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## Increased frequency of and population exposure to extreme heat index days in the United States during the 21st century

To cite this article: Kristina Dahl *et al* 2019 *Environ. Res. Commun.* 1 075002

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## Environmental Research Communications



## PAPER

## Increased frequency of and population exposure to extreme heat index days in the United States during the 21st century

## OPEN ACCESS

## RECEIVED

23 April 2019

## REVISED

6 May 2019

## ACCEPTED FOR PUBLICATION

7 June 2019

## PUBLISHED

16 July 2019

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Kristina Dahl<sup>1,4</sup> , Rachel Licker<sup>2,4</sup> , John T Abatzoglou<sup>3</sup> and Juan Declet-Barreto<sup>2</sup> <sup>1</sup> Climate and Energy Program, Union of Concerned Scientists, Oakland, CA, United States of America<sup>2</sup> Climate and Energy Program, Union of Concerned Scientists, Washington, DC, United States of America<sup>3</sup> Department of Geography, University of Idaho, Moscow, ID, United States of America<sup>4</sup> Co-primary authors.**Keywords:** climate change, heat waves, extreme heat, climate modelingSupplementary material for this article is available [online](#)**Abstract**

The National Weather Service of the United States uses the heat index—a combined measure of temperature and relative humidity—to define risk thresholds warranting the issuance of public heat alerts. We use statistically downscaled climate models to project the frequency of and population exposure to days exceeding these thresholds in the contiguous US for the 21st century with two emissions and three population change scenarios. We also identify how often conditions exceed the range of the current heat index formulation. These ‘no analog’ conditions have historically affected less than 1% of the US by area. By mid-21st century (2036–2065) under both emissions scenarios, the annual numbers of days with heat indices exceeding 37.8 °C (100 °F) and 40.6 °C (105 °F) are projected to double and triple, respectively, compared to a 1971–2000 baseline. In this timeframe, more than 25% of the US by area would experience no analog conditions an average of once or more annually and the mean duration of the longest extreme heat index event in an average year would be approximately double that of the historical baseline. By late century (2070–2099) with a high emissions scenario, there are four-fold and eight-fold increases from late 20th century conditions in the annual numbers of days with heat indices exceeding 37.8 °C and 40.6 °C, respectively; 63% of the country would experience no analog conditions once or more annually; and extreme heat index events exceeding 37.8 °C would nearly triple in length. These changes amount to four- to 20-fold increases in population exposure from 107 million person-days per year with a heat index above 37.8 °C historically to as high as 2 billion by late century. The frequency of and population exposure to these extreme heat index conditions with the high emissions scenario is roughly twice that of the lower emissions scenario by late century.

**Introduction**

For much of the contiguous United States, the frequency of extreme heat events has been increasing since the mid-1960s (Abatzoglou and Barbero 2014, Vose *et al* 2017) and the number of high temperature records has outpaced the number of low temperature records, particularly since the mid-1980s. Cities throughout the country have experienced not only more frequent extreme heat over the last 60 years, but also more intense and longer-lasting heat waves (Habeeb *et al* 2015), although the metric by which ‘heat wave’ is defined can influence whether or not a trend is detectable (Shiva *et al* 2019). Trends in daytime heat extremes over the past century across the US show a lack of long-term trends (Peterson *et al* 2013a). Hypothesized reasons for the lack of longer-term trends in heat extremes in the US are tied to land-surface feedbacks that modify the ratio of sensible to latent heat flux. For example, chronically dry land-surface conditions and higher Bowen ratios during the 1930s Dust Bowl are hypothesized to have promoted stronger warming of daytime temperature extremes across much of the central US (e.g., Abatzoglou and Barbero, 2014), while increased cropland intensification across portions

of the Midwest over the past half-century have reduced Bowen ratios and contributed to local cooling of daytime heat extremes (Mueller *et al* 2017).

A growing body of work attributes both the trends in extreme heat as well as specific extreme heat events to the influence of anthropogenic greenhouse gas emissions (Diffenbaugh and Scherer 2013, Knutson *et al* 2013, Knutson and Ploshay 2016). As anthropogenic greenhouse gases continue to accumulate in the atmosphere, extreme heat is projected to become more frequent and more severe for all parts of the country (e.g. Wuebbles *et al* 2014, Vose *et al* 2017).

Extreme heat, defined broadly as conditions that are hotter and/or more humid than is typical for a location (CDC 2019), is one of the most fatal natural hazards in the US and poses grave risks to human health (NWS 2019a, Medina-Ramón *et al* 2006, Borden and Cutter 2008, Anderson and Bell 2011, Vose *et al* 2017). Groups such as children (Xu *et al* 2012), the elderly (Anderson and Bell 2011), and individuals with low socio-economic status (Harlan *et al* 2013, Schmeltz *et al* 2015) are particularly susceptible to heat-related illness. Recent studies have highlighted the importance of humidity in the occurrence of days with extreme heat stress (Raymond *et al* 2017), but most projections of extreme heat in the US have relied heavily on temperature-based projections (e.g. Peterson *et al* 2013a, 2013b, Habeeb *et al* 2015, Vose *et al* 2017). Those studies that do provide projections of heat stress for the US tend to use wet bulb globe temperature (e.g. Willett and Sherwood 2012, Dunne *et al* 2013, Buzan *et al* 2015, Coffel *et al* 2018).

In contrast, the heat index (HI; also known as apparent temperature) combines temperature and relative humidity to produce a 'feels like' temperature. The HI serves as a primary basis for the issuance of heat advisories by the US National Weather Service (NWS) and has been correlated to heat-related mortality (Davis *et al* 2003). While two known studies have assessed global-scale changes in the HI at low spatial resolution (Delworth *et al* 1999, Russo *et al* 2017), higher spatial resolution projections of HI for the US are absent from the literature. Because the probability of extreme heat events is expected to increase with continued global temperature increases (Karl and Knight 1997), understanding how the exposure of the US population to high HI conditions is projected to change is critical for developing strategies to help people and communities cope with and adapt to extreme heat.

The HI was formulated to estimate how combinations of temperature and relative humidity feel to a 'typical adult human' and was intended to be valid for conditions that were 'exceeded on less than 1% of the Earth's surface and for less than 1% of the time' (Steadman 1979a, p 862). Beyond those conditions, at high temperature and relative humidity, skin humidity levels can exceed 90%, it becomes difficult for the human body to cool itself by sweating or to dissipate heat, and the NWS HI calculation becomes invalid (Steadman 1979a, Ostro *et al* 2009, Sherwood and Huber 2010). We hypothesized that future warming would increasingly cause 'no analog' conditions that fall outside the range considered by Steadman (1979a) and the NWS.

In this study, we employ the NWS HI algorithm to construct daily HI projections through the end of the 21st century for the contiguous US across multiple climate models and two future emissions scenarios. We examine changes in the occurrence of days when NWS heat advisory and excessive heat warning conditions are exceeded and evaluate the frequency with which conditions fall outside the bounds of the NWS's current HI formulation. We then combine the frequency of these high HI conditions with a range of population projections to evaluate the change in population exposure to such conditions.

## Methods

### Data sources

Daily maximum HI values were calculated using daily temperature and relative humidity for the 2006–2099 period from 18 statistically-downscaled climate models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5; table S1). We also analyzed historical (1950–2005 and 1971–2000) simulations from these models and the gridded meteorological dataset (1979–2012) used to develop the downscaled data (Abatzoglou 2013). Data were statistically downscaled to a spatial resolution of 4 km using training data from Abatzoglou (2013) and the Multivariate Adaptive Constructed Analogs (MACA) method (Abatzoglou and Brown 2012). This method uses daily output provided directly by GCMs and multivariate analog approaches for spatial downscaling. MACA's use of equidistant quantile mapping allows it to preserve changes in the distribution of daily GCM output, thus making it more likely to properly capture changes in the magnitude of extremes than simpler bias correction procedures (e.g. Pierce 2015). The models used in this study were chosen because they provided daily maximum temperature and daily minimum relative humidity.

### Method for calculating daily maximum heat index

The HI is typically calculated using instantaneous or hourly temperature (T) and relative humidity (RH) data. Ideally, modeled projections of HI would do the same, as at least one study has shown that using

non-instantaneous model output to calculate temperature-humidity metrics can lead to overestimation of 0.5–1.0 °C (Buzan *et al* 2015). Given the importance of using a suite of models to develop robust climate projections (e.g. Zhao *et al* 2015) and the desire for high-resolution coverage of the US, we sought to develop an approach for calculating daily maximum HI using daily summaries provided by downscaled data such as MACA. To determine whether to use maximum, minimum, or average T and RH data to construct daily maximum HI values, we calculated hourly HI values for the year 2012—a year of exceptional heat for much of the US (Peterson *et al* 2013b)—using weather station data from five representative US locations (NCEI 2018). HI calculations using  $T_{\max}$  and  $RH_{\min}$  best matched the reported daily maximum HI values (figure S1 is available online at [stacks.iop.org/ERC/1/075002/mmedia](https://stacks.iop.org/ERC/1/075002/mmedia)). We therefore used the daily  $T_{\max}$  and  $RH_{\min}$  from MACA data to construct daily maximum HI values.

Implicit in this choice is the assumption that T and RH are consistently inversely related and that that relationship does not change in the future. Changes in atmospheric circulation—either short- or long-term—could alter the temperature-relative humidity relationship in the future. This method also assumes that biases of using daily summary data rather than hourly data do not change substantially with time (Buzan *et al* 2015). Studies have shown that bias-correction methods can alter to co-variability of variables used to calculate heat stress (Buzan *et al* 2015, Im *et al* 2017). Additionally, some studies have highlighted the importance of employing multivariate bias correction procedures to correct for changes in co-variance structure through time (e.g. Cannon 2018). The MACA downscaling procedures explicitly consider daily  $T_{\max}$  and  $RH_{\min}$  from GCMs and would be capable of reflecting any changes in co-variance under future climates, but do not explicitly employ joint bias correction procedures for  $T_{\max}$  and  $RH_{\min}$ . We evaluated whether the downscaling procedure systematically affected our results by performing the same heat index calculations on the raw, non-bias-corrected GCM data that the downscaled data used as an input.

All HI calculations were performed using the NWS HI algorithms, which employ a regression that operationalizes the HI values developed by Steadman (1979a) and several adjustments that account for relatively extreme combinations of temperature and relative humidity (NWS 2018, Rothfusz 1990; see supplementary material). An assessment of different HI algorithms determined that the NWS algorithm best agreed with the values in Steadman’s original matrix (Anderson *et al* 2013).

Note that the Steadman (1979a) formulation of the HI is based on specific physiological assumptions. Wind speed and solar radiation are not included in the Steadman (1979a, 1979b) formulation or the NWS algorithms and were therefore excluded in this study. However, both are known to have an effect on HI (Steadman 1979b, Li and Bou-Zeid 2013).

### Calculating daily heat index values and no analog conditions

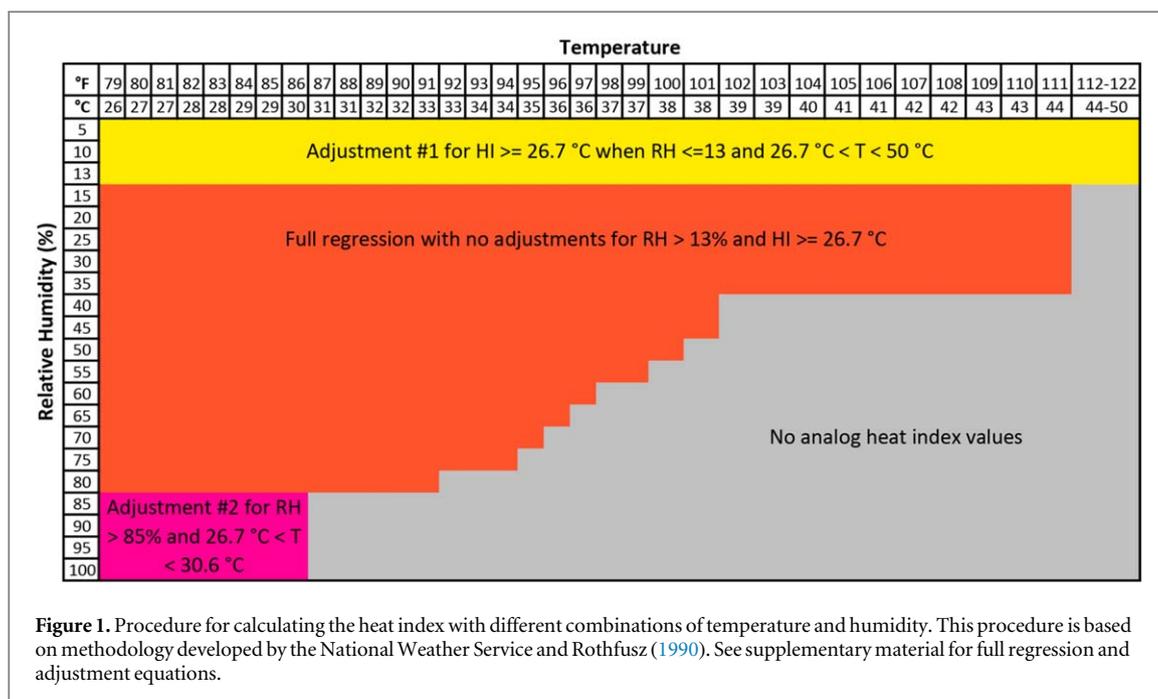
We use MACA data to calculate daily maximum HI values for historical (1971–2000) midcentury (2036–2065) and late century (2070–2099) time periods for the RCP4.5 and RCP8.5 emissions scenarios. When calculating HI values, we flag days when the combined  $T_{\max}$  and  $RH_{\min}$  would lead to an out-of-range HI value. We hereafter refer to such days as ‘no analog’ days (figure 1).

In addition to calculating the frequency of no analog HI days, we compute the number of days with a maximum HI above two thresholds: 37.8 °C (100 °F; hereafter HI100+) and 40.6 °C (105 °F; hereafter HI105+). These thresholds are based on the NWS’s general heat advisory guidance, which states that a heat advisory should be issued when the HI is expected to be 37.8 °C or higher and an excessive heat warning should be issued when the HI expected to be 40.6 °C or higher (NWS 2019b). The actual issuance of heat advisories or warnings is at the discretion of NWS offices and is dependent on additional factors such as the duration and seasonal timing of an anticipated heat event, geography, and local acclimatization to extreme heat. Additionally, NWS offices in the Western US have recently adopted an experimental ‘HeatRisk’ forecast that only considers temperature (NWS 2019c).

We tabulated the occurrence of HI100+, HI105+, and no analog days for each of the downscaled models from April through October (figures S4–S6). We also calculated, for each year and model, the longest consecutive number of days with HI100+ conditions to quantify changes in the duration of extreme heat events lasting longer than one day. The number of HI100+ days includes all days above the HI100+ threshold, including HI105+ and no analog days. Similarly, the number of HI105+ days includes the no analog days. The reported results reflect the multi-model unweighted mean of all 18 models.

### Evaluating the performance of the MACA data with respect to observations

The MACA methodology requires training historical model data to an observational dataset. In this case, the full historical model period (1950–2005) was trained to the gridMET 1979–2012 gridded meteorological observation dataset (Abatzoglou 2013). We evaluated the bias of the downscaled model output in matching observations for the historical period by comparing the multi-model mean number of days above our specified



heat index thresholds, including the number of no analog HI days, and the equivalents for the gridMET dataset. Because of the training procedure described above, we compare the 1950–2005 model results with the 1979–2012 gridMET to provide the best statistical comparison. We also compare the 1971–2000 historical model results to the 1979–2012 gridMET and the full historical model period to evaluate the suitability of using the 1971–2000 historical model period as a baseline for comparison to future projections.

### Population projections and regional aggregation

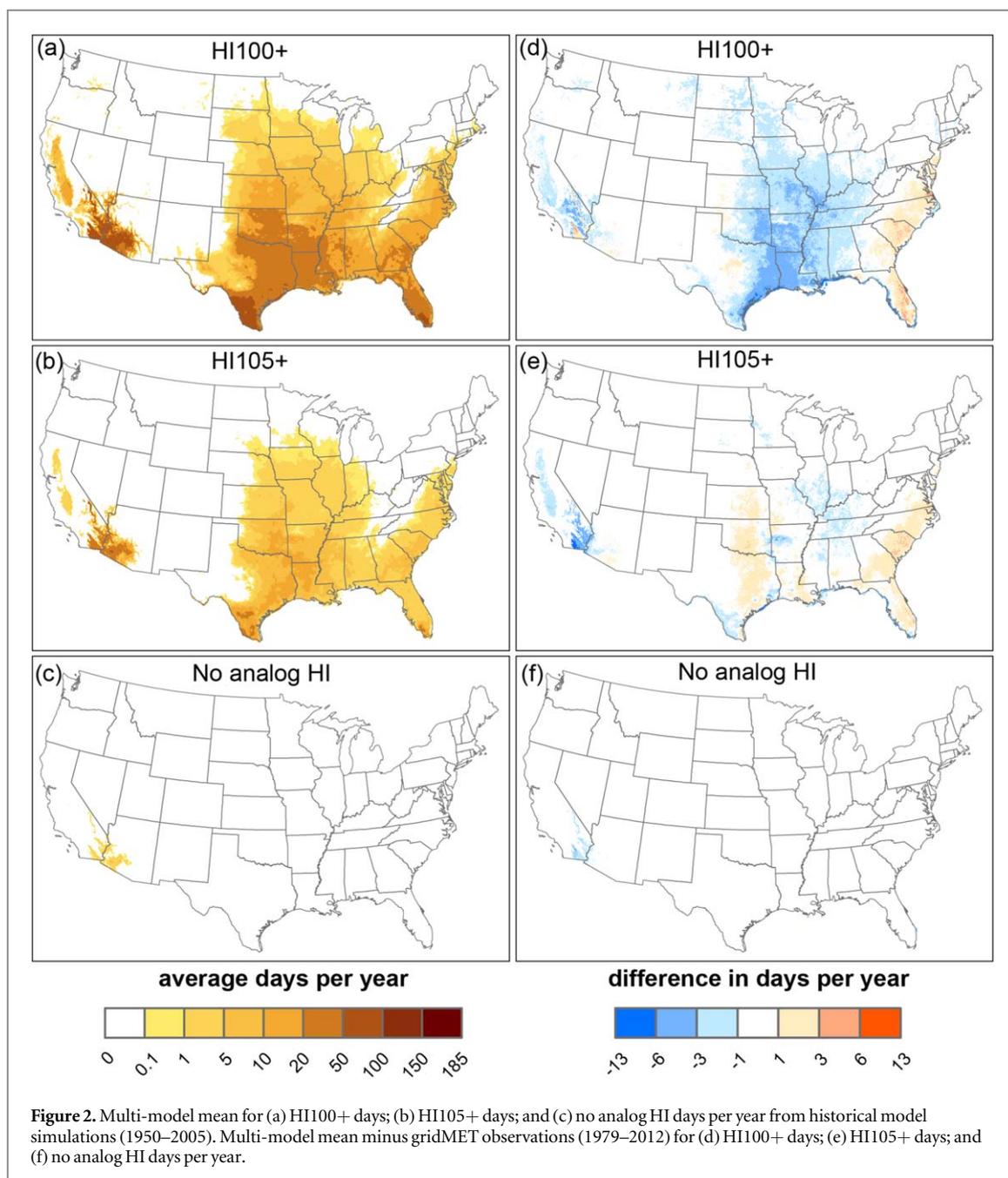
To evaluate the total exposure of US population to HI extremes, we employ three spatially explicit population projections and a baseline population estimate for the year 2000. These previously published projections were downscaled to a 1-km resolution and are consistent with the Shared Socioeconomic Pathways (SSPs; Jones and O’Neill 2016, Gao 2017). The three projections we employ—SSP2, SSP3, and SSP5—capture a range of population change scenarios that project an end-of-century US population of 447 million, 277 million, and 664 million, respectively. We calculate person-days per year by multiplying the average number of days of HI extremes within a 30-year time period by the modeled population for the decade nearest the midpoint of the 30-year period. This yields a spatially explicit assessment of population-weighted exposure to heat extremes (Jones et al 2018). We aggregate our person-days per year results using regions defined by the fourth US National Climate Assessment (USGCRP 2018).

## Results and discussion

### Historical simulations and model bias

The climatological distribution of HI100+, HI105+, and no analog days generally adheres to latitudinal, maritime, and topographic patterns with the highest frequency of extreme HI days across the desert southwest, southern Great Plains and southeastern US (figures 2(a)–(c)). Days exceeding HI105+ are exceedingly rare to absent across much of the Northwestern US, Intermountain West, and New England. No analog days do not occur outside of the warmest reaches of the desert southwest, where there are currently up to five no analog days per year. These areas amount to less than 1% of the land area of the contiguous US. For the contiguous US, the mean number of days per year for the historical period is 13.6 for HI100+, 5.2 for HI105+, and zero for no analog conditions. Combined with baseline population estimates, the exposure to HI100+, HI105+, and no analog conditions amounts to 106.7 million, 24.4 million, and 0.08 million person-days per year, respectively.

Comparable climatological summaries were found for the frequency of HI100+, HI105+, and no analog days between downscaled historical model simulations and gridMET observations (figure 2). The largest differences were for HI100+ days, for which 11% of the US has absolute biases exceeding three days per year. The models tend to underpredict the number of HI100+ days per year for much of the central US. Less than 1% of the US had absolute biases exceeding three days per year for HI105+, and the number of no analog HI days shows nominal bias. Results were similar when comparing climatologies based on model years 1971–2000 to

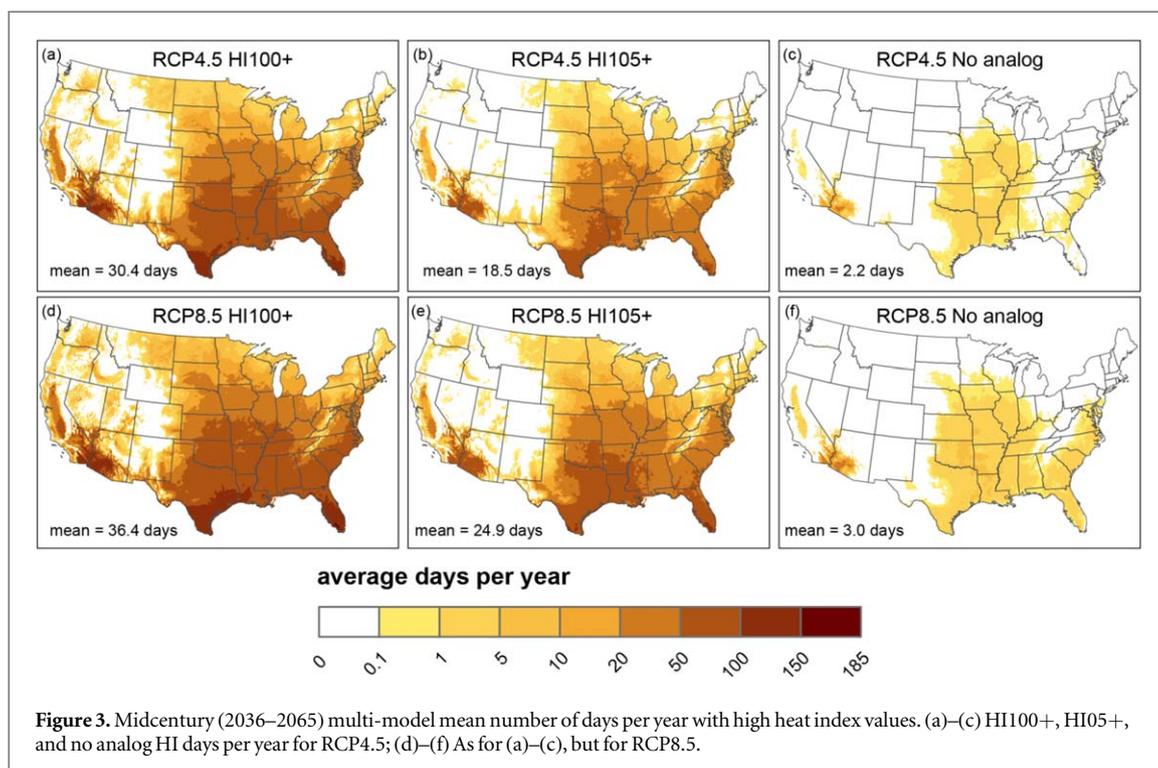


gridMET (figure S2), suggesting that using 1971–2000 as our historical baseline does not meaningfully change the results presented here.

Both quantitatively and qualitatively, the frequencies of high HI days between the MACA data and raw, non-bias-corrected CMIP5 data are similar. This indicates that bias correction in the downscaled data did not appear to systematically over- or under-estimate projected changes in HI (figure S3). Previous studies have also found similarly minimal effects resulting from bias correction, in particular in mid- and high latitudes, where temperature and humidity biases have a compensatory effect (Willett and Sherwood 2012, Fischer and Knutti 2013, Zhao *et al* 2015, Im *et al* 2017).

### Midcentury results

Across most the US, we find that the frequency and geographic range of high heat index days increase markedly by midcentury under both RCP4.5 and RCP8.5 (figure 3). Country-wide, the warming incurred between the late 20th century and the middle of this century would more than double the number of HI100+ days, triple or more the number of HI105+ days, and cause no analog HI days in more than 25% of the country by area. In this time period, the differences between the two RCP scenarios are relatively small but consistent, with RCP8.5 having slightly larger increases in HI days than RCP4.5.



On a regional basis and for both RCP scenarios, the Southeast and Southern Plains regions experiences the largest increase in the number of HI100+ and HI105+ days per year (figure 3, table 1). Within these regions, states such as Texas, Louisiana, Oklahoma, Arkansas, and Florida that experienced 20 to 40 HI100+ days per year historically are projected to undergo roughly a doubling in the number of such days with either scenario. The southernmost portions of Texas and Florida are projected to experience 100 to 150 HI100+ days per year. More limited areas—eastern Texas, Louisiana, and south Florida—are projected to experience 50 to 100 HI105+ days per year, a five-fold increase from historical conditions.

The spatial pattern of these increases in the southern half of the US is qualitatively similar to that identified by a lower-resolution, temperature-only assessment of the number of days per year exceeding a temperature of 40.6 °C (100 °F) in scenarios where global average temperatures are 1.5 to 2 °C above 1986–2005 levels (Wobus *et al* 2018) as well as in the raw GCM HI projections identified by this analysis (figure S3). The changes exhibited here are both larger and more extensive than temperature-only assessments, possibly owing to the use of the heat index rather than temperature alone.

High-altitude areas across the western US that historically have no HI100+ days remained void of such conditions in the mid-21st century. However, lower-altitude regions that historically experience few to no HI100+ or HI105+ days per year, such as New England and the northernmost Midwestern states, are projected to experience 10 to 20 HI100+ days and up to 10 HI105+ days per year by midcentury.

No analog HI days become more widespread by midcentury with both RCP scenarios (figure 3). With RCP4.5, much of the central US and southeast coastal regions are projected to experience up to five no analog HI days per year. In addition, parts of the Sonoran Desert region are projected to experience more than 30 no analog HI days per year. RCP8.5 yields notably more no analog days than RCP4.5 in this timeframe.

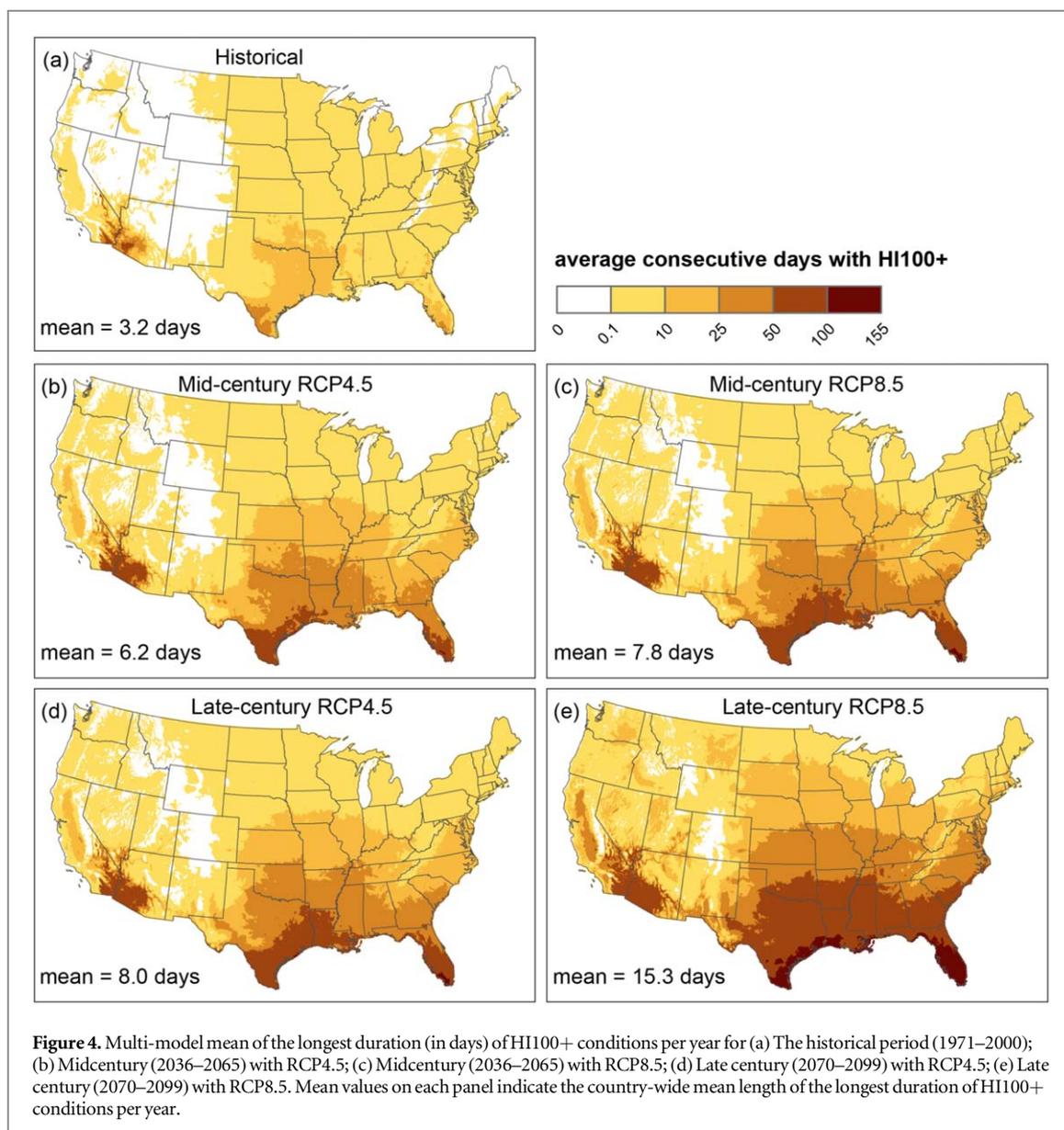
The longest consecutive number of HI100+ days per year increases from a country-wide average of 3.2 days per year historically to 6.2 days per year with RCP4.5 and 7.8 days per year with RCP8.5 (figures 4(a)–(c)). The increased duration of these HI100+ extreme heat events is particularly notable in the Southern Plains, Southeast, and southern Midwest regions.

Depending on the trajectory of population and emissions increases, the country-wide number of person-days per year increases four- to eight-fold for HI100+ conditions and 10- to 20-fold for HI105+ conditions by midcentury (figure 5). In the Southwest, Southern Plains, and Southeast regions the combination of warming and population growth results in approximately 3-fold, 4-fold, and 5-fold increases in the person-days of exposure to HI100+ conditions, respectively, with either RCP scenario compared to late 20th century exposure.

Trends in the exposure to HI105+ conditions follow similar patterns, with most regions projected to experience roughly an order of magnitude increase in the number of HI105+ person-days per year for the mid-21st century with either RCP and any SSP scenario. Whereas historically the US experiences less than 100 000 person-days per year with no analog conditions, that would rise to 6.9 to 9.9 million person-days per year with

**Table 1.** Multi-model mean number of days per year with HI100+, HI105+, and no analog HI conditions spatial averaged over each of the NCA regions.

Time period	Scenario	Threshold	Midwest	Northeast	N. Plains	Northwest	Southeast	S. Plains	Southwest	CONUS
Historical	—	HI100+	5.7	3.3	2.7	1.2	14.9	20.9	22.7	13.6
Midcentury	RCP4.5	HI100+	21.8	9.7	8.0	3.2	51.5	51.3	21.6	30.4
Midcentury	RCP8.5	HI100+	29.8	14.3	11.8	4.3	65.0	61.4	24.3	36.4
Late century	RCP4.5	HI100+	26.7	12.4	10.3	4.0	59.5	56.8	23.6	34.2
Late century	RCP8.5	HI100+	53.1	32.3	24.3	10.6	95.8	88.1	35.3	54.0
Historical	—	HI105+	2.6	1.6	1.6	4.5	7.3	13.4	0.0	5.2
Midcentury	RCP4.5	HI105+	11.7	5.2	3.7	1.4	27.0	29.8	17.4	18.5
Midcentury	RCP8.5	HI105+	17.4	7.7	5.7	2.1	39.5	39.0	17.2	23.9
Late century	RCP4.5	HI105+	15.3	6.8	4.8	1.9	34.3	34.7	17.5	21.9
Late century	RCP8.5	HI105+	37.6	19.7	14.0	4.8	72.9	65.5	21.9	39.7
Historical	—	No analog	0.0	0.0	0.0	0.0	0.0	0.0	2.2	0.0
Midcentury	RCP4.5	No analog	1.6	1.0	1.1	0.0	1.7	2.0	6.2	2.1
Midcentury	RCP8.5	No analog	2.4	1.2	1.3	1.0	2.6	3.5	8.4	3.0
Late century	RCP4.5	No analog	2.2	1.1	1.2	1.0	2.2	3.0	7.2	2.7
Late century	RCP8.5	No analog	7.3	3.0	2.7	1.6	12.1	12.1	9.7	8.6



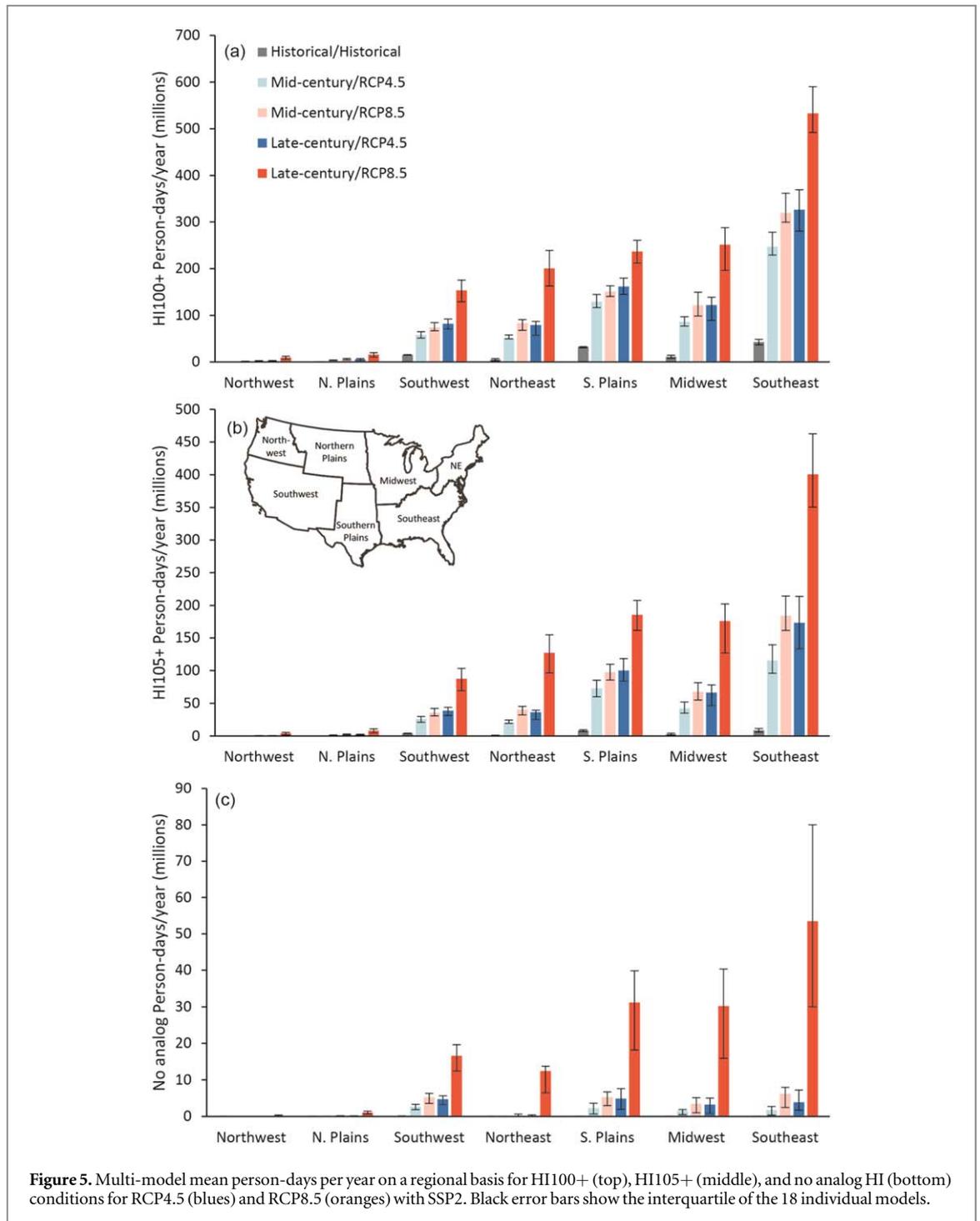
RCP4.5 and to between 17.0 and 24.4 million person-days per year with RCP8.5 depending on the SSP scenario. The largest rise (for RCP8.5 and SSP5) would amount to 250 times as many no analog person-days per year compared with contemporary exposure (table S2). The increase in exposure is driven primarily by changes in climate rather than population change: Even in the absence of population growth, country-wide exposure increases three- to four-fold for HI100+ conditions and seven- to 10-fold for HI105+ conditions.

#### Late century results

By late century, there are large differences between the RCP4.5 and RCP8.5 scenarios. The following discussion focuses on results with the RCP8.5 scenario as results for RCP4.5 are relatively unchanged from the midcentury.

Country-wide, with RCP8.5 HI100+ days are projected to quadruple and HI105+ days to increase nearly eight-fold in frequency compared to historical conditions. With this scenario 63% of the country's area is projected to experience no analog conditions, and 13% of the country would experience an average of two weeks or more with such conditions (figure 6). The total population exposure to no analog conditions is between 89.5 and 216.7 million person-days per year while exposure to HI100+ days could exceed 2 billion person-days per year depending on the SSP.

By late century, large portions of the Gulf Coasts states—including Texas, Louisiana, Mississippi, Alabama, and Florida—are projected to experience 120 HI100+ days per year or more while more limited areas in Texas and south Florida are projected to experience 150 or more HI105+ days per year. These results are in line with published work showing that heat waves of three or more consecutive days with an apparent temperature of 40 °C would have a 90%–100% annual probability of occurring in this part of the US when global average



temperatures reached  $4^{\circ}\text{C}$  above preindustrial levels, the amount of warming projected for late century under RCP8.5 (Russo *et al* 2017).

Areas with minimal exposure to HI100+ or HI105+ conditions either historically or by midcentury, such as the Pacific Northwest and northern New England, are projected to experience 10 to 20 HI100+ days and up to 10 HI105+ days per year by late century. The mean duration of the longest HI100+ event per year for the country as a whole is 15.3 days—a more than four-fold increase from historical conditions (figures 4(d)–(f)). Southern Texas and the majority of the state of Florida are projected to experience an average of 100 or more consecutive HI100+ days per year in this time frame.

No analog HI days become much more frequent and widespread, with portions of Texas, Louisiana, Arkansas, and Oklahoma projected to experience 20 to 30 days per year. Within the Midwestern region, entire states—such as Iowa, Missouri, and Illinois—that historically have not experienced no analog HI conditions are projected to experience between five and 20 such days per year.

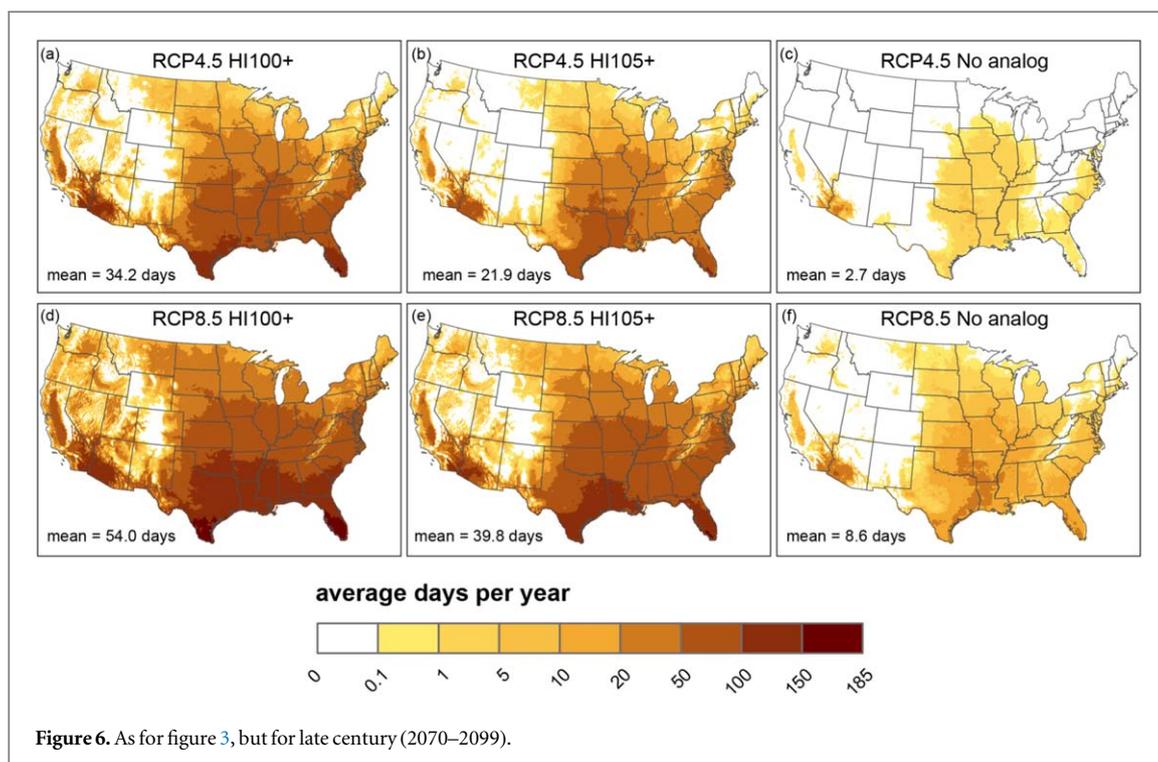


Figure 6. As for figure 3, but for late century (2070–2099).

We find large increases in population exposure by late century with 1.4 billion, 988.9 million, and 145.0 million person-days per year of HI100+, HI105+, and no analog conditions, respectively, for RCP8.5 and a moderate population change scenario (SSP2). With high population growth (SSP5), exposure of HI100+ rises to more than 2 billion person-days per year. As in midcentury, however, the emissions scenario had a greater bearing on the number of person-days per year than the population change scenario (figure 5; table S2). With the lower emissions of RCP4.5 after midcentury, changes between mid- and late century for this scenario are minimal. On the whole, with RCP4.5 the country is projected to experience half (or fewer) as many person-days per year with high HI conditions as with RCP8.5.

The magnitude of the population exposure changes identified here is larger than that identified by studies of temperature-only extremes. Using a population-based method, Jones *et al* (2015) found a four- to six-fold increase exposure to extreme temperature—rather than heat index—conditions in the US by the end of the 21st century. The larger increase in exposure that we project may result from the fact that the joint consideration of temperature and humidity can result in much larger increases than the consideration of temperature alone (Coffel *et al* 2018).

Our findings regarding the relative increase in population exposure between RCP4.5 and RCP8.5 are consistent with previous studies. Although the lower spatial resolution of these studies makes them difficult to apply regionally within the US as is done here, global population exposure to different heat extremes through 2100 has been shown to be reduced by at least 50% under RCP4.5 compared to RCP8.5 (Liu *et al* 2017, Mora *et al* 2017, Jones *et al*, 2018). These studies have similarly found that climate forcing associated with the choice of emission scenarios had a greater bearing on the population exposed to heat extremes than population growth scenarios.

Identifying the climatological processes responsible for the increases in the frequency of high heat index days we identify is beyond the scope of this study. However, recent work examining changes in the frequency of different types of extreme heat days (considering both temperature and humidity) in CMIP5 projections after using a multivariate quantile mapping approach similar to the MACA methodology finds that large-scale warming, rather than changes in regional circulation, is the primary driver of future changes in extreme heat (Schoof *et al* 2019).

### Limitations

Given the sensitivity of human health to extreme heat and humidity conditions, the results of these studies demonstrate that future climate change in the form of increasingly frequent extreme HI days will pose a growing danger to human health and that future population growth will compound exposure (Kalkstein and Davis 1989, Åström *et al* 2011, Gasparrini *et al* 2017). Moreover, with the widespread increase in the number of no analog days identified here, the current NWS system for warning the US public about extreme heat conditions will be

insufficient for truly communicating risk. Additional heat stress metrics and their sensitivities to changes in temperature and humidity may also be considered to better elucidate hazards to human health (Sanderson *et al* 2017, Sherwood 2018).

There are several important considerations that limit the application of our results to a comprehensive understanding of future heat stress. For example, we did not evaluate the daily minimum heat index, which influences heat-related morbidity and mortality (Karl and Knight 1997, Basara *et al* 2010, Oleson *et al* 2015). These projections do not incorporate the effects of future urban development or land-cover change that could alter future heat extremes, nor do they assess how exposure will vary among vulnerable subpopulations. Human adaptation or acclimatization to heat could reduce the overall risks associated with extreme heat exposure (Medina-Ramón *et al* 2006, Sheridan *et al* 2009, Anderson and Bell 2011, Sheridan and Lin 2014, Ebi *et al* 2018), and the degree to which acclimatization keeps pace with a warming climate and how such efforts are integrated across socioeconomic groups will be critical for determining the magnitude of heat related impacts.

Finally, further modeling efforts to improve our understanding of the use of daily model output data and the assumption of constant co-variability between temperature and relative humidity, as well as dynamically downscaled data that resolve both local circulation patterns and land-surface coupling, could advance the applicability of these results.

## Conclusions

This study shows that the frequency of and population exposure to extreme heat index conditions in the US will increase substantially by mid-21st century under a range of emissions and population change scenarios. By late century, depending on the scenario, these changes amount to a 4- to 20-fold increase in person-days per year of high heat index conditions from 107 million historically to as high as 2 billion. The current extreme heat alert system used by the National Weather Service relies on specific heat index thresholds. This work illuminates how, across much of the country, those seldom-crossed thresholds become frequently surpassed over the course of this century, putting millions of people at risk.

Economic development, technological advances, and improved communication efforts have reduced heat-related mortality in the US in recent decades (Davis *et al* 2003). Given the future frequency and extent of dangerous heat events, however, additional efforts to help people cope with extreme heat, particularly in places unaccustomed to such heat historically, will likely become necessary. With late century extreme heat index conditions and exposure under RCP8.5 being roughly double of that under RCP4.5, reductions in global greenhouse gas emissions are a complementary strategy for managing the future impacts of extreme heat in the US.

## Acknowledgments

The authors would like to thank Keith Brill, Jonathan Buzan, Brenda Ekwurzel, Geeta Persad, and Erika Spanger-Siegrfried, and three anonymous reviewers for thoughtful input into the development of this work. This research was funded by grants from the Barr Foundation, the Energy Foundation, the Common Sense Fund, the Scherman Foundation, the Rauch Foundation, the MacArthur Foundation, the Rockefeller Foundation, one anonymous funder, and members of the Union of Concerned Scientists (KAD, RL, JDB), as well as NOAA grant NA15OAR4310145 (JTA).

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