RESEARCH ARTICLE

Reframing Future Risks of Extreme Heat in the United States

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Abstract The goal of this study is to reframe the analysis and discussion of extreme heat projections to improve communication of future extreme heat risks in the United States. We combine existing data from 31 of the Coupled Model Intercomparison Project Phase 5 models to examine future exposure to extreme heat for global average temperatures of 1.5, 2, 3, and 4 °C above a preindustrial baseline. We find that throughout the United States, historically rare extreme heat events become increasingly common in the future as global temperatures rise and that the depiction of exposure depends in large part on whether extreme heat is defined by absolute or relative metrics. For example, for a 4 °C global temperature rise, parts of the country may never see summertime temperatures in excess of 100 °F, but virtually all of the country is projected to experience more than 4 weeks per summer with temperatures exceeding their historical summertime maximum. All of the extreme temperature metrics we explored become more severe with increasing global average temperatures. However, a moderate climate scenario delays the impacts projected for a 3 °C world by almost a generation relative to the higher scenario and prevents the most extreme impacts projected for a 4 °C world.

Plain Language Summary Extreme heat events or heat waves are public health threats and can also cause damages or disruptions to infrastructure, transportation, agriculture, and water or energy resources. Extreme heat events are already more frequent and more intense than they were a generation ago, and they are expected to become even more frequent and more intense as global average temperatures continue to increase. The way most climate scientists describe future changes in the risk of extreme temperatures can be confusing to nontechnical audiences, who may find it challenging to relate to the projections. In addition, the metric most relevant to what any one person, location, or sector cares about can vary. For example, an urban planner may be concerned about surpassing the temperature threshold at which asphalt softens or rails warp, while a water manager may want to track the number of consecutive days in a heat wave to prepare for changes in water supply, and a public health official may care about high minimum (usually elevated nighttime) temperatures to plan appropriate health adaptation responses. To help characterize risk of extreme heat events to multiple audiences, this analysis uses notable heat waves from the recent past as a benchmark and shows how the frequency and severity of events like these are projected to change in the future for specific levels of global warming (1.5, 2, 3, or 4 °C) above preindustrial levels. With this method, an individual or community can use their own experience as context for understanding how future changes in the frequency, intensity, or duration of such events may differ from current conditions where they live, or from their recollection of a recent heat wave. For instance, someone who remembers the Atlanta heat wave on 10 August 2007 will learn that peak temperatures similar to that event will occur on average 19 times each year, or approximately once every 8 days each summer, if global temperatures rise 4 °C. Having a better and more intuitive understanding of the risks of extreme heat events can inform mitigation, adaptation, or other decision-making activities.

1. Introduction

Extreme heat affects multiple sectors in the United States, including public health (Kaiser et al., 2007), water resources (e.g., Fant et al., 2017), infrastructure and transportation (Coffel et al., 2017), and energy (Miller et al., 2008; Sathaye et al., 2013). Although high temperature records can be broken even without external forcing from global climate change, the frequency and intensity of these recorded high temperature events are projected to increase with continued warming (U.S. Global Change Research Program [USGCRP], 2017). Already, new high temperature records are being recorded in the United States approximately twice as

frequently as low temperature records (Meehl et al., 2009, 2016), and extreme heat events and their impacts make national news headlines nearly every summer (e.g., Astor, 2017; Fritz, 2017). Across each of the impacted sectors, the risks posed by extreme heat are projected to worsen throughout the 21st century (USGCRP, 2017).

Although the risks posed by extreme heat are far reaching, the metrics and thresholds used to define *extreme* and to quantify these impacts can vary within and across sectors. For example, the transportation sector may use absolute temperature thresholds for projecting the effects of extreme heat on the integrity of pavement or railroad lines (Chinowsky et al., 2017), whereas the public health sector may incorporate alternate measures such as nighttime low temperatures (Murage et al., 2017; Royé, 2017), combined heat and humidity (Davis et al., 2016; Horton et al., 2016), or temperatures relative to regionally defined thresholds (Anderson & Bell, 2009; Kent et al., 2014). Recently, several studies have focused on how extreme heat metrics have changed based on observational data (e.g., Alexander, 2016), but less attention has been given to how those measures of risk might change with future conditions, or how measures of relative risk might vary across the United States. Cross-sectoral variations in relevant metrics, along with the nonlinear and spatially variable changes expected due to ongoing global-scale warming, make it challenging to adopt a "one size fits all" approach for characterizing extreme heat vulnerabilities nationwide. However, better communication of risks associated with extreme heat events will promote effective management of those risks.

Much of the previous research on projected changes in extreme heat has been framed in terms of the impacts anticipated under future climate scenarios utilized by the Intergovernmental Panel on Climate Change (IPCC, 2014; e.g., representative concentration pathway [RCP] 8.5 in 2100, or RCP4.5 in 2050). The conditions associated with these scenarios, while useful from a modeling perspective, are understood only by technical experts and therefore lack relevance to the general public and many policymakers. More recently, extreme heat and other climate impacts have been modeled in terms of how these risks might change for different targeted amounts of global warming, such as for scenarios that reach 1.5 or 2 °C above preindustrial average temperatures by the late 21st century (e.g., Guo et al., 2017; King & Karoly, 2017; Matthews et al., 2017; National Research Council, 2011; Russo et al., 2017). The results of these analyses may be somewhat easier to communicate to the general public, as they can be directly tied to more familiar targets of projected increases in global temperature such as those agreed upon in the Paris climate conference in 2015 (United Nations Framework Convention on Climate Change, 2015). However, even these metrics can be abstract, since they are not generally rooted in individuals' experiences or local perspectives.

Compounding the challenge of communicating extreme heat risks to the public is the fact that the extreme temperature thresholds relevant to different individuals and sectors can vary by time and location, and definition of risk can encompass changes in likelihood of occurrence, severity, duration, or timing. Recent research and practice in climate change assessment and communication underscore the value in better characterizing risk as a means to convey information to the general public and to inform mitigation, adaptation, or other decision-making activities (Ballard & Lewandowsky, 2015; National Academies of Sciences, Engineering and Medicine, 2016; Weaver et al., 2017). Specifically, research indicates that individuals who have experienced an extreme climate event are more likely to perceive climate change as a threat (Konisky et al., 2016; Reser et al., 2014; Sisco et al., 2017). By extension, framing future climate risks in terms of tangible past experiences should also be a key component of an effective risk communication strategy.

With this in mind, the goal of this study is to analyze existing temperature projections from Coupled Model Intercomparison Project Phase 5 (CMIP5) and to reframe the discussion of future changes in extreme heat exposure to more directly align with individuals' prior experiences with extreme heat events. Rather than reporting results at specific time periods under alternative climate scenarios, we present location-specific projections of extreme heat risk, in terms of both frequency and intensity, based on global average temperature increases of 1.5, 2, 3, and 4 °C above a preindustrial baseline. To more accurately reflect individuals' past experiences, we also explore future temperature extremes in the context of both absolute thresholds (e.g., 100 °F days) and locally relevant thresholds (e.g., historical hottest day of the year by location). Using this method, we can report our results on future changes in the risk of extreme heat events in a format relevant to any given local history. We conclude with a summary of when the selected global temperature thresholds are expected to be reached under alternative climate scenarios.

2. Methods

For examining future temperature extremes, we extracted daily gridded temperature data for 21-year time slices from each of 31 global climate models (GCMs), centered on the year that each model is projected to reach a global average temperature threshold of 1.5, 2, 3, and 4 °C above a preindustrial baseline (1850–1879). The year in which each model reaches these specified temperature thresholds was determined using mean global temperatures from the GCMs and RCPs (Moss et al., 2010) used in the CMIP5 archive (e.g., Taylor et al., 2012). Projections were then adjusted to account for preindustrial warming using differences in Hadley Climate Research Unit Temperature's mean global temperature between the preindustrial period (1850–1879) and the baseline period used in other climate impact studies (1986–2005). This time-sampling method follows the approach described in detail in Swaine and Hayhoe (2015). By using this method, which is particularly helpful in identifying differences in risk of extreme events (James et al., 2017), the results shown in section 3 do not have a year associated with them but occur whenever each model reaches that temperature threshold is reached. Note that the "baseline" period used for our modeling (defined as 1986–2005 for consistency with other recent climate impacts studies, e.g., USGCRP, 2017) already includes an approximately 0.86 °C warming above preindustrial temperatures.

We used daily data for maximum, minimum, and average surface temperature from each model. For each GCM, we regridded the daily temperature outputs onto a uniform 1° × 1° grid for the contiguous United States (CONUS) to match the 1° resolution of the Berkeley's Earth Surface Temperature (BEST) data, using a linear interpolation between grid cells. Since our analysis is focused on temperature extremes resulting from different levels of global average temperatures, we examined only the RCP8.5 ensemble of models. We chose the RCP8.5 scenario because the GCMs running the RCP4.5 scenario do not reach 4 °C above preindustrial temperatures, whereas using the RCP8.5 scenario allows us to examine a full range of global average temperature increases between 1.5 and 4 °C above a preindustrial baseline. Further, recent work suggests that different RCPs do not introduce different spatial patterns of temperature change for a given global warming level (e.g., King et al., 2018; Tebaldi & Knutti, 2018), justifying our use of a single RCP for our analysis.

To more accurately reflect the frequency, magnitude, and timing of local U.S. extremes, we bias corrected the GCM modeled temperature data for the r1i1p1 model run for each of the 31 GCMs. Bias correction allows us to combine the ability of the GCMs to capture the changing large-scale statistics of the background climate with the ability of observational data to summarize site-specific information about local temperatures at a resolution that GCMs are unable to capture. Our bias correction method relies on a gridded, historical temperature data set from the University of California, BEST (Rohde, Muller, Jacobsen, Muller, et al., 2013; Rohde, Muller, Jacobsen, Perlmutter, et al., 2013) project. The BEST data contain gridded daily surface temperatures from the preindustrial baseline through the present day. For our bias correction step, we extracted 1° × 1° gridded data from BEST summarizing minimum, maximum, and average daily temperature for the CONUS over the 1986–2005 period. For each GCM, we then bias corrected daily temperatures using a process similar to that described by Thrasher et al. (2012). Specifically, for each 1° × 1° grid cell, we bias corrected the maximum temperature for each day of the summer by quantile mapping of the full distribution of GCM-modeled temperatures over a 31-day moving window over the 20 years where the BEST data and GCM overlap (620 observations). The bias correction derived in this manner for each GCM grid cell and each summer day was then applied to the GCM forecast prior to further analysis. A detailed summary of the bias correction methods and summary results is included in the supporting information.

Once the 21-year windows were extracted for each of the specified temperature thresholds from each GCM, we used the bias-corrected data to extract a range of metrics describing extreme heat risks resulting from different global temperature changes. Because we focused our analysis only on temperatures during the 153 days of summer (defined herein as 1 May to 30 September), we defined the projected annual maximum temperature as the peak temperature expected with a 1/153 probability (e.g., the 99.35th percentile temperature). Over the 21-year time slices for each global temperature threshold, this temperature can be considered the average hottest summer day during that period. As a measure of statistical significance, we also compared the average change in annual maximum temperature projected by the full suite of models to the variability across the models. Changes are described as statistically significant where the projected change in the mean across all models exceeds two times the standard deviation in the mean across all models.

We also explored projected changes in extreme heat using a range of metrics to define heat waves. We used three different definitions of heat waves in our modeling, each based on a 3-day duration. In the first definition, a heat wave was defined as three or more consecutive days with an average daily temperature above 95 °F. In the second definition, a heat wave was defined as three or more consecutive days with an average temperature above the historical annual summertime maximum for each location. And in the third definition, a heat wave was defined as three or more consecutive days where the daily minimum temperature does not drop below 80 °F. In each case, we compare the total number of days per summer that each grid cell has experienced heat waves in the past, and the total number of days per summer each cell is projected to experience heat waves under each future temperature threshold. For example, if a grid cell experiences three different heat waves with durations of 3, 5, and 8 days in a summer simulation for one GCM, the total days under heat waves for that year and GCM would be 16. In all cases, we report for each grid cell the average of these values across all GCMs, and across all 21 years, for each global temperature threshold. Though humidity is particularly relevant to evaluating health risks, this analysis does not consider metrics such as wet bulb temperature or heat index nor does it include other confounding conditions that may present health risks, such as direct sunlight or strong winds. Heat index measures are both less well recorded historically and more challenging to model than temperature metrics.

Finally, to place future extreme heat projections in the context of past experience, we also compared temperature projections for each global temperature change to a set of historical events at a number of cities across the United States. We selected one city broadly representative of each region of the United States and extracted from the BEST data the maximum daily temperature in that grid cell during a historic heat event in the baseline period. We then compared to that threshold the full distribution of projected summertime temperatures across the full GCM ensemble, to evaluate how the frequency of comparable events might change under each temperature change threshold.

3. Results

3.1. Spatial Patterns of Future U.S. Temperature Extremes

In the historical baseline (1986–2005), average annual maximum temperatures exceeding 100 °F are common across much of the central and Southern Great Plains, and portions of the Southeast. Average annual maximum temperatures exceeding 110 °F are found only in the extreme desert conditions found in parts of the southwestern United States, including Death Valley and the Mojave Desert (Figure 1). For a 1.5 °C global warming change, statistically significant increases in annual summertime maximum temperatures are projected for much of the western United States and parts of the southern Great Plains, but there is limited intermodel agreement across much of the eastern part of the country, as illustrated by the white hash mark patterns in Figure 1. For global temperature changes of 2 °C or higher, increases in the projected average maximum annual temperature are statistically significant for virtually all of the CONUS. At this threshold in global average temperature, average maximum annual temperatures of 105 °F become common in a broad swath from southern Texas through central Nebraska, and average annual maximum temperatures exceeding 110 °F become common in north Texas. At a global average temperature threshold of 4 °C, much of the south-central United States, including virtually all of Texas, Oklahoma, Kansas, Missouri, and Arkansas, is projected to experience peak summer temperatures exceeding 110 °F every year—temperatures similar to what is currently experienced only in the Mojave Desert and southern Arizona.

Intermodel variability dominates the signal of warming in Alaska at much higher global temperature thresholds, possibly reflecting differences in the ways different GCMs treat the processes that lead to Arctic amplification (e.g., Holland & Bitz, 2003; Pithan & Mauritsen, 2014). Thus, the temperature changes projected for much of Alaska do not become statistically significant until an increase in global average temperature of 4 °C. However, at a global average warming of 4 °C, average annual maximum temperatures exceed 85 °F for a large portion of Alaska and exceed 95 °F for a small part of interior Alaska.

3.2. Number of Days Above Absolute and Relative Extreme Heat Thresholds

In addition to changes in average annual summertime maximum temperatures, we also calculated projected changes in the number of days per year that U.S. locations will experience extreme heat across the United States. The picture painted by these data varies according to the "extreme heat" definition.
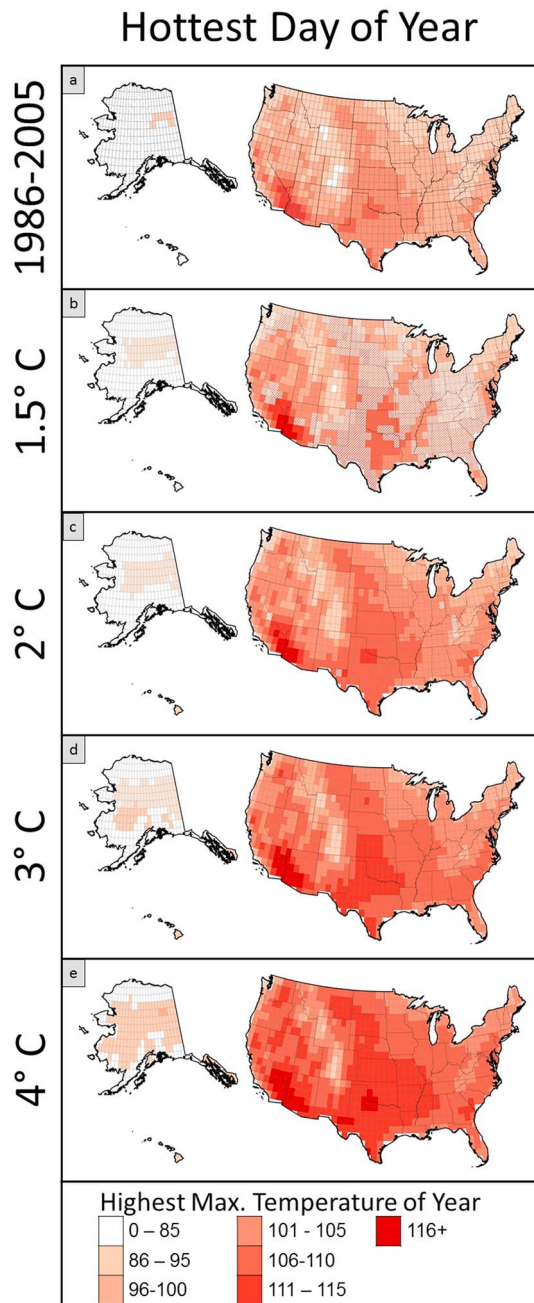
Hottest Day of Year

Figure 1. Projected hottest day of the year during baseline period (1986–2005) and at warming thresholds of 1.5, 2, 3, and 4 °C above the preindustrial baseline. Values are averages across all 31 global climate models used.

For example, if we consider days with a maximum temperature above 100 °F, a metric commonly cited for extreme heat impacts, the southwestern and south-central U.S. areas appear to be the most impacted by extreme heat in both the historical and future periods (Figure 2). In the historical baseline, for example, the data indicate that much of the southern Great Plains is accustomed to experiencing an average of 1–2 weeks per summer above 100 °F, and north-central Texas commonly experiences a total of 2–4 weeks above this threshold. Large parts of the Mojave Desert typically experience more than 8 weeks above 100 °F historically. All of these regions are projected to see an increase in the number of days above 100 °F with each incremental increase in global average temperature. For example, for a 2 °C warming, most of Texas is projected to experience more than a doubling in the number of days above 100 °F. Some parts of north Texas are projected to see more than 6 weeks per year above 100 °F, and parts of south Texas are expected to experience more than 8 weeks per year. At a 4 °C warming, most of the south-central United States, including virtually all of Texas and Oklahoma, and most of Louisiana and Arkansas, are projected to see more than 8 weeks per year with temperatures above 100 °F. The same is true for the southern half of Arizona and much of southeastern California.

Although these maps indicate that much of the southern United States will spend more than half of the summer experiencing temperatures >100 °F, there are parts of the United States that emerge as refugia from extreme heat in this absolute temperature reference frame. For example, even for 4 °C warming, large parts of the Northeast, the upper Midwest, and the central and northern Rocky Mountains are projected to see no more than 1 day per year, on average, above 100 °F. These northern, coastal, and high-elevation regions may perceive their future extreme heat risks to be limited based on this absolute temperature metric. However, if we examine extreme heat from the perspective of local norms, the future risks of extreme heat are much more widely distributed across the United States, as summarized below.

By definition, the entire country experiences its historical annual summertime maximum temperature an average of 1 day per summer in the baseline; Figure 1 shows the distribution of these annual maximum values across the country. As global average temperatures warm, extreme heat risks based on this relative metric form a very different pattern than that seen in the absolute temperature reference frame. For example, for 2 °C global warming nearly all of the United States is projected to experience more than a week per summer of temperatures historically experienced only once per year, and a broad region around the lower Mississippi and Ohio River valleys is projected to see more than 2 weeks per summer above this historical threshold. For 3 °C warming, most of the country is projected to experience more than 2 weeks per summer above their historical annual maximum summertime temperature, with parts of southern Florida and Texas projected to see these temperatures more than 6 weeks each summer. Finally, for a 4 °C warming, most of the country is projected to see more than 4 weeks each summer above temperatures currently experienced only once per year, and parts of the southeastern United States could spend more than half their summer at temperatures exceeding their historical annual summertime maximum. Using this locally defined framework to define what constitutes "extreme," there are no parts of the United States that emerge as refugia from extreme heat.
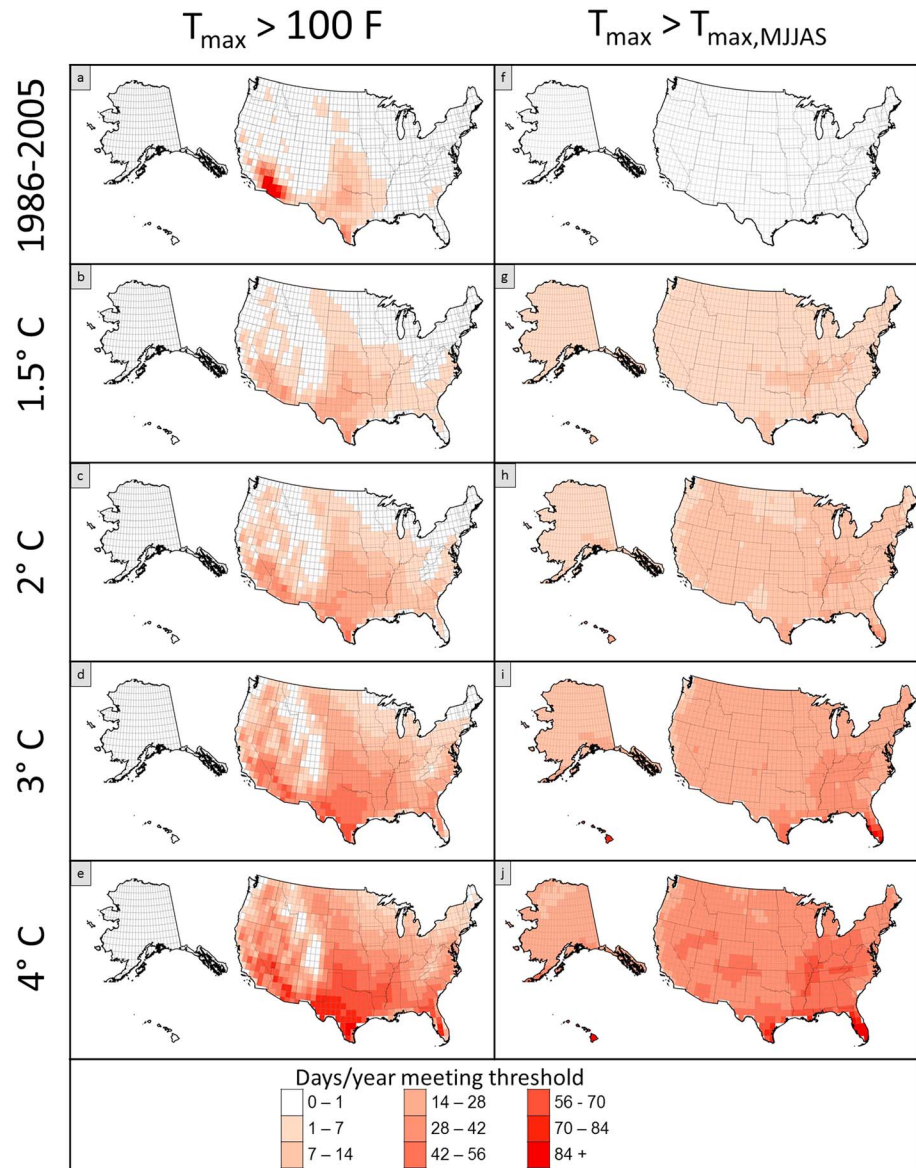
Figure 2. Frequency of days exceeding absolute and relative metrics of daily maximum temperature. Historical data (top row) show absolute number of days exceeding each threshold; subsequent rows show the additional days projected for each warming threshold. Absolute temperatures associated with column 2 are shown in top panel of Figure 1.

3.3. Projected Changes in Heat Waves Across the United States

A heat wave can be defined based on the number of days exceeding a minimum daily threshold, an average daily threshold, or other temperatures of interest (e.g., Sarofim et al., 2016; Smith et al., 2013). As summarized in section 2, to provide metrics that can be applicable to a range of different sectors, we defined heat waves in a variety of ways, as three consecutive days above absolute or relative thresholds of average or minimum temperature. Although much of the country clearly shows increasing risks from heat waves with increasing global average temperatures (USGCRP, 2017), these heat wave risks show different spatial patterns of change depending on the metric used.

The projected number of days with heat waves increases with global warming under both absolute (Figures 3a–3e) and relative (Figures 3f–3j) 3-day average temperature thresholds. In the historical baseline, only parts of the southernmost tip of Texas and the Mojave Desert experience a total of more than 6 weeks
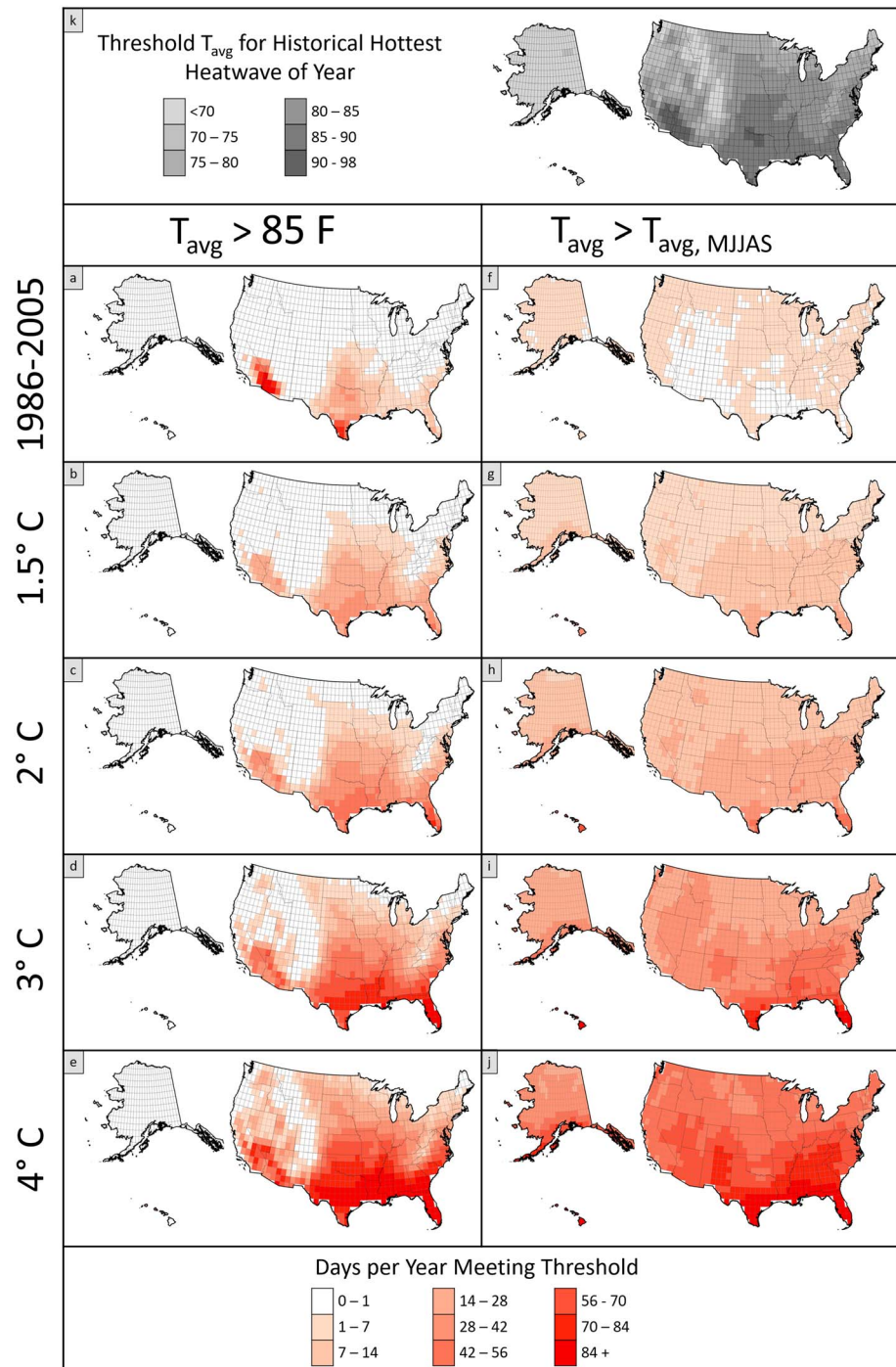
Figure 3. Average number of days per year that U.S. locations are projected to experience heat waves based on metrics of absolute and relative measures of average daily temperatures. The top panel (k) shows the absolute temperature associated with the annual maximum heat wave threshold. As shown in Figure 2, the historical plots (1986–2005) show the total number of days exceeding each threshold in the baseline, and subsequent plots show the increase in the number of days for each global warming threshold.

per year experiencing heat waves, when a heat wave is defined as 3 days with average daily temperatures exceeding 85 °F (Figures 3a–3e). The desert portions of the southwestern United States, the Southern Great Plains, and the Southeast are the only other parts of the nation that currently experience more than 1 week per year in heat waves based on this absolute temperature threshold. At a global warming of 2 °C,
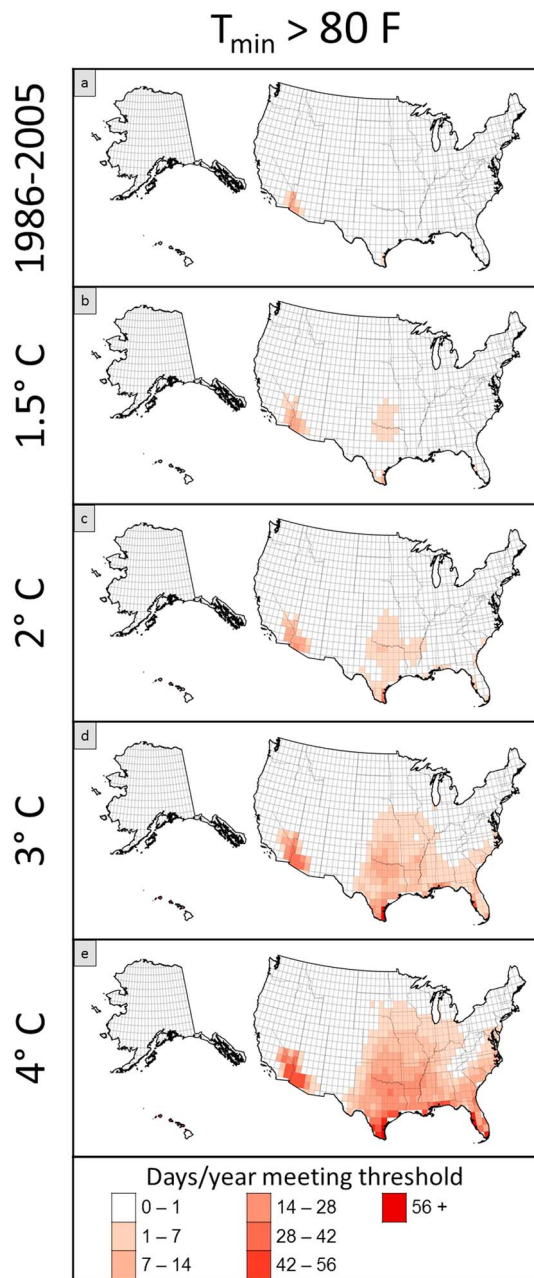
$T_{min} > 80\ F$

Figure 4. Average number of days per year U.S. locations are projected to experience heat waves based on 3-day minimum temperatures exceeding 80 °F. As shown in Figure 2, the historical plot (1986–2005) shows the total number of days exceeding the threshold in the baseline, and subsequent plots show the increase in the number of days for each global warming threshold.

heat waves defined as three consecutive days with average daily temperatures exceeding 85 °F become more common, with most of the central United States projected to experience at least one heat wave per year, and parts of the Deep South projected to experience heat waves for more than 6 weeks per year. For a 4 °C warming, virtually all of the eastern half of the nation can expect at least one heat wave per year, and the south-central and southeastern United States are projected to experience heat waves in more than 8 weeks per year.

When heat waves are defined by relative temperature metrics instead (e.g., the annual maximum 3-day average temperature), a larger fraction of the nation is projected to experience heat waves under each global average temperature change (Figures 3f–3j). For a 2 °C warming, for example, most of the southern half of the country is projected to experience more than 2 weeks per year in periods where average 3-day temperatures exceed the historical annual maximum 3-day average summertime temperature. For a 4 °C warming, if a heat wave is defined by three consecutive days with average temperatures exceeding the historical annual summertime maximum 3-day temperature, virtually the entire CONUS experiences heat waves for at least 4 weeks per year, and the entire southern half of the country can expect heat waves for more than 8 weeks per year.

The projected number of days with heat waves defined by a minimum, rather than average, temperature threshold also increases with global warming (Figure 4). For example, when heat waves are defined as three or more consecutive days where the minimum daily temperature exceeds 80 °F, the south-central and southeastern United States are projected to experience the greatest increase in heat waves as global average temperatures rise. For a 2 °C global average temperature increase, large parts of the south-central United States are projected to experience heat waves at least 1 week per year. For a 4 °C warming, many parts of the southern United States can expect more than 4 weeks per year in heat waves. Importantly, the regions most affected by heat waves under this definition include large parts of the Midwest and Southeast, which include major population centers.

3.4. Future Extreme Temperatures Framed by Past Experiences

We identified memorable historical heat events through a combination of evaluating the BEST reanalysis data and searching for news reporting of extreme heat events in each region of the United States. Recent extreme heat events that occurred within the baseline period defined by our data, and/or which had noteworthy impacts to human health and society, are listed for each of the National Climate Assessment regions (USGCRP, 2017) in Table 1. Note that due to the low spatial resolution of the BEST data, the gridded baseline data set is not able to capture factors such as urban heat island effects. Thus, the temperatures reported for these events at weather stations generally exceed the historical BEST temperatures.

To estimate how frequently U.S. locations are projected to experience events like these in the future, we extracted the maximum daily temperature recorded in the BEST data for each of these historical heat events and compared these historical thresholds to the projected distribution of summer temperatures for different global warming thresholds. In each example, we can then evaluate the change in likelihood of experiencing a heat event similar in magnitude to recent memorable local events at each global warming threshold.

Table 1
Examples of Memorable Historical Heat Events in Focus Cities

City	Memorable historical temperature event	Maximum daily T_{max} recorded at weather station during event (NCEI weather station)	Maximum daily T_{max} in 1° resolution BEST data during event	Summary of heat event
Chicago, IL	13 July 1995	106	96.8	Chicago experienced particularly extensive societal damage during this 1995 heat wave. The hottest temperatures occurred from July 12–16, and resulted in an estimated 739 heat-related deaths.[a,b]
New York, NY	2 August 2006	97	96.9	The New York Times reported that this heat wave killed or contributed to the deaths of 140 people. The overall death rate in NYC increased about 8% that summer.[c,d]
Dallas, TX	1–3 August 1998	106	107.0	In 1998 there were 29 consecutive days with the temperature at Dallas/Fort Worth international airport was above 100 °F.[e] 35 attributed deaths were recorded in the summer of 1998.[f]
Los Angeles, CA	27 September 2010	113	101.5	This event produced the highest temperature ever recorded in Downtown Los Angeles.[g] More than 11,000 residents lost power following an electrical closet explosion, which officials stated may have been provoked by elevated electricity demand.[h]
Atlanta, GA	22 August 2007	104	100.4	The 104 °F achieved on the 22nd set the record for any August and barely missed the all time record high in the capital city by a single degree. By the end of the month, Atlanta had experienced its warmest month ever with an average monthly temperature of 85.6 °F.[i]
Seattle, WA	28 July 1998	97	93.8	The temperature on 28 July 1998 was the hottest temperature reached that year in Seattle, and was the highest all-time recorded temperature until 2009.[j,k]
Fairbanks, AK	1 August 1991	78	66.4	
Honolulu, HI	18 August 2004	92	87.6	This heat event set an all-time minimum temperature record of 80 °Cs until 2015.[l]

Note. We show historical BEST maximum daily temperatures (1° resolution) corresponding to the memorable historical heat event. Due to this low resolution, the data does not capture localized effects, such as urban heat islands. Observations at weather stations (column 3) thus exceed historical BEST data (column 4), emphasizing the importance of the urban built environment as an amplifier of vulnerability and the potential for urban design heat mitigation strategies. Societal impacts associated with each historic event result from the combination of multiple climatic variables (e.g., humidity, length of period of sustained extreme heat, minimum temperatures) and are mediated by community-specific vulnerability and resiliency factors that are not constant over time. NCEI = National Centers for Environmental Information; BEST = Berkeley's Earth Surface Temperature.
[a]https://www.cdc.gov/mmwr/preview/mmwrhtml/00038443.htm [b]https://www.ncdc.noaa.gov/news/climate-history-july-1995-chicago-area-heat-wave [c]https://www.nytimes.com/2006/11/16/nyregion/16heat.html [d]https://www1.nyc.gov/assets/doh/downloads/pdf/vs/2006sum.pdf [e]https://www.weather.gov/fwd/danncon10 [f]https://www.cbsnews.com/news/record-setting-triple-digit-heat-scorching-texas/ [g]http://latimesblogs.latimes.com/lanow/2010/09/at-113-degrees-downtown-la-hits-all-time-record-high-temperature.html [h]http://www.bbc.com/news/world-us-canada-11432718 [i]https://www.weather.gov/ffc/clisum07 [j]http://www.cnn.com/2009/US/weather/07/29/washington.oregon.heat/ [k]https://www.seattletimes.com/seattle-news/data/as-seattle-sweats-few-air-conditioners-cool-us-down/ [l]https://www.wunderground.com/blog/weatherhistorian/update-crazy-summer-in-hawaii-record-rainfall-record-heat-and-snow.html

As expected, temperatures associated with these historical extreme heat events in select U.S. cities (horizontal lines in Figure 5) are near the extreme upper tail of the distribution of historical summer temperatures. With each incremental increase in global average surface temperature (dT), however, these extreme events become more and more common. For example, at a 4 °C warming threshold, the peak temperature associated with the 2007 Atlanta heat wave seen on 10 August 2007 is projected to occur on average 19 times per year, or approximately once every 8 days each summer. For New York City, the peak temperature observed on 2 August 2006, expected to occur only once per 3 years in the baseline period, becomes a
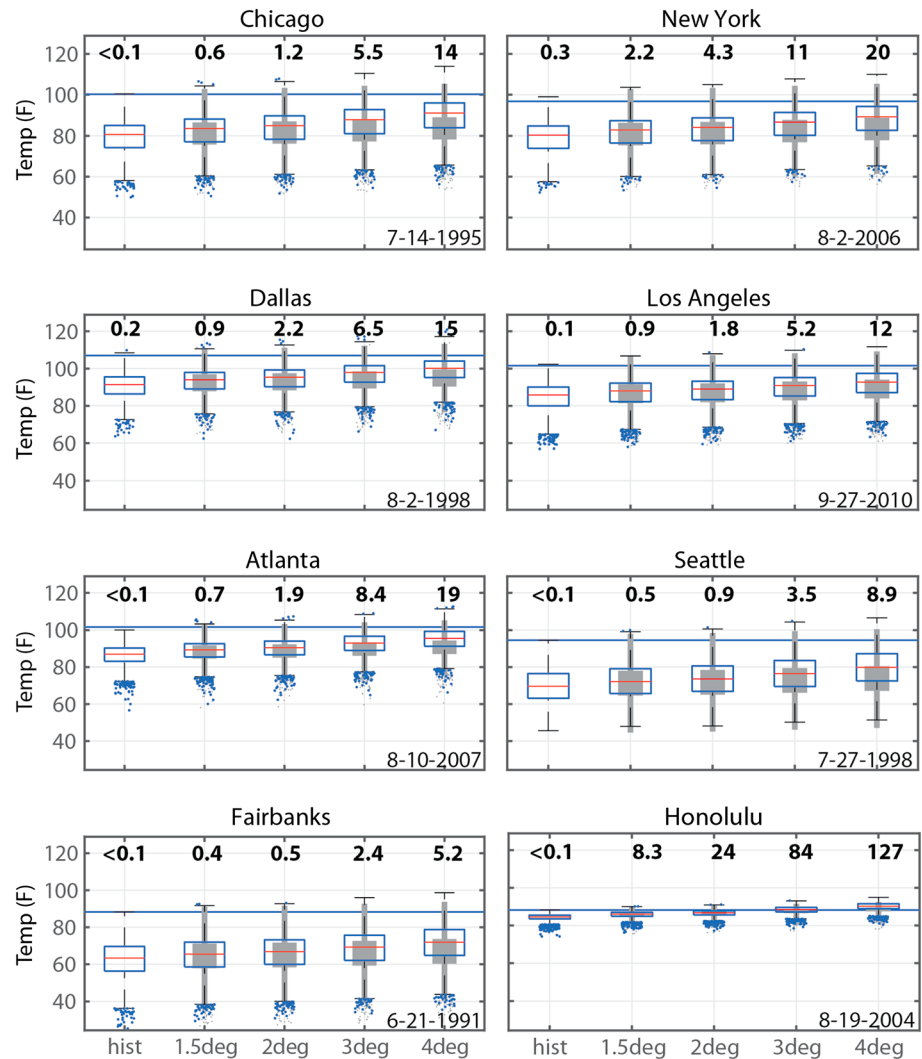
Figure 5. Distribution of summer temperatures in select U.S. cities at different warming thresholds. In each case, the blue horizontal line represents the Berkeley's Earth Surface Temperature modeled temperature representing the extreme heat event on the date specified. The distribution of all summer daily maximum temperatures is shown as a blue box and whisker plot for each global warming threshold, with the boxes representing the interquartile range of summer temperatures and the whiskers extending from the 5th to 95th percentiles. Numbers above each boxplot show the number of days per summer that these historical temperature extremes are expected to occur for each warming threshold. The gray box and whisker plot illustrates what the distribution of summer daily maximum temperatures would be if the historical distribution were shifted up by the average global warming.

temperature expected nearly 20 days per summer for a 4 °C warming. Projections for other U.S. cities are similar, although the degree to which these events become more common varies by region. One notable exception is Honolulu, where the entire summertime temperature distribution is extremely narrow due to the location of Hawaii in the tropical Pacific Ocean. In Honolulu, this narrow distribution shifts upward by approximately the same amount as the global average temperature change, so that a large fraction of summertime temperatures become higher than the observed historical maximum.

3.5. Timing of Future Extreme Heat Risks

In order to present our results in a common reference frame, each of the analyses summarized above shows expected impacts under a set of global average temperature changes relative to a preindustrial baseline (1.5, 2, 3, and 4 °C). The expected time to reach any of these global temperature thresholds varies by emissions scenario; thus, the timing and the likelihood of experiencing the extreme temperature changes shown in Figures 1–5 depend to a large degree on which greenhouse gas concentration pathway we follow.
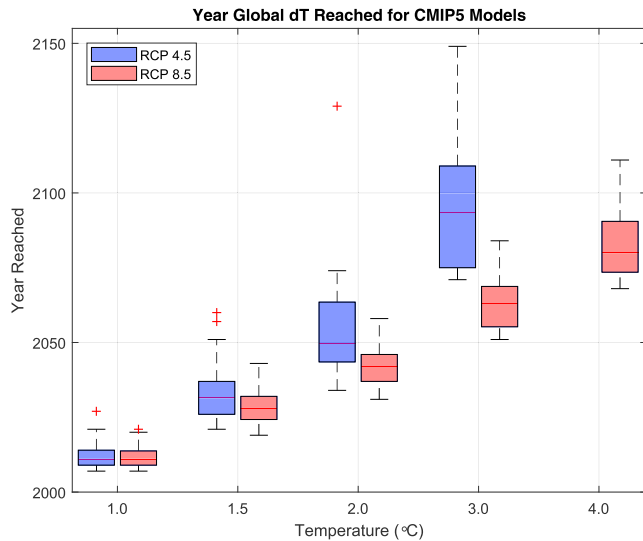
Figure 6. Year in which warming thresholds of global average surface temperature are met under different emissions trajectories. The horizontal lines within each box show the median time to reach each threshold across all available models, the boxes show the interquartile range based on all models, and the whiskers extend from the 5th–95th percentiles. CMIP5 = Coupled Model Intercomparison Project Phase 5.

Figure 6 shows the projected time to reach each of these global average temperature thresholds, based on the suite of 31 GCMs analyzed. As shown, the two RCPs broadly agree on the timing to reach 1 °C across all models; for many of the models, the median year to reach 1 °C has already passed. This is consistent with the fact that the globe has reached or nearly reached this global average temperature threshold already, depending on the instrumental data set and methods being used in the analysis (Haustein et al., 2017; USGCRP, 2017). The length of time required to reach each threshold increasingly diverges between the two RCPs as the global temperature change increases. Thus, a global average temperature increase of 1.5 °C above a preindustrial baseline is only slightly delayed under RCP4.5 compared to RCP8.5, the median time to reach 2 °C is almost a decade later under RCP4.5 than under RCP8.5 (~2050 vs. 2040), and the median time projected to reach 3 °C is nearly 30 years later under RCP4.5 than under RCP8.5. None of the models we evaluated reached 4 °C under RCP4.5; however, the vast majority of the models are projected to reach 4 °C before 2100 under RCP8.5.

4. Discussion and Conclusions

There is broad recognition in the climate modeling community that extreme heat events will become both more frequent and more severe in a warming world (Horton et al., 2016; IPCC, 2012, 2014; USGCRP, 2017). However, communicating the risks posed by these future extreme heat events can be confounded by the way climate model outputs are commonly portrayed. For example, while the frameworks established by the IPCC based on RCPs and time periods (e.g., RCP8.5 in 2100) may be useful from the perspective of harmonizing different model outputs, this framework may be completely opaque to policymakers and the general public. Similarly, framing extreme heat risks in the context of absolute temperature thresholds may be useful in sectors such as transportation or energy, where physical limitations of pavement or other materials can be exceeded, but these absolute thresholds may not be relevant to the people who may have been affected by extreme heat events well below these absolute thresholds.

In this contribution, we have used existing CMIP5 outputs to reframe future climate risks using metrics that we believe can be more directly tied to individuals' experiences. First, we have framed these risks in the context of future global average temperature changes, which may be more approachable or recognizable to the general public and policymakers than RCPs, in part due to widely publicized climate negotiations that are often based on temperature thresholds. And second, we have examined future extreme heat in terms of both absolute and locally relevant temperatures. While this analysis did not estimate sector-specific impacts, such as projected morbidity or mortality, use of other metrics, such as combined temperature and humidity, and other methods, such as population-based metrics (e.g., Jonses et al., 2015), may provide complimentary assessments of future risk.

Using this framework, we developed metrics of future extreme heat that may be more relatable for policymakers and the general public. While risks from both extreme temperatures and heat waves increase with each threshold step in global mean surface temperature, the spatial distribution of affected areas is dependent on whether absolute or relative measures are used. For example, while some parts of the country may remain refugia from 100 °F temperatures even for 4 °C global average temperature change, for that magnitude of warming, virtually all of the country is projected to experience more than 4 weeks per summer with temperatures exceeding their historical summertime maximum. Similarly, if heat waves are defined by average daily temperatures exceeding 85 °F, for 3 °C of warming only parts of the Southeast and Midwest are projected to experience more than 2 weeks per year experiencing these temperatures, whereas virtually the entire country can expect to see more than 2 weeks per year experiencing heat waves based on local historical maxima.

Once these risks are established based on absolute and relative metrics, it is also useful to evaluate when these projected futures might be expected to occur. As shown in Figure 6, the time at which we might

reach these different futures is strongly dependent on the greenhouse gas concentration pathway we follow. For example, if the world follows a high concentration trajectory exemplified by RCP8.5, and if we assume a generation is approximately 30 years, then a teenager in eastern Montana in 2075 might experience maximum summer temperatures that his or her grandparents would have had to travel to the Mojave Desert to see (e.g., Figure 1). Similarly, for RCP8.5, a child born in southern Texas in 2060 might experience as much as 6 weeks per summer when maximum temperatures are hotter than his or her grandparents experienced just once per year (e.g., Figure 2). And in this same future, a child in the southeastern United States can expect to spend more than half of his or her summer experiencing heat waves that would have occurred only 3 days per year for his or her grandparents (Figure 3). Importantly, in a world that follows a lower concentration scenario (RCP4.5) the extreme heat impacts projected for a 3 °C world are delayed by almost a generation, and the most extreme impacts found in a 4 °C world may never be seen by the generations to come.

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