Extreme events: trends and risk assessment methodologies

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Abstract

In this chapter we discuss extreme weather events as they relate to climate adaptation. First, we summarize the state of the science regarding how different kinds of extreme events have been or will be influenced by global warming. Second, we describe the different kinds of tools that exist for extreme event hazard assessment. These include extreme value theory, which allows inference of rare event statistics from observational records too short to resolve them; "catastrophe models" developed for the insurance industry; and dynamical models developed for climate science. Third, we describe how these different tools may be relevant to different activities that might fall under the broad rubric of "climate adaptation science". We advocate a pragmatic approach, recognizing that anthropogenic climate change is one of multiple factors influencing extreme event hazard, and that, when the most extreme events are considered, much human settlement and infrastructure is inadequately adapted even to the historical climate.

Impact of climate change on extremes

There is no simple statement which accurately describes the state of the science on how extreme weather events respond to climate change. Statements such as "climate change is making weather more extreme" are oversimplifications with the potential to be misleading. The statement in quotations above does carry two truths, however. First, much of the damage from climate change will be felt through changes in extreme events. Second, for many kinds of events, despite the uncertainties, current science justifies a legitimate concern that the *risk* – a probabilistic concept that can include scientific uncertainty as well as other forms – is increasing. But the dependence of extreme events on climate is substantially different for different types of events, as is our degree of scientific knowledge and understanding.

In this section we give a brief summary of the current understandings regarding a subset of extreme event types. The recent review by IPCC (2012) remains relevant and can be consulted for more details. The more recent National Academy (2016) report addresses individual extreme event attribution - the science of making quantitative statements about how different causes, including anthropogenic global warming, contribute to specific individual events - but contains a wider-ranging discussion illustrating the broader point that our confidence in our understanding of the human influence on any event type is affected by many factors, including the quality and length of observational records, the quality of numerical models in simulating and predicting that event type, etc. Fig. 1, adapted from that report, provides a graphical assessment of the state of attribution science for different types of extreme events, as explained briefly in the caption and in more detail in the report itself.

More broadly, the National Academy (2016) report emphasizes that our degree of scientific understanding of different types of events' relation to warming is greatest for events most closely related to atmospheric temperature, since temperature is the variable in which greenhouse gas influence is first and most directly felt. Thus the human influence is most clear on heat waves and cold snaps, as indicated by their position above and to the right of other event types in Fig. 1.

Heat Waves

Heat waves are now occurring frequently with a magnitude that was very rare until the last few decades. Dynamical climate models are able to simulate these frequencies with, but not without anthropogenic greenhouse gas emissions (e.g., Arblaster et al. 2014). The magnitude of the anthropogenic influence can depend, however, on whether one considers the change in probability of exceeding a fixed temperature threshold or the relative magnitude (in degrees) of the anthropogenic component compared to the natural variability component; the latter can be small while the former is large (Otto et al. 2012).

Heat waves illustrate, in a manner relevant to other event types as well, issues around the different roles of thermodynamic and dynamic effects, and different levels of uncertainty associated with them. The probability of a heat wave – defined as temperature exceeding some specified threshold for some specified duration – can be thought of as being influenced by the climatological mean temperature of the location of interest plus a fluctuating "weather" component related to the variable atmospheric circulation. In particular, a strong heat wave is generally associated with a persistent high pressure system. Changes in climatological mean temperature at most locations on earth increase roughly in sync with global mean temperature under greenhouse gas forcing (though at different rates, e.g., due to polar amplification) while the extent to which the frequency or intensity of high pressure systems may change in response to warming is much less clear. Many human populations are experiencing warming at a faster rate than the global mean due to the urban heat island effect as well as the fact that land is warming faster than ocean.

This is an instance of the more general fact that, under climate change, all aspects of atmospheric circulation change are much more uncertain than are changes in temperature or other thermodynamic quantities (e.g., water vapor) that are closely coupled to temperature (e.g., Trenberth et al., 2015). A simple null hypothesis is that mean temperature changes while circulation does not (e.g., Held and Soden 2006), and thus that the entire probability distribution of temperatures shifts to higher values while its shape remains unchanged. Though this hypothesis is not exactly true, it is useful as a starting point for understanding. That is, the global mean temperature increase is almost certainly the dominant driver of increasing heat wave frequency and intensity, with circulation modifying that trend quantitatively on a regional basis, but not qualitatively on the global scale.

Extreme precipitation events

Changes in regional mean precipitation over the past century are documented and statistically significant in many regions (e.g., Walsh et al. 2014), and it is plausible to expect that extremes should change as well. Consistent with this expectation, observations of precipitation show increasing trends in many regions in the intensity of rain falling in the heaviest events (e.g., Groisman et al. 2005), where "heaviest events" are typically defined as those exceeding some high percentile, say 99%, of the distribution from some set of earlier years. An example for the U.S. is shown in Fig. 2, where the threshold is defined by the two-day precipitation total occurring on average once every five years over a reference historical period. This too is predicted by numerical models as a consequence of warming (e.g., Kharin et al. 2007), and is supported by physical understanding: more water can be in the vapor phase at higher temperature (the Clausius-Clapeyron relation). Observations show increasing specific humidity on a global scale, and models predict with great consistency that this should occur as relative humidity changes remain small, a prediction that is also supported by dynamical understanding (Sherwood et al. 2010). While changes in global mean precipitation are controlled by radiative processes, extreme precipitation events are both largely unconstrained by such global budget considerations and mostly limited by available moisture in the atmosphere, so that the amount of rain that falls in such events is more closely coupled to atmospheric water vapor content than is global (or perhaps even regional) mean precipitation (Trenberth 1999; Allen and Ingram 2002).

A simple hypothesis is that precipitation extremes should scale with surface temperature as specific humidity does, approximately following the Clausius-Clapeyron relation and increasing approximately 7% per degree Celsius. Storm dynamics can also change, however, in response to the increased convective heating and other environmental changes associated with warming, leading to changes greater or less than this naïve estimate. Climate models uniformly show precipitation extremes increasing in magnitude with warming, but at different rates in different models – especially in the tropics – suggesting that dynamical feedbacks are both significant and uncertain (O'Gorman and Schneider 2009; Sugiyama et al. 2009).

Droughts

Droughts are multifaceted events, related to climate in multiple ways. Meteorological drought refers to deficits of precipitation (compared to historical climatology) over an extended period. As such it is inherently related to atmospheric circulation, and changes expected under warming are in principle quite uncertain. There is robust consensus among models that meteorological droughts should become more prevalent in some specific regions in a warming climate, however, and some dynamical understanding of those changes, leading to some confidence in those regions. A highly visible example is the Middle East, where increasing drought is strongly projected by models and recent droughts have been found difficult to explain in terms of natural climate variability, leading to the inference of an anthropogenic role (Kelley et al. 2015). Generally, though, meteorological droughts are subject to large low-frequency internal climate variability. Very long and severe "megadroughts" are apparent in the historical and paleoclimate records, and difficult to explain in terms of radiative forcings (Coats et al. 2016). This makes it more difficult to make strong statements about the role of human influence on present droughts in many cases, even in other regions where that influence is expected to be strong in future such as southwestern North America.

Hydrologic drought, on the other hand – defined as a deficit in surface water reservoirs, including snow and soil moisture – is influenced not just by precipitation, but also by temperature, through temperature's control on evaporation. Thus arguments for a human influence on hydrologic drought are compelling: the absence of precipitation may in many cases be largely natural, but the surface water then becomes still more depleted than it would otherwise be for the same precipitation deficit, due to warming, evaporation increase, and snowpack loss as found to be the case for the recent drought in the U. S. state of California (Diffenbaugh et al. 2015; Williams et al. 2015; Hartoonian 2018, this volume).

Tropical cyclones

The influence of global warming on tropical cyclones is a complex subject. Our understanding has evolved rapidly over the last dozen years or so, as summarized in recent reviews (Knutson et al. 2010; Walsh et al. 2015). The degree of agreement within the field is greatest for projections of the future, when we expect the influence of greenhouse gases to be larger than at present. The expectation is that warming will lead to "fewer but stronger" tropical cyclones. Increases in tropical cyclone intensity are expected with considerable confidence, supported by theoretical understanding via the theory of potential intensity as well as by numerical model results. The projection of decreasing tropical cyclone number, on the other hand, is primarily a result from global "high-resolution" (20-50 km horizontal grid spacing) models, and we lack a solid theoretical understanding of it. The most likely explanation involves increasing saturation deficit (difference between actual water vapor content and the maximum possible) in a warming atmosphere in which relative humidity changes are small (Emanuel 2010, Camargo et al. 2014), but this is not yet a very well developed or scrutinized argument. It also applies primarily at the global scale; tropical cyclone frequency changes in individual basins, on the other hand, are likely to be dominated by changes in regional climate and circulation, and are subject to all the uncertainties that go along with those. In particular, many models project a shift to an "El Nino-like" state in the Pacific, associated with a weakened Walker circulation, and this yields patterns in tropical cyclone activity typically associated with El Nino, with increases in the Pacific and decreases in the Atlantic (e.g., Vecchi and Soden 2007). But this projection results from a cancellation between competing processes in the atmosphere and ocean, and it remains possible that it could be wrong (DiNezio et al. 2009)

Perhaps the most confident projections we can make about tropical cyclones involve their hydrological aspects. Tropical cyclone precipitation is almost certain to increase - essentially for the same reason as other precipitation extremes, namely increased water vapor in a warmer atmosphere. The risk of storm surge-driven coastal flooding is essentially certain to increase in many regions as well, due to sea level rise. Even if statistics of storm frequency and intensity don't change, the higher baseline sea level increases the chance of a given water level's occurrence due to storm surge, relative to a fixed datum. It is theoretically possible that sufficiently large decreases in storm frequency could compensate, but that is highly unlikely, given the range of plausible estimates of sea level rise.

Attribution of changes in the recent historical record is more difficult due to the limitations of the data record and, especially, strong low-frequency natural variability. Many studies find statistically significant increases in intensity over the last few decades, but others find that these results depend to some extent on the data set and analysis method used (e.g., Kossin et al. 2013). Aerosol cooling has also likely compensated to a significant extent for the greenhouse warming, inhibiting tropical cyclone intensity increases (e.g., Sobel et al. 2016), though this compensation has already weakened, and will weaken further in future as greenhouse gas concentrations will almost certainly continue to increase while aerosol concentrations are likely to remain level or decrease.

Severe Convection

Severe convective storms (thunderstorms producing tornadoes, large hail or damaging straight-line winds) are relatively small and short-lived. Their expected behavior under climate change, as well as observed trends, has tended to be more uncertain than that of other extreme weather events (IPCC 2012; Tippett et al. 2015). Although severe thunderstorms occur around the world, observational records in much of the world are limited and incomplete, and climate analysis of even U.S. storm reports is difficult because of changing reporting practices (Verbout et al. 2006). To date, there is no strong evidence of trends in U.S. storm reports due to climate change, despite signs of increased clustering and variability (Brooks et al. 2014; Tippett et al. 2016) Projection of future severe convective storm activity is challenging because the spatial resolution of numerical models commonly used in climate change projections is not adequate to resolve thunderstorms. The best current understanding of how severe convective storm activity will change in the future comes from looking at changes in conditions that are favorable for severe convective storms. Climate projections show that the number of days with favorable environments will increase in the U.S., Australia and Europe (Diffenbaugh et al. 2013; Allen et al. 2014; Púčik et al. 2017). These increases are primarily due to increases in convective available potential energy (CAPE), which is understood to increase with warmer surface temperatures and enhanced low-level moisture (Seeley and Romps 2016). However, an important caveat when interpreting such findings is that favorable environments are not the same as storms' occurrence. Recent work suggests that increases in storm frequency and intensity in a warmer climate might be less than that indicated by changes in favorable environments (Trapp and Hoogewind 2016).

While hail occurrence and size might be expected to increase with increasing CAPE, warming temperatures increase the height of the freezing level and are expected to cause smaller hailstones to melt before reaching the ground (Dessens et al. 2014; Mahoney et al. 2012). On the other hand larger hail is less affected, so that hail frequency has been projected to decrease along with increases in maximum hail size (Brimelow et al. 2017). Decreases in the number of days with hail in China have been related to changes in the height of the freezing level (Li et al. 2016), and increases in hail kinetic energy have been observed in France (Berthet et al. 2011).

Human impacts

This section has summarized our current understanding of the effect of global warming on extreme events of different types considering only changes in the meteorological events themselves. The risks to human populations from these events, however, are also strong functions of social and economic variables, including adaptation options themselves. The same meteorological event may have very different human impacts if it occurs in two different locations where infrastructure and societal vulnerabilities are different. These aspects are considered in detail from a range of perspectives in the rest of this book. The following section, on modeling tools, continues our focus here on the meteorological component of risk, though with some brief consideration of the vulnerability component.

Catastrophe modeling and risk assessment for adaptation

The impacts of climate change are expected to occur, to a large extent, through changes in the frequency, intensity, or other characteristics of extreme events. Thus rational approaches to climate adaptation should include assessments of extreme event risk over the time scale being considered. In this section we consider the methodologies available for doing such risk assessments. Our description is by no means all-inclusive, but aims to give a broad sense of the types of tools available and their strengths and weaknesses, particularly those related to their representation of the extreme weather events themselves.

Risk is commonly defined as the product of hazard – the probability that a "natural" event of some given characteristics will occur – and the impacts to human society that would follow from such an event (fatalities, financial losses, health impacts, infrastructure damage etc.), so that risk as a whole refers to the probability of those impacts. Some of these apply only to the meteorological hazard, while others – particularly catastrophe models – also include representations of some kinds of vulnerability, and thus can be said to model risk.

Historical Observations and Extreme value theory

For some purposes and some types of events, it is common to estimate hazard directly from historical observations. Records are often too short to characterize the extreme events that are of greatest interest by direct means, however – that is, by simply counting how many of the events of interest have occurred over a given time period. The damage from natural disasters is generally found to be "fat-tailed", meaning that a disproportionately large fraction of it comes from the rarest and largest magnitude events (Muir-Wood 2016). Let us say that "rarest" here means, for specificity, annual probabilities of 1/100 or less. To estimate the "200-year" event, for example - the one with an annual probability of 1/200 - reliably and directly from historical data, one needs a data record at least several times longer than 200 years. Good historical weather data are often not available for periods of even 100 years, however. One obviously cannot estimate the 200-year flood directly from, say, 50 years of data. Perhaps the most commonly used method to address this problem directly and empirically – that is, without constructing explicit physical models - is extreme value theory (e.g., Coles 2001; Embrechts et al. 1999).

Consider a random process at a point, represented by a single time series. If the events represented by the data satisfy some assumptions, then extreme value theory says that the statistics of the extremes – represented either by "block maxima", e.g., the set of annual maxima, or "peaks over threshold", the set of all values in the data exceeding some specified threshold value – can be approximated asymptotically by general distributions with only small sets of free parameters that can, in principle, be estimated even from a time series that is short compared to the return periods of interest. Knowing those parameters, the shape of the tail can be determined and the magnitude of an event of any given frequency can be estimated, including those more rare and extreme than are present in the data.

Due to low-frequency climate variability, however, meteorological variables cannot be assumed to be truly satisfy the assumptions of extreme value theory over periods of decades to centuries. In particular, observations from one epoch may not be representative, and return periods computed from records even several decades to a century long may not accurately reflect the present or future hazard (Jain and Lall 2001), even without considering nonstationarity due to anthropogenic global warming (which only compounds this problem).

In addition, extreme value theory in its standard form assumes a time series which is populated at a regular interval by physically meaningful values (including zeros), and it considers only point processes. These assumptions are problematic for some events of interest. Continuous time series are available for variables like temperature or precipitation, but not for specific types of rare events, such as tropical cyclones, which are absent nearly all the time. In addition, many (really, all) real meteorological events have spatio-temporal structures which are not captured by standard extreme value theory, but which are important to the events' impacts. In the case of a tropical cyclone, extratropical wind storm, or major flood event, for example, the damage-inducing extreme values of meteorological variables (wind, precipitation, storm surge-induced flooding, etc.) are often distributed over a wide area. The damage at different spatial locations within that footprint is thus highly correlated. That correlation will not be captured by independent applications of extreme value theory at nearby locations, but is terribly important to assessing the overall risk[1]. While it is possible to generalize extreme value theory to account for such correlation, it makes more sense in many applications to move to models which have explicit knowledge of the spatio-temporal structures of the events of interest.

Catastrophe models

The approach used in the insurance industry - and to some extent in other arenas - involves "catastrophe models". These are used to estimate the risk of insured financial losses from extreme weather events (as well as other natural and, to some extent, human-made disasters).

[1] The standard theory used to set insurance premiums, for example, assumes that individual claims are uncorrelated, something that cannot be assumed about property damage claims in regions prone to natural hazards (Kunreuther et al. 2013).

Catastrophe models used in insurance have three components: a hazard module, which estimates the probability of an event with given physical characteristics in the atmosphere, ocean, or land surface; a vulnerability module, which contains data on the assets at risk (i.e., buildings or other physical structures) and "vulnerability curves" which predict the fraction of their value that would be destroyed if a given physical variable (e.g., wind speed or flood water depth) were to reach a given threshold; and a financial module, which estimates the insured loss that would result from such damage.

The strength of catastrophe models is that they are integrated tools that assess risk, rather than just hazard. The different components are ideally developed in tandem, and evaluated together. The desired risk is that of a loss of a given magnitude, and ideally data on losses from past events is available to calibrate the model.

The existing catastrophe models used in insurance have several limitations, however, that may limit their application to climate adaptation (though they are not particularly problematic for their traditional use in insurance, that being of course the reason they have developed as they have).

First, they are not open source, and the science going into them is not fully documented in the peer-reviewed literature, or even visible to their users. The models used most widely are commercial products provided by catastrophe modeling firms whose business models require some degree of proprietariness. Open-source models are only recently being developed (e.g., Bresch 2014), and are not the standard in industry.

Second, catastrophe models developed in the insurance industry do not generally address impacts other than insured financial losses, such as loss of life or livelihood, or even financial losses in regions (such as much of the developing world) where insurance penetration is limited. Catastrophe models have begun to be adapted more widely for a range of problems in international development finance and disaster risk reduction (e.g., Cummins and Mahul 2009; Joyette et al. 2015; Linnerooth-Bayer Hochrainer-Stigler 2015; Souvignet et al. 2016; Bresch 2016); these applications are for the most part similar to those in industry, focusing on financial loss, but considering a wider range of assets and in some cases considering risk transfer mechanisms different than traditional insurance. Some models are explicitly designed to consider the impacts of specific adaptation actions (e.g., Souvignet et al. 2016), though any model which includes the vulnerability of physical assets can in principle represent such actions through changes in the representation of those assets and their vulnerabilities.

Third, and of greatest interest here, the hazard components of standard catastrophe models are based closely on historical observations, and incorporate little if any of the physics that relates extreme weather events to the large-scale climate. This limits the models' utility for assessment of changing risks under climate change. Some important facets of climate change can be handled relatively straightforwardly – for example, sea level rise can be incorporated into coastal flood risk calculations, as those are generally treated by physical models for storm surge and inland flooding (e.g., Hallegatte et al. 2011, 2013). Other facets of climate change cannot be so easily incorporated. For example, capturing changes in the frequency and intensity of tropical cyclones or extreme precipitation events requires some degree of physical modeling, as one is attempting to predict the behavior of the climate system outside the regime in which the historical observations were taken. Hybrid statistical-dynamical approaches which generate large sets of synthetic events cheaply, in the spirit of traditional catastrophe models, but using enough physics to tackle the climate change problem, are beginning to be developed, pioneered by Emanuel (2006).

Dynamical models

The primary tools for making predictive statements about climate change are dynamical models, also known as “climate models” or “earth system models”. These are renderings of the deterministic physical (and, to some extent, chemical and even biological) laws governing the atmosphere, ocean, and other components of the climate system into discrete mathematical equations and solved on computers. The models often represent the whole globe, as is appropriate for representing climate change. Regional models can be used if higher resolution is needed – this is known as “dynamical downscaling” - using lateral boundary conditions from another source, generally a global model. The choice of domain and the influence of the boundary data invoke distinct sets of potentially vexing problems, however, both technical and scientific. Global models with variable resolution, “zoomed in” over some region of interest, offer an intermediate approach which is now being explored with greater intensity (Harris and Lin 2013; Duvel et al. 2017).

Dynamical models have the great advantage that they can, in principle, represent behavior outside the historical record, since the laws governing the system will presumably remain the same in the future as in the past even as greenhouse gas concentrations and other “forcings” change. They have the disadvantage that their representations of the climate inevitably contain “biases”, or persistent errors, whose magnitudes may or may not be significant enough to compromise their utility in risk assessment. As a class, dynamical models generally represent some kinds of extreme events well and others poorly. The difference depends in large part on whether the physics of the event in question critically involves fluid-dynamical processes at scales smaller than the models can resolve (that resolved scale being, generally, hundreds of km, at best tens of km). Heat waves, for example, being a result of large-scale weather systems, are represented quite well. Tropical cyclones and heavy rain events, on the other hand, are represented much more poorly. Some higher-resolution models exist which perform much better than earlier generations on these latter types of events (e.g., Shaevitz et al. 2014, Van der Wiel et al 2016), but these require great computational power and are, at present, not accessible to many researchers. Some kinds of events – tornadoes come to mind – occur at such small scales that they remain inaccessible to any climate model, and can only be represented by some form of statistical downscaling which relates the events to larger-scale environmental conditions that the models can simulate (e.g., Tippett et al. 2012, Diffenbaugh et al. 2013).

Different questions

We can identify several types of inquiry regarding extreme events and their relation to climate. What question one asks might influence which scientific tools are most appropriate to the problem and how they might best be used.

1. Risk assessment. If we are doing risk assessment for the present, and our results need not be valid far into the future (say, because we will re-do the analysis every year, as in the reinsurance industry where contracts are written annually) we arguably do not need to consider human influence explicitly at all for some kinds of events, and can base our analysis on the historical record, either directly or using some empirical or semi-empirical method, such as extreme value theory or a catastrophe model, to extrapolate from it to generate probabilities for rare events. One could argue that even there, however, inasmuch as the present is already different from the past due to human influence, one should consider that change explicitly, and use a method that recognizes the difference between the earlier and later parts of the historical record. For some kinds of events (e.g., heat waves), where the change in the mean is large enough compared to the width of the historical range of natural variability, this could make some difference. For others (e.g., tropical cyclones), where natural variability is large and anthropogenic trends have not yet been conclusively detected, it may or may not.

2. Detection and Attribution (e.g., Stott et al. 2010). Detection of trends, almost by definition, involves observational data alone. Attribution, however compares the detected trends to what would have been expected with and without human influence, and that must involve a model of some kind. Attribution of trends in extreme events is generally done using some form of climate model, and thus has been done more (and with greater confidence) for the events which are most amenable to simulation in such models, such as heat waves. The issues around attribution of individual events (National Academy 2016) are similar.

3. Projection of future change, given climate forcing scenarios. Here one is interested explicitly in the change between the future and the present, rather than the present and the past. Since there are no observations of the future, predictive models become yet more critical. For events which are not handled well by global dynamical models, one could imagine using a catastrophe model designed for such events, if it had appropriate sensitivity to the climate state. The climate state could be obtained from global models, using a downscaling approach. This has been done for tropical cyclones and storm surge (Lin et al. 2010, 2012) with the downscaling model of Emanuel (2006).

For climate adaptation, which activity is most needed, and therefore which tools? The term “adaptation” is often taken to imply an adjustment to a change in external circumstances. This would mean that climate adaptation studies should focus on measures needed in order to deal with the effects of anthropogenic climate change, and thus that the tools needed to do so should be those associated with climate projection (or perhaps with attribution, if we consider the anthropogenic change that has already occurred). This implicitly assumes, however, that the systems being studied were already “adapted” to the historical climate. When we consider the most damaging extreme events, this is often not the case. Because the most damaging events are also quite rare – having return periods longer than a human lifetime, and much longer than the time in office of a typical political leader – much physical infrastructure and human settlement is very vulnerable to such events, having been constructed under the assumption (conscious or not) that such extreme events will not occur (e.g., Sobel 2014, Muir-Wood 2016).

We advocate that climate adaptation studies take a pragmatic view in which anthropogenic global warming is considered as one factor influencing future extreme event risk, but is not assumed a priori to be the dominant one. Whether it is important or not, and what tools should be used for extreme event risk assessment in any given application, depend on the time horizon and the extreme event types being considered. If one is planning decades ahead and considering heat extremes, global warming is almost certainly important and dynamical models may be practical. If one is considering tropical cyclone risk for a single year (as in writing reinsurance contracts) then standard catastrophe models, without climate change, may be adequate. When deciding whether to rebuild a facility or community after a disaster, event attribution might be relevant; a finding that climate change played a significant role, implying continued increasing risk in the future, could inform a decision not to rebuild (in itself a possible form of adaptation). For other purposes, we need to make nuanced judgments, and the right tools may not yet exist in some cases.

On virtually any time scale, however, risk assessment for climate adaptation should be probabilistic, considering the full range of possibilities, and considering internal climate variability as well as human-induced climate change (e.g., Goddard et al. 2009). While accurate, high-resolution, robust decadal predictions, for example, would certainly be very valuable and constitute a worthy target for research (e.g., Meehl et al. 2009; Shukla et al. 2009), adaptation planning need not wait for them. Where present vulnerabilities to historical levels of hazard are large, an obvious and conservative adaptation strategy is simply to build resilience to a wide range of plausible extreme events. As a starting point, this range can be inferred from the historical record, interpreted through methods such as extreme value theory or catastrophe modeling to correct for the shortness of that record (so that the full range of plausible extreme events may not have been sampled). Changes in hazard due to climate change should by all means be considered to the fullest extent allowed by current science, but science's perfection should not become the enemy of adaptation's good.

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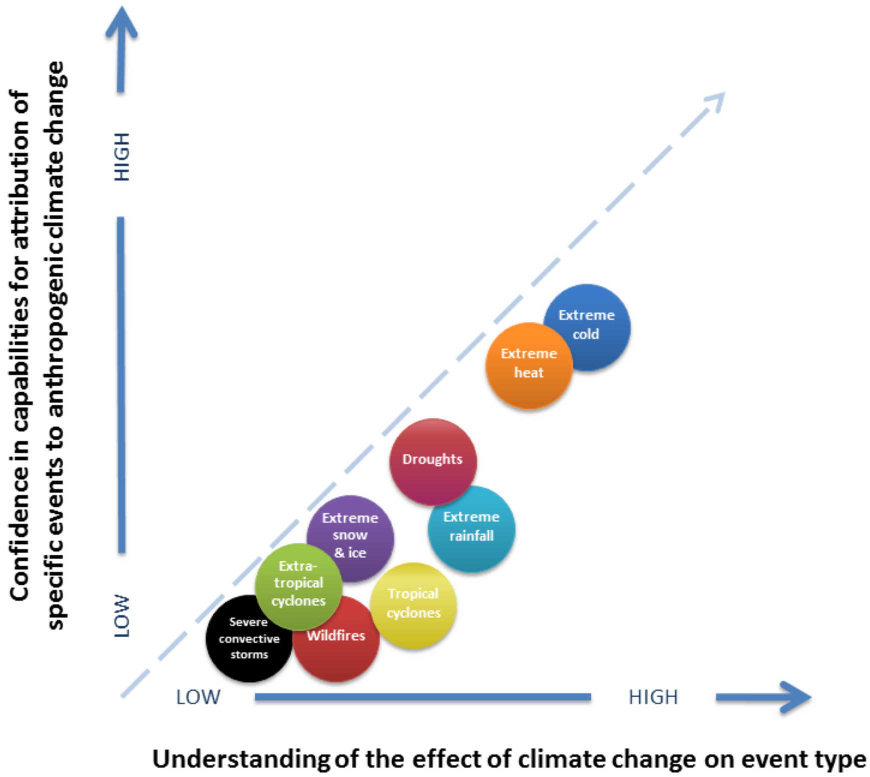

FIGURE 1. Schematic depiction of the state of attribution science for different event types. The horizontal position of each event type reflects an assessment of the level of understanding of the effect of climate change on the event type. The vertical position of each event type indicates an assessment of scientific confidence in current capabilities for attribution of specific events to anthropogenic climate change for that event type. 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 potential to increase event attribution confidence by overcoming remaining challenges that limit the current level of understanding, as indicated by the blank space in the upper

right corner. Figure and caption adapted from National Academy (2016), where more detailed explanation can be found.

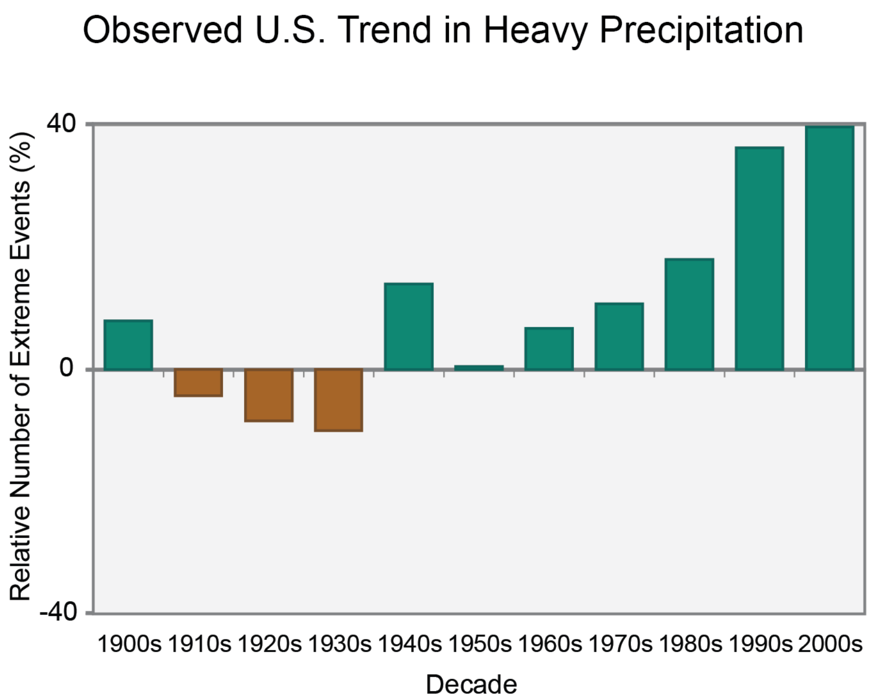

FIGURE 2. One measure of a heavy precipitation event is a 2-day precipitation total that is exceeded on average only once in a five-year period, also known as a once-in-five-year event. As this extreme precipitation index for the United States during 1901-2012 shows, the occurrence of such events has become much more common in recent decades. Changes are compared to the period 1901-1960, and do not include Alaska or Hawai'i. The 2000s decade (far right bar) includes 2001-2012. Figure and caption adapted from Walsh et al. (2014), originally from Kunkel et al. (2013).