initiated and led the U.S. Navy's Task Force on Climate Change, and he also served on the staff of the U.S. Commission on Ocean Policy. After retiring from the Navy with the rank of Rear Admiral, Dr. Titley served as the Deputy Undersecretary of Commerce for Operations, the Chief Operating Officer position at the National Oceanic and Atmospheric Administration. He has spoken on various domestic and international stages, including Congressional Hearings, the International Panel on Climate Change, and a TEDx talk, among others. Dr. Titley serves on the CNA Military Advisory Board, and he has served on National Academies of Sciences, Engineering, and Medicine committees as a member and co-chair. He is a fellow of the American Meteorological Society. He earned a Ph.D. in Meteorology from the Naval Postgraduate School.

Dr. Gabriele Hegerl is Professor of Climate System Science at the University of Edinburgh. Her interests are in determining the causes of observed climate changes, focusing on mean and extreme temperature and precipitation. She works on the interface between climate modeling and climate observations, with a focus on uncertainty, on variability and change in climatic extremes, and on the use of palaeo-proxy data to study climate variability and change during the last millennium. Dr. Hegerl is a fellow of the Royal Society of Edinburgh and has a Wolfson fellowship by the Royal Society. She is one of the co-leads of the World Climate Research Programme's Grand Challenge on climate extremes. Dr. Hergerl has been a lead author and coordinating lead author on the Intergovernmental Panel on Climate Change.

Ms. Katharine L. Jacobs is the Director of the Center for Climate Adaptation Science and Solutions (CCASS) and a Professor in the Department of Soil, Water and Environmental Science at the University of Arizona. From 2010 to 2013, Ms. Jacobs served as an Assistant Director in the U.S. Office of Science and Technology Policy (OSTP) in the Executive Office of the President. Ms. Jacobs was the Director of the National Climate Assessment (NCA), leading a team of 300 authors and more than 1,000 contributors who wrote the Third NCA report. The report was published in May of 2014. She also was the lead advisor on water science and policy and climate adaptation within OSTP. Prior to her work in the White House, Ms. Jacobs was the Executive Director of the Arizona Water Institute from 2006-2009, leading a consortium of the three state universities focused on water-related research, education, and technology transfer in support of water supply sustainability. She has more than 20 years of experience as a Water Manager for the Arizona's Department of Water Resources, including 14 years as Director of the Tucson Active Management Area. Her research interests include water policy, connecting science and decision making, stakeholder engagement, use of climate information for water management applications, climate change adaptation, and drought planning. Ms. Jacobs earned her M.L.A. in Environmental Planning from the University of California, Berkeley. She has served on eight National Research Council (NRC) panels and was Chair of the NRC panel on Adapting to the Impacts of Climate Change and a member of the panel on America's Climate Choices.

Dr. Philip W. Mote is a Professor in the College of Earth, Oceanic, and Atmospheric Sciences at Oregon State University (OSU); Director of the Oregon Climate Change Research Institute (OCCRI) for the Oregon University System; and Director of Oregon Climate Services, the official state climate office for Oregon. Dr. Mote's current research interests include scenario development, regional climate change, regional climate modeling with a super-ensemble generated by volunteers' personal computers, and adaptation to climate change. He is the co-leader of both the National Oceanic and Atmospheric Administration–funded Climate Impacts Research Consortium for the Northwest and the Northwest Climate Science Center for the U.S. Department of the Interior. Since 2005 he has been involved in the Intergovernmental Panel on Climate Change, which shared the 2007 Nobel Peace Prize. He is also a coordinating lead author and advisory council member for the U.S. National Climate Assessment and has served on numerous committees for the National Research Council. He earned a B.A. in Physics from Harvard University and a Ph.D. in Atmospheric Sciences from the University of Washington, and he arrived at OSU to establish OCCRI in 2009.

Dr. Christopher J. Paciorek is an Associate Research Statistician, as well as a lecturer and the statistical computing consultant in the Department of Statistics at the University of California, Berkeley. His statistical expertise is in the areas of Bayesian statistics and spatial statistics, with primary application to environmental and public health research. Dr. Paciorek's work in recent years has focused on methodology and applied work in a variety of areas, in particular: quantifying trends in extreme weather, quantifying millennial-scale changes in vegetation using paleoecological data, and developing computational software for hierarchical modeling (the NIMBLE project). He has also worked on measurement error issues in air pollution epidemiology, Bayesian methods for global health monitoring with a focus on combining disparate sources of information, and spatio-temporal modeling of air pollution. Before coming to Berkeley, he was an Assistant Professor in the Biostatistics Department at the Harvard School of Public Health. He finished his Ph.D. in Statistics at Carnegie Mellon University in 2003 and also has an M.S. in Ecology from Duke University and a B.A. in Biology from Carleton College.

Dr. J. Marshall Shepherd, a leading international expert in weather and climate, was the 2013 President of the American Meteorological Society (AMS) and is Director of the University of Georgia's (UGA's) Atmospheric Sciences Program. Dr. Shepherd is the Georgia Athletic Association Distinguished Professor of Geography and Atmospheric Sciences and hosts The Weather Channel's Sunday talk show *Weather Geeks*. In 2014, the Captain Planet Foundation honored Dr. Shepherd with its Protector of the Earth Award. (Recent recipients include Erin Brockovich and former Environmental Protection Agency Administrator Lisa Jackson.) He is also the 2015 Recipient of the Association of American Geographers Media Achievement award and the 2015 UGA Franklin College of Arts and Sciences Sandy Beaver Award for Excellence in Teaching. Prior to UGA, Dr. Shepherd spent 12 years as a Research Meteorologist at the National Aeronautics and Space Administration (NASA) Goddard Space Flight Center and was Deputy Project Scientist for the Global Precipitation Measurement mission. In 2004 he was honored at the White House with a prestigious PECASE (Presidential Early Career Awards for Scientists and Engineers) award. Dr. Shepherd is a Fellow of the American Meteorological Society and recipient of its Charles Anderson Award. Two national magazines, the AMS, and Florida State University, have also recognized Dr. Shepherd for his significant contributions. He is frequently sought as an expert on weather and climate by major media outlets like CBS's *Face the Nation*, *USA Today*, *Time*, CNN, NOVA, and *The Today Show*. His TEDx Atlanta Talk on "Slaying Climate Zombies" is highly regarded and cited. Dr. Shepherd is also frequently asked to advise key leaders at NASA, National Science Foundation, National Oceanic and Atmospheric Administration, the White House, Congress, and various agencies. He is on the board of Mothers and Others for Clean Air, a partnership with the American Lung Association. He has more than 75 peer-reviewed scholarly publications and numerous editorials. Dr. Shepherd received his B.S., M.S., and Ph.D. in Physical Meteorology from Florida State University. He co-authored a children's book on weather called *Dr. Fred's Weather Watch*.

Dr. Theodore G. Shepherd obtained a B.Sc. in Mathematics and Physics from the University of Toronto in 1979, and a Ph.D. in Meteorology from the Massachusetts Institute of Technology in 1984. After a postdoctoral fellowship at the Department of Applied Mathematics and Theoretical Physics at the University of Cambridge, he took up a faculty position in the Department of Physics at the University of Toronto in 1988. In 2012 he moved to the Department of Meteorology at the University of Reading to become the inaugural Grantham Professor of Climate Science. His research interests range from theoretical geophysical fluid dynamics to climate modeling and data analysis, with a focus on atmospheric circulation. He has held leadership roles in scientific assessments of both climate (Intergovernmental Panel on Climate Change) and stratospheric ozone (World Meteorological Organization/United Nations Environment Programme), as well as in the World Climate Research Programme, and he is a Fellow of the American Meteorological Society, the American Geophysical Union, and the Royal Society of Canada. From 2001-2005 he was Chief Editor of the *Journal of the Atmospheric Sciences*. In 2014 he was honored as a Thomson Reuters Highly Cited Researcher.

Dr. Adam Sobel is a Professor at Columbia University's Lamont-Doherty Earth Observatory and Fu Foundation School of Engineering and Applied Sciences. He is an atmospheric scientist who specializes in the dynamics of climate and weather, particularly in the tropics, on timescales of days to decades. A major focus of his current research is extreme events, such as hurricanes, tornadoes, floods, and droughts, and the risks these pose to human society in the present and future climate. He is leading a new Columbia University Initiative on Extreme Weather and Climate. Dr. Sobel holds a B.S. in Physics and a B.A. in Music from Wesleyan University and a Ph.D. in Meteorology from the Massachusetts Institute of Technology. In the past few years, he has received the Meisinger Award from the American Meteorological Society, the Excellence in Mentoring Award from the Lamont-Doherty Earth Observatory of Columbia University, an AXA Award in Extreme Weather and Climate from the AXA Research Fund, and an Ascent Award from the Atmospheric Sciences Section of the American Geophysical Union. Dr. Sobel is author or co-author of more than 100 peer-reviewed scientific articles, and his book *Storm Surge: Hurricane Sandy, Our Changing Climate, and Extreme Weather of the Past and Future*, published in October 2014 by HarperCollins, received the 2014 Atmospheric Science Librarians International Choice Award in the popular category.

Dr. John Walsh received his B.A. in Mathematics from Dartmouth College in 1970 and his Ph.D. in Meteorology from the Massachusetts Institute of Technology in 1974. He spent a postdoctoral year at the National Center for Atmospheric Research. He was a faculty member at the University of Illinois for 30 years and, more recently, at the University of Alaska in Fairbanks. While at Illinois, he led a polar research group and co-authored an undergraduate textbook, *Severe and Hazardous Weather: An Introduction to High-Impact Meteorology*. He also spent 1 year as the Chair in Arctic Marine Science at the Naval Postgraduate School in Monterey, California. At the University of Alaska

Fairbanks, Dr. Walsh is currently the Chief Scientist of the International Arctic Research Center. His recent research has addressed Arctic climate change; seasonal to decadal variability of sea ice; predictability of climate change in high latitudes; and changes in arctic weather in the context of climate change. In 2009 he received the Usibelli Distinguished Researcher Award from the University of Alaska. He is a Fellow of the American Meteorological Society.

Dr. Francis W. Zwiers, before becoming Director of the Pacific Climate Impacts Consortium, served as a Research Scientist (1984-2006), Chief of the Canadian Centre for Climate Modelling and Analysis (1997-2006), and Director of the Climate Research Division (2006-2010), all at Environment Canada. He is an Adjunct Professor in the Department of Mathematics and Statistics of the University of Victoria and in the Department of Statistics and Actuarial Science of Simon Fraser University. His expertise is in the application of statistical methods to the analysis of observed and simulated climate variability and change. Dr. Zwiers is a Fellow of the Royal Society of Canada and of the American Meteorological Society, a recipient of the Patterson Medal (Meteorological Service of Canada), and a recipient of an Honorary Doctorate from Western University. He has served as an Intergovernmental Panel on Climate Change (IPCC) Coordinating Lead Author of the Fourth Assessment Report and as an elected member of the IPCC Bureau for the Fifth Assessment Report.