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Delineating and characterizing changes in heat wave events across the United States climate regions

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Abstract

Exposure to extreme heat, or heat waves, represents a public health threat as well as an environmental health threat. With projections for further increases in temperature in some regions, resulting from global environmental change, it is important to understand the spatiotemporal impacts of heat waves in order to minimize risk. To understand heat wave impacts, one cannot look solely at the spatial and temporal temperature regimes but much also consider key heat wave characteristics: duration, size, magnitude, frequency, and region of impact. To understand the consequences of heat wave events, it is critical to analyze such extreme events based on the cumulative impacts of these characteristics. This study, which is conducted across the whole of the continental United States, looks to map and analyze such cumulative impacts of heat wave characteristics. Heat waves were spatially defined for the period of May–September of each year. Using persistence analyses and the development of a new index (combined heat wave characteristics index (CHCI)), we can define regions of consistent heat wave exposure and impact. Results show that there are large differences across the United States in terms of heat wave exposure and impacting heat wave characteristics. Across much of the analysis, a clear east versus west difference in patterns is seen. Overall, such work shows how and where differing but covarying heat wave characteristics impact the United States. Information from this work can be combined with demographic and health metrics to better pinpoint susceptibility to heat waves—and therefore inform better management decisions.

Keywords Heat waves · United States · Heat wave magnitude · Heat wave duration · GIS · Heat wave persistence · Heat wave index

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1 Introduction

A single extreme event (e.g., flood, drought, and heat wave) can, without a doubt, have a large impact on the socioeconomic condition as well as environmental and human health (Kravchenko et al. 2013; Keellings & Waylen 2014a, b; Chen & Li 2017). When an area is repeatedly impacted by extreme events, especially those as impactful as heat waves, there are longer term socioenvironmental impacts to consider. The frequency, intensity, and duration of heat wave events have increased over time as seen in regions such as Europe, China, Australia, and the United States (US) (Field et al. 2012; Seneviratne et al. 2014; Keellings & Moradkhani 2020). Additionally, these events are projected to increase as climate change progresses leading to more frequent, more intense, and longer-lasting events in the future (Meehl & Tebaldi 2004; Barros et al. 2014; Lopez et al. 2018). Recent work suggests that around half of the world's population will be annually exposed to deadly heat waves by 2100 and that even in the US there will likely be a four-to-six-fold increase in exposure to heat waves by 2070 (Jones et al. 2015; Mora et al. 2017). Despite the severity of these projections, heat waves are not universally defined thus hindering inter-regional transferability of knowledge about these events.

Heat waves are typically defined as a sequence of days with temperature exceeding a high threshold of daily maximum or mean temperatures. The heat wave threshold is often between the 90^{th} and 99^{th} percentiles of the local temperature distribution, and it may or may not include some measure of humidity. Numerous heat wave metrics have been developed (Meehl & Tebaldi 2004; Hajat et al. 2006; Tan et al. 2007; Anderson & Bell 2009; Peng et al. 2011; Keellings & Waylen 2014a, b; Photiadou et al. 2014; Russo et al. 2014), yet there is still much debate as how best to define heat waves, and no definition or metric has been widely accepted (Perkins-Kirkpatrick et al. 2016). In practice, the US National Weather Service (NWS) issues excessive heat watches and warnings based on elevated heat index (combination of temperature and relative humidity) temperatures. However, the NWS-defined heat index temperature threshold for excessive heat varies across forecast offices and is based on a collaboration between local NWS offices and local partners. Unlike other extremes, such as hurricanes and tornadoes, heat waves have no universally accepted definition, and this complicates comparisons between heat wave events and the analysis of their impacts. This lack of an accepted definition of heat waves highlights the need for exploration of how best to conceptualize these events and how to develop a more unified definition. There is substantial knowledge on physical drivers of heat waves, but there is need for further quantification of the relationships between drivers and heat wave characteristics across larger regions and more events (Perkins 2015).

Extensive research has been conducted to understand, characterize, and predict heat waves (Baldwin et al. 2019). Recent research has found that heat waves in North America are increasing in number and spatial extent at the continental scale, but they are becoming smaller and more fragmented at the local level (Keellings et al. 2018). Adverse impacts of these events have been reported, including declines in agricultural yields (Mishra & Cherkauer 2010; Wreford and Neil 2010), elevated human mortality (Guo et al. 2017; World Meteorological Organization 2015; Merte 2017; Singh et al. 2021), failure of critical infrastructure (Clark et al. 2019), and increased energy demands (Miller et al. 2008; Zhao et al. 2018). The level of vulnerability of a system to the effects of heat waves varies by location, dictated by the system's physical, social, and demographic characteristics. For example, urban residents are more vulnerable to the impacts of heat waves due to the compounding effect of urban heat island effect (Habeeb et al. 2015; Zhao et al. 2018), and even in these areas, vulnerability is highest in inner cities compared to peripheral locations (Fenner et al. 2019). Yet, lacking in current literature is an understanding of the spatial dynamics and what drives aspects like areal extent and intensity of heat waves as changes in these spatial characteristics could have serious implications for socioecological impacts (Hattis et al. 2012; Kloog et al. 2015; Lee et al. 2016; Keellings & Moradkhani 2020). In addition, only a few heat wave characteristics have been studied (especially frequency, magnitude, and/or intensity), leaving out other important characteristics that potentially drive observed heat wave patterns. The current study presents a novel approach for characterizing spatial dynamics in heat waves across the contiguous US by assessing spatiotemporal patterns in the most persistent and longest/shortest-duration heat wave events.

In this study, we present a methodology for identifying regions impacted by differing and/or compounding heat wave characteristics. We use Geographic Information Systems (GIS) and overlay analysis to identify regions where temperatures are persistently extreme and compute at multiple scales (monthly, seasonal, and decadal) various characteristics associated with the heat wave regions.

This study looks to highlight new approaches to studying heat wave impacts that are both multivariate in nature and spatially explicit. It is widely recognized that heat waves will intensify as the climate changes. Hence, effective tools are necessary for quantifying and assessing heat wave incidences for better planning and management (Das et al. 2020). Indices have commonly been used as they reveal how multiple variables interact, aggregate, and affect a given location (Defne et al. 2020). In heat vulnerability studies, several indices have been proposed including heat wave duration index (HWDI) (Frich et al. 2002), heat wave magnitude index (HWMI) (Russo et al. 2014), and excess heat factor (EHF) (Nairn & Fawcett 2014), among others. Over time, the combined effects of heat wave characteristics have been recognized and necessitated the need for indices that integrate different aspects of heat waves. Recently, the combined heat wave index (CHI) was proposed (Das et al. 2020). By integrating heat wave magnitude, duration, and extent, CHI allows for greater discrimination among events, thus enabling one to chronicle fine scale impacts on the landscape. Elsewhere, the Heat Severity and Coverage Index (HSCI) combines magnitude, frequency, areal extent, and duration to characterize heat waves more comprehensively (Keellings & Moradkhani 2020). Two metrics are developed in this study: persistence and the combined heat wave characteristics index (CHCI). At its simplest, the persistence metric highlights how many times a heat wave, over time, has consistently impacted the same area. Further, we breakdown the heat wave data based on duration of events, therefore further identifying whether a region has been consistently impacted by long- or short-duration events. CHCI, the other metric develop in this study, looks to combine all heat wave characteristic variables into a single index. This is different from the aforementioned indices related to heat waves in that CHCI also include an output called CHCI components that helps the index users to interpret what heat wave characteristic variable is driving the CHCI trends.

Analysis in this study was performed per climate region in the contiguous US, and a comparative analysis was performed to reveal patterns and any significant differences in the occurrence, duration, region of impact, and severity of heat waves in the regions.

2 Materials and methods

2.1 Data

The Parameter elevation Regression on Independent Slopes Model (PRISM) daily temperature is utilized to identify heat waves (see Keellings & Moradkhani 2020). These data are a combination of meteorological station observations with a digital elevation model that yields a gridded surface for the continental US with a spatial resolution of 4 km from 1981 through 2018 (Daly et al. 2008; Thornton et al. 2014). PRISM has gone through quality control, been validated against heat wave metrics from four reanalysis products, and is widely used in climatological studies (Schoof et al. 2017).

This study was conducted across the continental US, though analysis was subdivided by the NOAA climate regions (Karl & Koss 1984) (Fig. 1). There are nine climate regions in total: Northwest, Southwest, West, West North Central, South, East North Central, Central, Northeast, and Southeast. While the analysis was done at the regional level, the comparison and statistical analysis highlights patterns across the continental US. NOAA climate regions were selected as the unit of analysis given that climate patterns extend beyond state borders.

Heat wave data were delineated using the methodology outlined by Keellings & Moradkhani (2020). A threshold equal to the 95th percentile of local (grid cell) daily maximum temperature for each extended summer month (May through September) in each year is used to define heat waves. Heat wave events must also last for at least three consecutive days, and events are considered temporally independent if separated by four or more days of below threshold temperatures. A hierarchical clustering algorithm works in combination with indicator semivariograms to identify clusters of heat and delineates heat wave events by Euclidean distance between clusters. A bounding polygon is then drawn around all heat clusters belonging to a single heat wave, and the polygon is tracked spatially at the daily time-step. As the heat wave is tracked from genesis to lysis, metrics are calculated daily to determine the heat wave area, magnitude, duration, and fragmentation of heat within the bounding heat wave polygon. To perform this, spatial analysis of heat waves requires fine-resolution gridded data, and as such, the PRISM dataset (https://prism.oregonstate.edu) was chosen as it has been utilized extensively in applied climatological studies. Numerous studies have made use of PRISM to analyze extreme temperatures or heat waves using similar event definitions and similar or shorter lengths of record (see, for example, Lu and Kueppers 2015; Schoof et al. 2017; Keellings and Moradkhani 2020). It should also be noted that our analysis is undertaken at a regional scale and is based on spatially identifying events rather than examining individual time series at single locations. Therefore, a single event encompasses potentially thousands of grid cells that have crossed their local heat wave threshold and the bounding event polygon will also encompass grid cells that have not crossed their local heat wave threshold, but are nonetheless within the identified heat wave area.

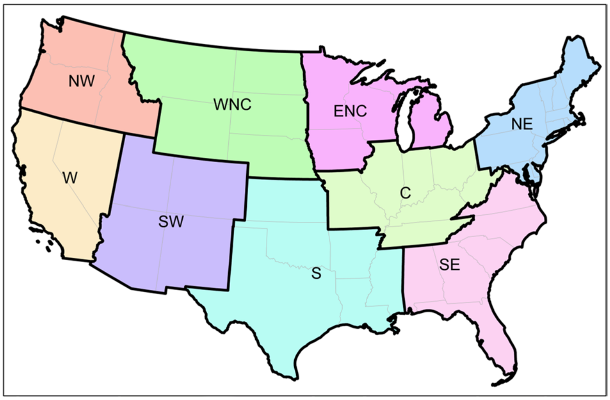

Fig. 1 NOAA's US climate regions used in this study. These regions include Northwest, Southwest, West, West North Central, South, East North Central, Central, Northeast, and Southeast

2.2 Methods

This section describes methods used in this study. These include systematic data thresholding, polygon flattening, and variable compositing applied to various heat wave characteristics.

2.2.1 Computing heat wave persistence

A GIS model was developed to compute heat wave persistence. This model, developed in ArcPy and implemented in ArcGIS Pro, was generally used to define and count the number of overlapping heat wave polygons at a location. The initial heat wave polygons can be thought of as a set of rings A, B, and C with overlaps (Fig. 2). This tool will flatten the rings and produce polygons with no overlap. The output includes more features than the input, and each feature has a count equivalent to the number of polygon overlaps. The counts represent heat wave persistence. The methodology for computing heat wave persistence is as follows: initially, the model creates an empty point feature class. It then creates a feature class containing polygons generated from areas enclosed by input heat wave polygons, while using the empty point feature class to label the polygons. The output polygons are then converted to points. Finally, attributes from the point feature class are spatially joined with the polygons. At this step, only important heat wave characteristics (see Table 1) are recalculated and retained in the output feature class.

2.2.2 Identifying regions of most and least extreme heat waves

This analysis was initially conducted per climate region. To identify areas with the most (least) extreme heat waves, we selected areas in the upper (lower) quartile based on the heat wave duration variable. This data reduction step allowed us to compare between the most (TOP25) and least (BOTTOM25) extreme heat wave event durations within each climate region. With such a breakdown of the data, we can not only look at extreme long duration events but also the impact of events which might be short in nature but extreme in other aspects, say magnitude or size. One key aspect of this paper is an analysis of

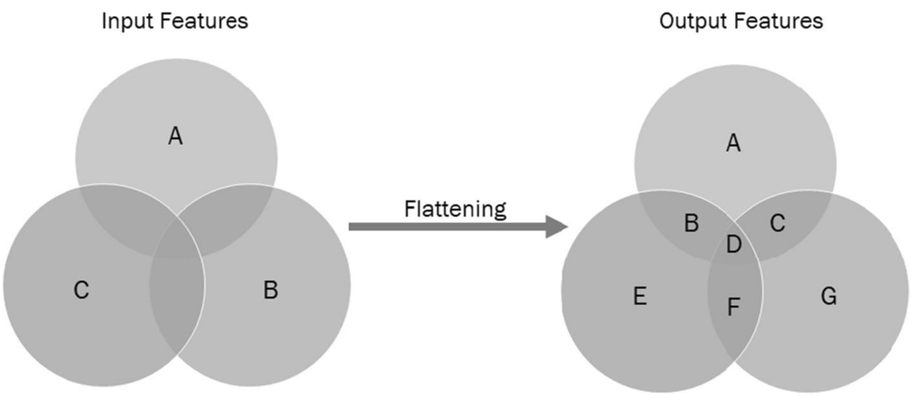

Fig. 2 Illustration of how heat wave persistence was computed in this study. Output features in this illustration will have persistence values of 1 (**A**, **E**, **G**), 2 (**B**, **C**, **F**) and 3 (**D**)

Table 1 Heat wave characteristics analyzed in this study

Variable	Definition
Average heat	Average temperature (°C) for the heat wave
Fragmentation	Connectivity index indicating fragmentation of heat within a heat wave polygon, ranges from 0 (fragmented) to 1 (cohesive)
Heat wave duration	Length of the heat wave in days
Mean magnitude	Average magnitude of the heat wave above the threshold
Number of patches	Number of individual isolated patches of heat within each heat wave
Heat wave persistence	Number of heat wave areas identified for each region
Area	Area extent of the heat wave in km^2

multiple heat wave characteristics on the landscape, and this is done via the breakdown between the top 25 and bottom 25 percent duration events. Next, we computed heat wave persistence using the model described in Fig. 2. A second round of thresholding was performed by identifying regions in the upper quartile based on heat wave persistence. The outputs were then merged to generate regions across the US on which the next part of the study focused. This was done on both TOP25 and BOTTOM25 polygons. Descriptive statistics were computed to characterize average temperatures, area, duration, fragmentation, persistence, magnitude, and number of patches for the identified heat wave regions.

2.2.3 Combined heat wave characteristics

Since multiple heat wave variables were assessed in this study, it was necessary to generate composites, with the aim of identifying patterns in the ways these variables covaried across the climate regions. To achieve this, heat wave fragmentation, mean magnitude, number of patches, and mean area were each standardized and then combined by multiplication to compute a combined heat wave characteristics index (CHCI). See Eq. 1 below.

$$\mathrm{CHCI} = \mathrm{MeanArea} * \mathrm{MeanMag} * \mathrm{MeanNP} * \mathrm{MeanFrag} \tag{1}$$

where CHCI is the combined heat wave characteristics index, Mean Area is the mean size of heat wave events during the set time scale by pixel, Mean Mag is the mean magnitude of heat wave events during the set time scale by pixel, Mean NP is the mean number of patches of heat wave events during the set time scale by pixel, and Mean Frag is the mean fragmentation score of heat wave events during the set time scale by pixel. The fragmentation score was developed and presented by Keelings and Moradkhani 2020.

The outputs here would therefore represent the spatiotemporal variability of heat waves driven by these four variables at locations with the longest (or shortest) and most persistent heat wave events. Another composite was generated to indicate categorized values for each of the four variables at a location using Eq. 2 below. To do this, we first reclassified the standardized variables into three classes defined below.

1. Low—values from 0 to the lower quartile
2. Mid—values from the lower to the upper quartiles
3. High—values from the upper quartile to 1

$$\begin{aligned} \text{Comp} = & (\text{Mean Area} * 1000) + (\text{Mean Mag} * 100) \\ & + (\text{Mean Frag} * 10) + (\text{Mean NP} * 1) \end{aligned} \tag{2}$$

where Comp is the component of CHCI, Mean Mag is the mean magnitude, Mean NP is the mean number of patches, and Mean Frag is the mean fragmentation score. All four heat wave variables in this equation were reclassified into the three classes above.

The results from this computation were maps indicating the categorized components of heat wave events at each location. For instance, a pixel with a Comp value of 3213 indicates that the heat wave at the pixel had high mean area, mid mean magnitude, low mean fragmentation, and high mean number of patches. This composite would therefore help in explaining the observed patterns in the CHCI.

To ensure a detailed characterization of heat wave events in the US, we performed these analyses over several temporal scales including the entire 38 years (1981–2018), by decade (1981–1990, 1991–2000, 2001–2010, and 2011–2018), and by month (May, June, July, August, and September). The 38-year time span was determined based on data availability. This would provide better insights into how most (and least) extreme heat wave events have changed over time in the US. The flowchart (Fig. 3) shows the main steps and analyses performed.

3 Results

This study delineates (using GIS overlay, thresholding, and data compositing methodologies) and characterizes long-term seasonal, decadal, and monthly heat wave patterns in US climate regions.

3.1 Heat wave extent per climate region

This study found that, generally, longer heat wave events (TOP25) covered vastly more of the climate regions compared to the shortest events (BOTTOM25). TOP25 heat wave regions constituted as much as 57% of the land area in Northwest, 51% of the Southwest, and 47% of the area in Eastern North Central (refer to Fig. 4). Top three climate regions by area include the Southwest (> 557,000 km^2), South (> 524,000 km^2), and Northwest (> 368,000 km^2). Proportions of area with BOTTOM25 events, on the other hand, ranged from 11% in Central US to 41% in the Southwest. Based on land area, Southwest, South, and Western North Central regions were top ranked for BOTTOM25 events, with the shortest-duration heat waves extending over > 452,000 km^2, 262,000 km^2, and > 229,000 km^2, respectively. Regions affected by BOTTOM25 and TOP25 events were similar (in size and location) for Western North Central (19% vs. 22%), Western (32% vs. 39%), and the Southwest (41% vs. 51%).

Different patterns were observed in heat waves over the decade scale (Fig. 5). Separability tests show statistically significant trends between TOP25 and BOTTOM25 both by region and across decades; however, the *n* for such statistics is too small to present. Additionally, statistics work is being developed that looks at the statistical difference for both persistence and the CHCI index at the pixel rather than event scale. In the 1980s, TOP25 events were commonest in the Northeast (> 73% of land area), Northwest (> 64% of area), and Central US (> 53%). In the 1990s, the Northwest topped with over 70% of its area experiencing TOP25 events, followed by the Southwest (> 65%)

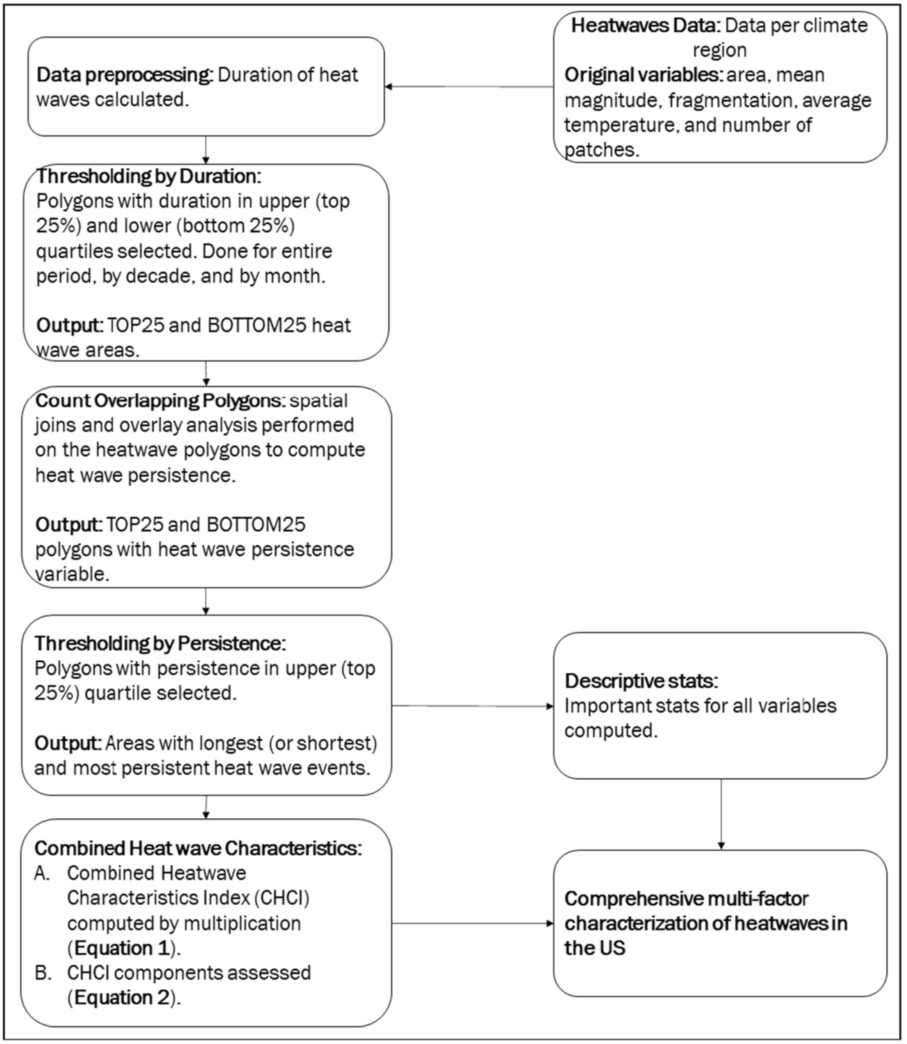

Fig. 3 Analyses performed in the study

and the Northeast (> 55%). Different patterns were observed in the 2000s, in which the West region was ranked second (having TOP25 events in over 70% of land area) after the Northwest (> 72%). The Southeast was ranked third in this decade with over 67% of its land area experiencing these extreme heat events. Northwest, West, and Northeast regions had the highest proportions of area under TOP25 heat waves (approx. 67%, 62%, and 59%, respectively). Proportions of area under BOTTOM25 events were always lower than those for TOP25 events, except for West North Central (in the 1980s), Southwest (1980s), Central (in the 1990s), East North Central (in the 1990s and 2010s), and South (in the 2000s). Proportions of land under heat waves generally increased from a decade to the next in Northwest and Southeast, except for the 2000s to 2010s. Consistent expansion of area under heat waves was observed in the West North Central region.

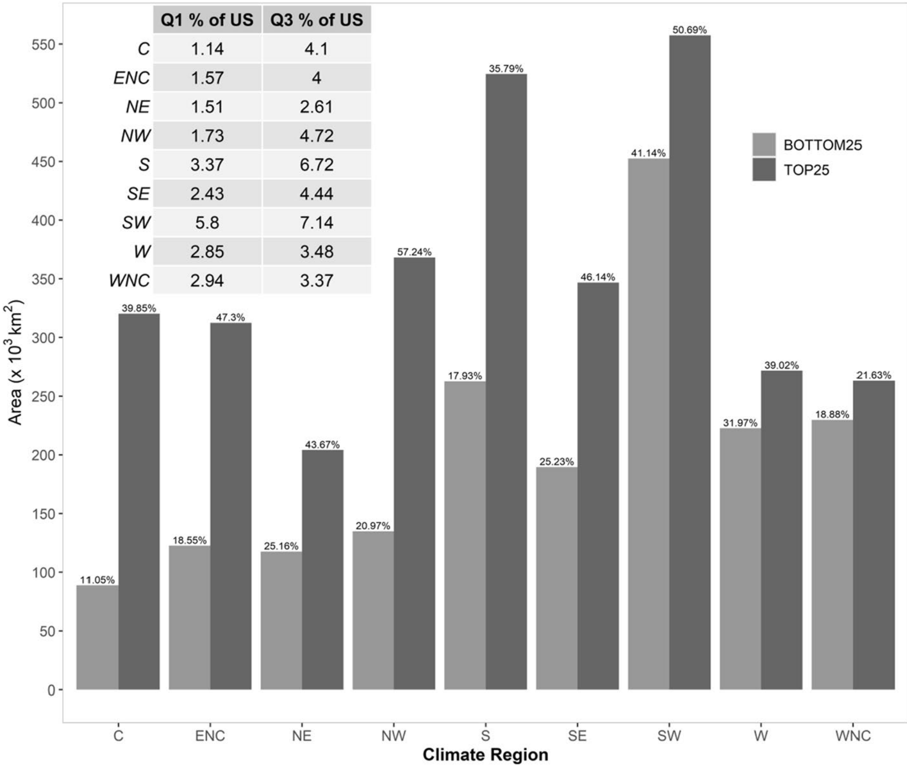

Fig. 4 Proportions of area under BOTTOM25 and TOP25 heat waves for each climate region for the entire period (1981–2018). The inset shows the percent proportion of the area under heat waves to the total area of the contiguous United States. It should be noted that Q1 and Q3 represent lower quartile (BOTTOM25) and upper quartile (TOP25), respectively

The study found that, for some climate regions, heat waves extended over more land in the months when extremely high temperatures were expected to subside (Fig. 6A, B). For instance, the highest proportions of area under TOP25 heat waves were observed in the month of May for the Southwest, Southeast, Northeast, and South (84%, 78%, 71%, and 60%, respectively, see Fig. 6A). Similar patterns were observed in Northwest and Central regions for the month of September (Fig. 6A, B). Here, heat waves were respectively identified in approx. 96% and 81% of the land area (Fig. 6A). This indicates that the severe heat wave period is expanding for these climate regions. Proportions of land under TOP25 heat waves generally exceeded proportions of land under BOTTOM25 events, except for Northwest in May (0% vs. 22%) and West North Central in August (16% vs. 17%).

3.2 Long-term heat wave characteristics

Heat wave characteristics generally showed similar patterns among the shortest- and longest-duration events. While area of heat waves was significantly higher for the TOP25 group compared to BOTTOM25 (US averages of 606,000 vs 481,000 km^2, respectively), there were similar spatial patterns in distribution (Fig. 7A). In both groups, heat wave events

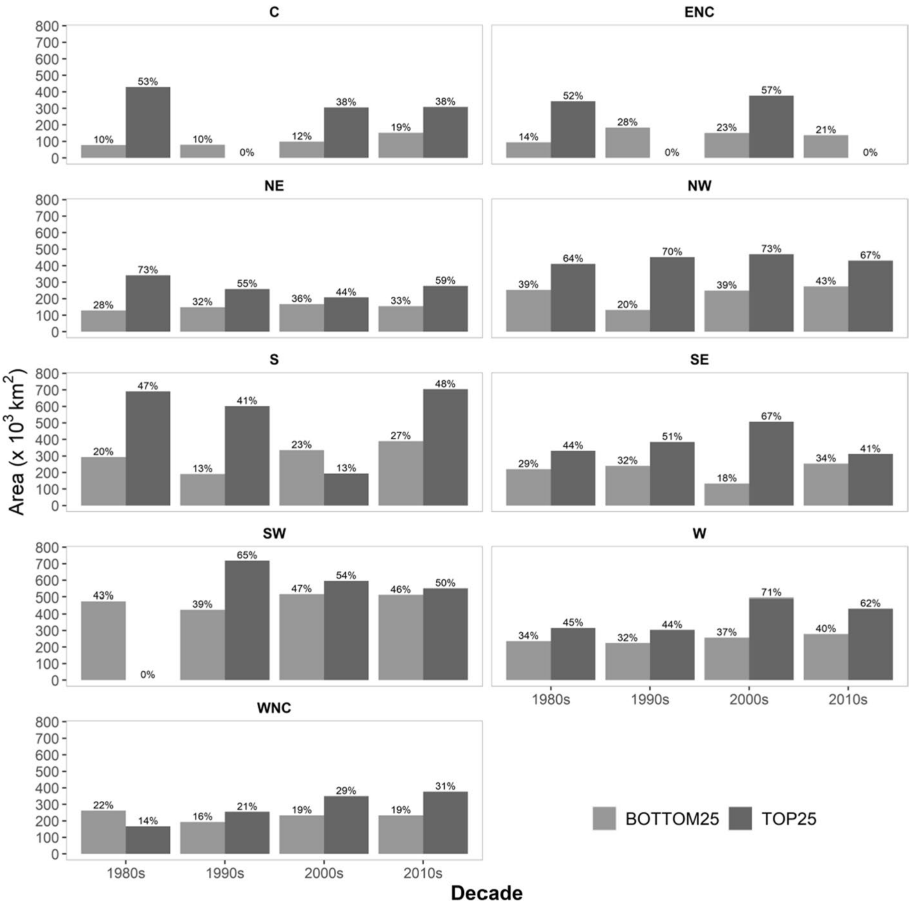

Fig. 5 Proportions of area under BOTTOM25 and TOP25 heat waves for each decade per climate region

were highly extensive in the South and Southwest regions. Events in these regions, respectively, had average areas of 887,000 km^2 and 758,000 km^2 (TOP25) and 597,000 km^2 and 667,000 km^2 (BOTTOM25).

The least expansive heat wave events of all were found in Northeast in both TOP25 and BOTTOM25 groups (average area of 312,000 km^2 and 254,000 km^2, respectively) and East North Central (265,000 km^2) in the BOTTOM25 group. Average temperatures ranged between 28 and 38 °C for the shortest-duration events (US average of 32.7 °C) and 30 to 38 °C for the longest-duration events (US average of 34.6 °C). BOTTOM25 events in the Northwest and Northeast regions experienced comparatively lower temperatures (Fig. 7B). Temperatures averaged 28.4 and 30.1 °C in these regions, respectively.

West region events in both groups (TOP25 and BOTTOM25) were found to have the highest mean magnitude (Fig. 7F)—averaging 1.83 (Celsius above T95 threshold) for BOTTOM25 events and 1.94 (Celsius above T95 threshold) for TOP25 events. TOP25 events in this region were also the most persistent of all (Fig. 7E), meaning there were large numbers of overlapping heat wave events over time. Heat wave persistence averaged 2000 events for this region compared to a US average of 475. The least persistent heat

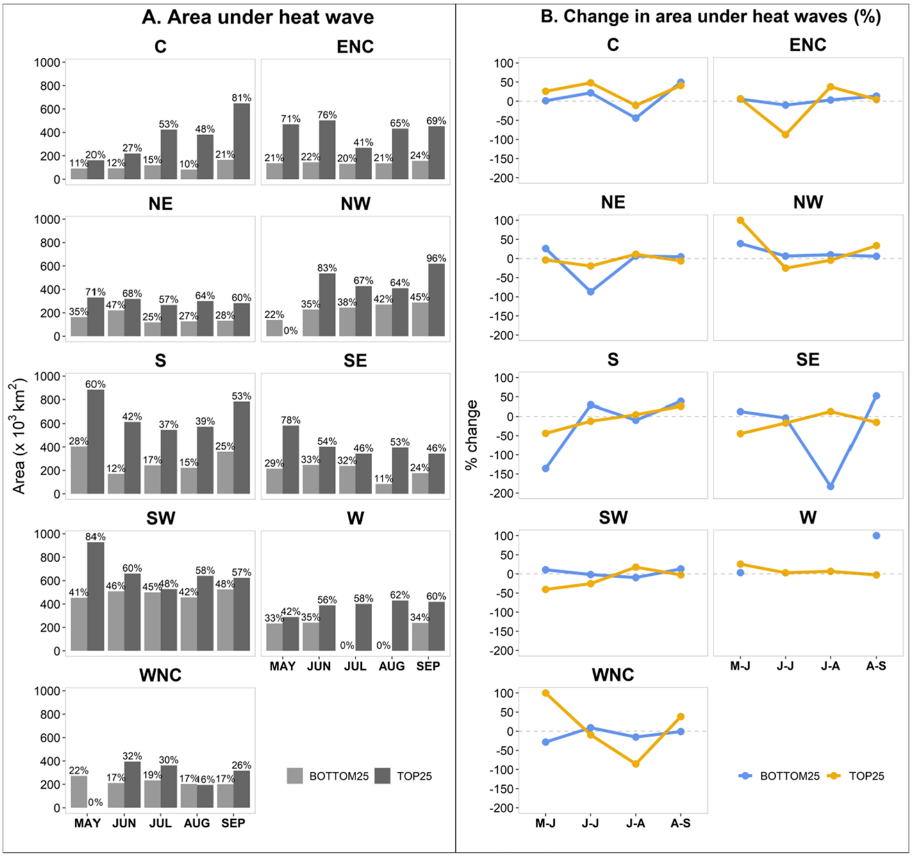

Fig. 6 **A** Proportions of area under heat waves for each climate region for each summer month. **B** Percent change in month-to-month areal coverage of heat waves. It should be noted that M-J, J-J, J-A, and A-S represent May–June, June-July, July–August, and August–September changes, respectively

wave events (i.e., lower number of overlapping heat wave events over time) were found mainly in the East North Central, Central, and Northeast regions (mean persistence < 183 events). Further, heat wave events experienced in the eastern half of the US were more cohesive than the western ones as shown by the fragmentation statistic (Fig. 7D). Events in the East North Central were most cohesive of all with an average fragmentation statistic of 0.69 and 0.76 for the shortest-duration and longest-duration events, respectively. The Southwest had the most fragmented events, with the fragmentation statistic for the shortest-duration and longest-duration events averaging 0.18 and 0.2, respectively. The study also found that the shortest-duration events were generally less patchy (ranging from 2200 to 12,000 patches or individual heat wave event clusters) compared to the longest-duration events which ranged from 4200 to over 19,700 patches (Fig.7G). The longest-duration events in the South, East North Central, and Central had the greatest number of patches (> 15,000). TOP25 events exhibited significantly different durations compared to BOTTOM25 events. The former events lasted longer (14–99 days) than the latter (2.8–9.6 days) on average (Fig. 7C). However, this results from the initial use of this variable in defining BOTTOM25 and TOP25 heat wave events. Clear inter-region differences were observable

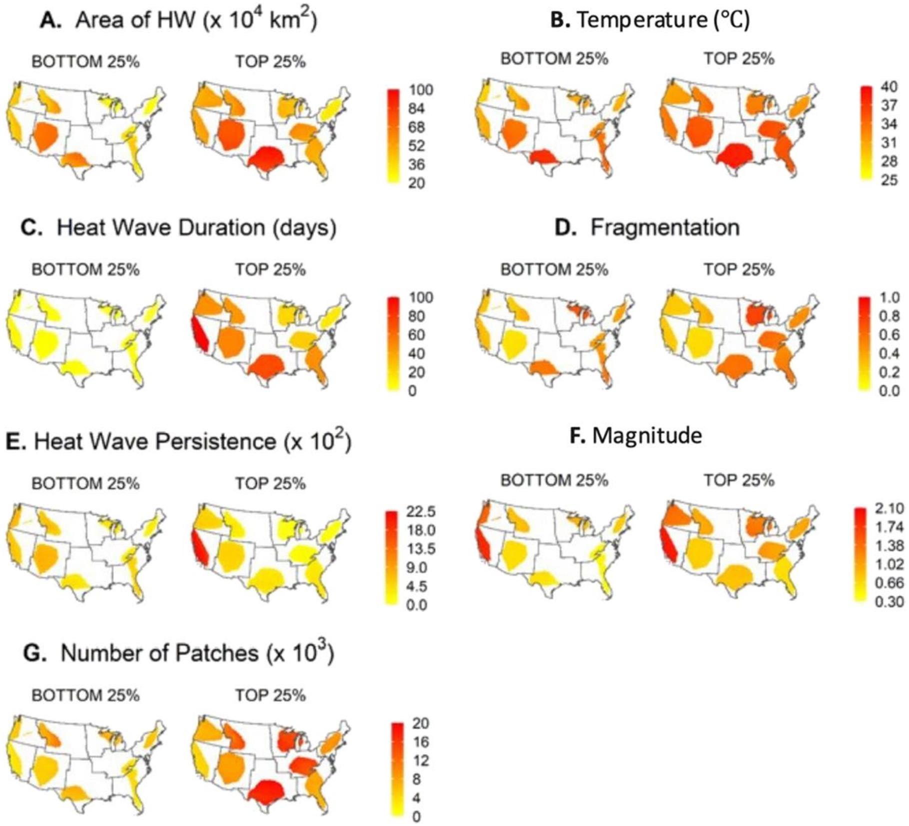

Fig. 7 Heat wave characteristics for the entire study period (1981–2018). The top and bottom 25% are representative of the duration of the event. The color ramp indicates the mean trends in the variable (e.g., number of patches and magnitude) presented

in this variable especially in the TOP25 events. The West and South events lasted the longest (more than 98 and 71 days, respectively).

3.3 Decadal heat wave characteristics

Spatial patterns observed in the decadal distribution of heat wave characteristics were similar to those found in 1981–2018. For example, heat wave events in both groups were most cohesive in East North Central and generally most fragmented in Southwest (compare Figs. 8 and 7D). However, the study found that the higher-than-average fragmentation statistic in East North Central was influenced greatly by events in the 1980s and 2000s (average fragmentation statistic was 0.77 and 0.73, respectively). Further, the highest magnitude (for both groups) and most persistent events (for the longest-duration group) were consistently observed in the West region. In this region, mean magnitude was > 1.79 overall while mean persistence ranged 399–620 (for the longest-duration events). However, by splitting the data into individual decades, the study found that while the shortest-duration events occurred in each decade for all climate regions, the longest-duration events were absent in East North Central (in the 1990s and 2010s) and

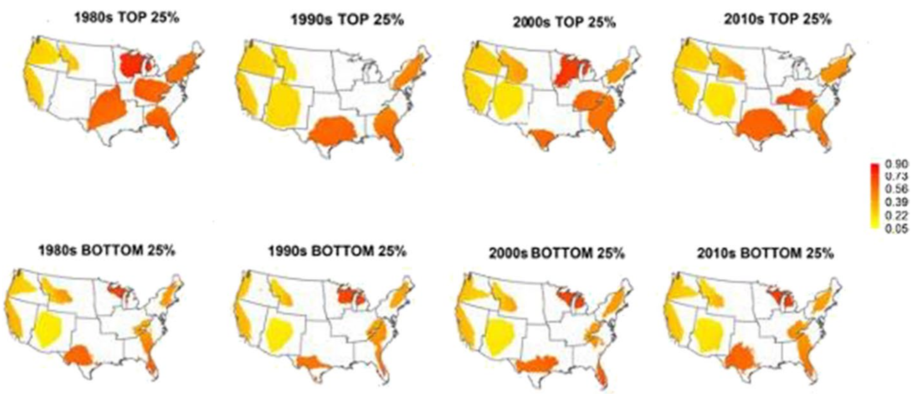

Fig. 8 Heat wave fragmentation for the shortest-duration (BOTTOM 25%) and the longest-duration (TOP 25%) events for the 1980s (**A**), 1990s (**B**), 2000s (**C**), and 2010s (**D**) decades for the summer months

Central region (in the 1990s). Furthermore, number of individual patches in TOP25 heat waves varied significantly—highest in the South in the 1990s and 2010s and only average in the 1980s and 2000s. The high number of patches in East North Central in the 1981–2018 period is attributed to the highly patchy events in the 1980s.

In addition, the study quantified changes in average heat wave characteristics per climate region. Results indicate that, generally, average heat wave characteristics varied more for the longest-duration events compared to the shortest-duration events. Among the characteristics, number of patches and heat wave persistence showed greater variability across the decades (Fig. 9). The highest increases in average heat wave persistence occurred in TOP25 events in West North Central (+ 377% in the 1990s–2000s), Southwest (+ 306% in the 1990s–2000s), Southeast (+ 279% in the 1980s–1990s), and South (+ 251% in the 1980s–1990s and + 125% in the 2000s–2010s). The greatest changes in number of patches were found in West North Central (+ 318% in the 1990s–2000s) and South (+ 128% and + 176% in the 1980s–1990s and 2000s–2010s, respectively). Other TOP25 heat wave characteristics that saw major increases include mean area (+ 75% in South in the 2000s–2010s, + 71% in West North Central in the 1990s–2000s), average fragmentation (increase of 67% in West North Central in the 1990s–2000s), and mean magnitude (58% increase in South in the 2000s–2010s). The greatest changes in BOTTOM25 events were found in number of patches in the Southwest, West (respective increases of 96% and 70% in the 1990s–2000s), and Central (+ 72% in the 2000s–2010s) regions. Average temperatures showed the least variability across decades for both event groups. Rates of change for most of the variables in the South were lower for 1990s–2000s compared to the other two periods. Contrasting patterns were seen for most heat wave characteristics in West North Central, as well as some elsewhere (e.g., number of patches and persistence in the Northwest, Southwest, and West). These patterns are more detectable in TOP25 events.

3.4 Monthly heat wave characteristics

The temporal heat wave characteristic results fall in line with seasonal temperature trends common in the U.S. during the summer months. As previously mentioned, heat wave events were defined based on crossing the T95 threshold which is determined for each

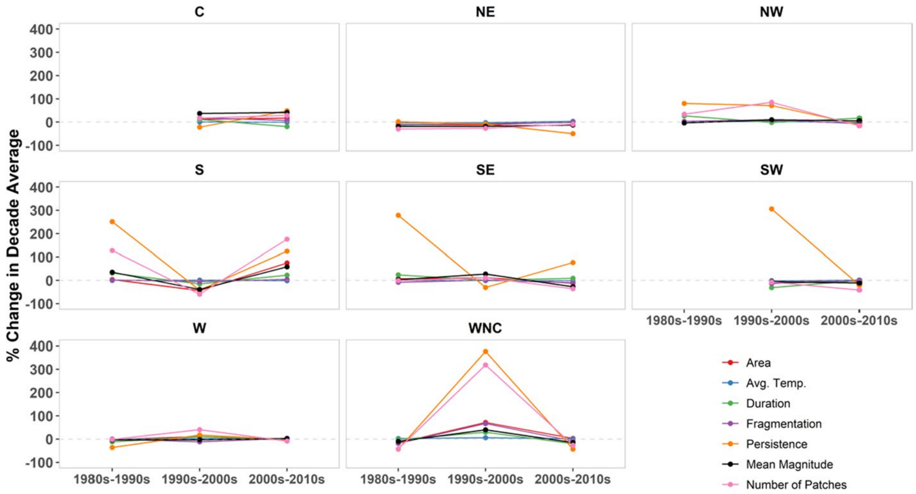

Fig. 9 Percent changes in decadal average heat wave characteristics for TOP25 events per climate region. It should be noted that Eastern North Central was excluded because of missing values

month of the year. Meaning that as we progress throughout the summer season and temperature patterns increase, we see a similar trend of increasing heat wave persistence. Specifically, across this study period, heat wave persistence, for both the top and bottom 25% events, shows a distinct pattern that varies both temporally and spatially (Fig. 10). The highest persistence is seen in events in July and August (for the TOP25 group) and in May and September (for the BOTTOM25 group). For the top 25%, in May, the average persistence across the US was 20. However, the South and Southeast regions were above this average with 41 and 25, respectively. In June, the average US-wide persistence for the top 25% was 71, 255% higher than May. This average was greatly influenced by persistence in

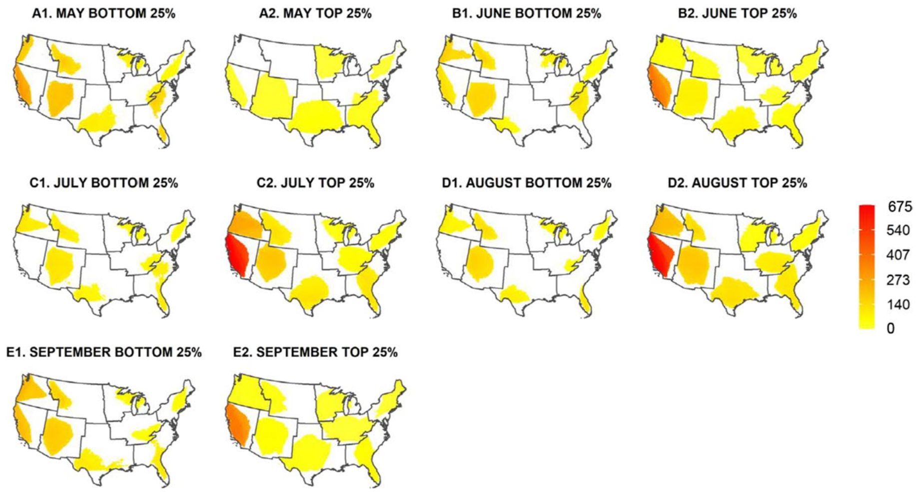

Fig. 10 Heat wave persistence for the shortest-duration (BOTTOM 25%) and longest-duration (TOP 25%) events for May (**A**), June (**B**), July (**C**), August (**D**), and September (**E**) over the 1981–2018 period

events occurring in West, Southwest, and South which, respectively, had persistence values of 333 (+1981% from May), 78 (+457% from May), and 71 (+73% from May). In July, the West persistence values further increased by 77% compared to June. Overall, in July, the US-wide persistence averaged 168 but the West, Southwest, and parts of the Northwest were above this average. August had a shockingly similar spatial pattern to the July persistence with a US-wide average of 170. Lastly, in September, the persistence dropped to 58 across the US. All regions exhibited a sharp decline in the persistence values at this time. Overall, in September, the US pattern of persistence was homogenous, except for events in the West (average persistence of 339).

A higher persistence of heat wave events was seen in the beginning of the season for the bottom 25% events but a switch was observed as summer progressed, and the persistence numbers were higher for the top 25%. In May, the average persistence value for the bottom 25% was 144, almost six times greater than during top 25%. Average persistence in June reached 107 for the US which was 49% higher than the top 25%. These values continued dropping to 87 in July. However, in August, the average persistence switched to 94 and continued to increase to 128 in September. For the bottom 25%, there was a distinct difference in the persistence between the eastern and western portions of the country. In May, the western regions (West, Southwest, and Northwest) had the highest persistence across the whole country. In June, this pattern was observed in the same western regions and West North Central in addition. It was also observed that bottom 25% events were generally homogenous across the summer months compared to top 25% (which had many extremely persistent events especially in West).

Conversely, to the persistence metric, the heat wave patch counts do not align perfectly with summer seasonal temperature trends (Fig. 11). Overall, we see that heat waves are more patchy at the start and end of the summer season and less patchy (i.e., more cohesive) during the middle most extreme portion of the summer season. More specifically, within the top 25% group, the maximum number of patches, generally, was seen in May (US mean of 16,100), June (US mean of 14,100), and September (US mean of 15,000), a result in contrast to the persistence results which exhibited higher values during the months of July

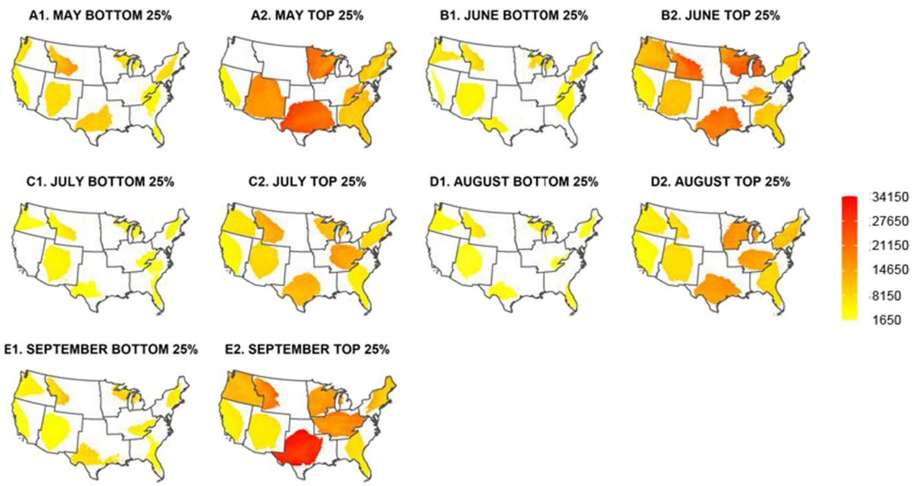

Fig. 11 Number of patches for the shortest-duration (BOTTOM 25%) and longest-duration (TOP 25%) events for May (**A**), June (**B**), July (**C**), August (**D**), and September (**E**) over the 1981–2018 period

and August. Further, for the top 25%, the South region consistently had the highest number of patches compared to all other regions (ranging 12,500–29,600). The West coast regions, Northwest and West, had some of the lowest number of patches, for the top 25%, across May, July, and August when compared with the other regions. In May, for instance, number of patches for heat wave events in the West averaged 5042 compared to the US average of 16,058. The number of patches for the lower 25% heat waves was significantly lower than the top 25% (e.g., US average of 5249 and 14,084 patches for bottom 25% and top 25% events, respectively, over the month of June). Additionally, there is not a large difference in number of patches across the summer months for the shortest-duration events. The highest numbers were observed in the West North Central region (average range of 5664–13,075 across the summer months) compared to the rest of the study area.

Other major changes include significant areal coverage increases in mean magnitude (+72%), fragmentation (+57%), and mean area (+47%), in the West North Central during the August–September period. More specifically, in this region, larger swaths of land are being impacted by longer duration and higher magnitude, area, and fragmented heat wave events. Mean magnitude also increased consistently in the South region from a −26% change in June-July to a +84% in August–September. Events in East North Central also experienced a similar change in mean magnitude with a 30% decrease in June-July and a 51% increase in July–August.

3.5 Combined heat wave characteristics

The CHCI values ranged from 0 to about 0.145 (Fig.12A). The top 25% version of the CHCI exhibited the highest values overall. For this group, CHCI values ranged from 0 to 0.145 and averaged 0.031 across the US. The highest CHCI averages occurred in the East North Central (0.086), South (0.085), and Central (0.063) regions. Ironically, while the three regions with higher CHCI values are adjacent to one another, the variables driving the index pattern differ (Fig. 12B). Within the South region, the CHCI components were either 3223 or 3233. These index values show that heat waves in this region were of mid (average) magnitude and higher-than-average area and number of patches. What differs across the South region is the fragmentation of the heat waves. Regions in yellow (Fig. 12B) had heat waves that were significantly more cohesive (higher fragmentation statistic). Within the Central region, all the CHCI component values were the same (2233). This value indicates an average area and magnitude but a significantly above average fragmentation pattern (more cohesive events) and number of patches. Lastly, within the East North Central, the CHCI component values included 1233 and 1333. This indicates that heat wave events around the Great Lakes and into Wisconsin and parts of Minnesota were highly cohesive and had more than average number of patches and lower than average area, while their magnitude varied from average in some locations to greater than average in others. Across the entirety of the region, most of the heat waves had a larger than average fragmentation pattern and number of patches.

In terms of the bottom 25% CHCI, a completely different pattern and distribution of CHCI is exhibited (Fig. 12A). Overall, CHCI values ranged from 0 to 0.097 across all the US with an average of 0.0124. Regions exhibiting the highest CHCI values include West North Central and South. Within the West North Central, the CHCI values range from 0.005 to 0.097, with the higher values occurring across Montana and Wyoming. Within the South region, the values ranged from 0.009 to 0.059 with component scores including 3133, 3233, 2233, and 2133. Such CHCI component values highlight that the

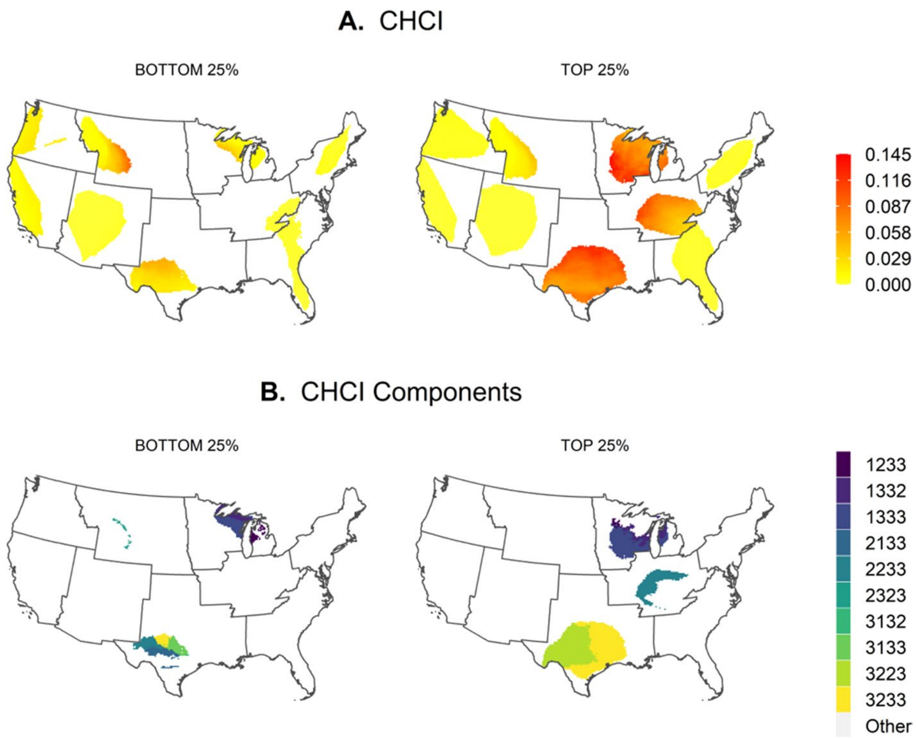

Fig. 12 **A** Distribution of CHCI for the shortest-duration vs. longest-duration events. **B** Locations and important components of CHCI. It should be noted that all areas shown here have at least two of their CHCI variables in the mid class

fragmentation and number of heat wave patches were significantly high across those areas with significant CHCI. What varies, in terms of heat wave characteristics, across the region is the mean area and magnitude of the heat wave.

4 Discussion and conclusions

4.1 Spatial patterns of heat waves across US climate regions

This study comprehensively characterized spatial patterns in the longest/shortest-duration and highly persistent heat waves in US climate regions. Varying spatial patterns were observed per heat wave characteristic and climate region, and this variability influences the level of heat wave impacts on socioecological systems. For instance, both the longest and shortest-duration events in the West region had the highest magnitude. The highest persistence was observed in the longest-duration events in West, while the longest-duration events in the South and Southwest were the most expansive. Events with the highest number of patches were found in the South, East North Central, and Central regions, mostly in the longest-duration group. Highly cohesive events were observed in the East North Central region. In addition, significant variability was found in these events over decades and summer months, indicating the dynamic nature of heat waves. Prior studies have found that, generally, heat waves in the US are intensifying in duration, intensity, and frequency (Habeeb et al. 2015; Schoof et al. 2017). While an investigation of large-scale drivers of heat wave trends is beyond the scope of this paper, it should be noted that past studies have linked upward trends in heat wave characteristics to modes of natural climate variability and the impact of long-term human-induced climate change (DeGaetano and Allen 2002; Meehl and Tebaldi 2004; Hoerling et al. 2013; Keellings & Waylen 2014b; Jones et al. 2015; Mora et al. 2017). Due to the enhanced soil moisture-temperature coupling, warming temperatures have been found to amplify the intensity of heat waves in dry areas of southern and southwestern U.S. but not in energy-limited regions of northern and northeastern U.S. (Cheng et al. 2019). In addition, spring precipitation deficits limit soil moisture, reduce evapotranspiration, and increase sensible heating that is then amplified by the presence of anticyclonic blocking (Lau & Nath 2012). Indeed, exceptional heat waves across the Great Plains of the U.S., including those of the 1930s Dust Bowl era, have been found to be preconditioned by springtime drought and strengthened by continental-scale anticyclonic flow and warm air advection (Cowan et al. 2017). Synoptic systems are also associated with heat waves, as stationary high pressure sits adjacent to affected areas for an extended period, resulting in advection of warm and dry air (Dole et al. 2011; Marshall et al. 2014; Miralles et al. 2014; Schumacher et al. 2019). Moist tropical and dry tropical are the synoptic weather types most associated with heat events (Sheridan & Kalkstein 2004), and the frequency of such weather types has increased in several regions (Senkbeil et al. 2017; Vanos et al. 2015). Such conclusions underscore the importance of characterizing spatial dynamics in heat waves per climate region and calls for region-specific measures, given differing climate regimes (e.g., winds and humidity), to deal with the impacts of heat waves.

4.2 Novelty and meaning of persistence

Persistence analysis was developed to follow trends in environmental health and/or productivity using the Normalized Difference Vegetation Index (NDVI) (Tsai et al. 2014; Waylen et al. 2014; Bunting et al. 2018). Within the original context of persistence, one can see the landscape impacts over time, even being able to pinpoint the time in which landscape change occurred and its duration. However, the NDVI version of persistence does not give context as to the drivers of change, such as climate extremes. With our application of persistence, we look to further define the spatial dimensions of heat waves as it can impact socioenvironmental health. This metric maps regions consistently impacted by heat waves of intensities which, when overlaid with information on human demographics, health, and environmental health, can be used to pinpoint not only triggers and timeframe of change but also rates of and susceptibility to change. For instance, the highly persistent 2013–2015 North Pacific marine heat wave (Di Lorenzo & Mantua 2016) has been linked to significant alterations in the biological composition and structure of the ocean and coastal ecosystems (Cavole et al. 2016). Changes in heat wave persistence may be more relevant to society than changes caused by mean temperature changes alone (Lorenz et al. 2010).

4.3 Novelty and meaning of CHCI index

The CHCI index presented in our study looks to build on such work by highlighting the combined heat wave impacts in a cumulative fashion that is both spatially explicit and representative of temporal variations. First, through quartile thresholding of heat wave events based on duration and persistence and finally computing CHCI using magnitude, number of patches, fragmentation, and areal extent parameters, heat wave events were comprehensively characterized using all six variables. Secondly, standardized variables were used in computing CHCI, thus permitting a comparative assessment of heat waves across climate regions in the contiguous US. Lastly, by exploring the components of CHCI for each pixel, important information was revealed about the main characteristics driving heat wave impacts in each climate region. For instance, the high CHCI values in the South were related to high mean area and number of patches, average magnitude, and at least average fragmentation statistic. In the East North Central region, on the other hand, CHCI was associated with events that were highly cohesive, had more-than-average number of patches, lower-than-average area, and at least average magnitude. CHCI is calculated at the finest spatial resolution possible, as dictated by the data. The CHCI index represents a novel means to understand the impact of heat waves across the US.

4.4 Key contributions of this work

Heat waves impact a wide variety of processes including human health, environmental health, and management of systems. CHCI provides another context to study and develop policy within these arenas as the index highlights both the cumulative pattern of impact, spatial dimensions, and driving factors. The CHCI index and component are key contributions to the literature for several reasons. Other heat wave indices have not highlighted the driving characteristic behind the index value. Our study shows (1) the driving heat wave characteristics that contribute to the CHCI value and (2) that across the U.S. there is not one driving heat wave variable. Section 3.5 highlights the spatial diversity in heat wave impacts both within and across the differing climate regions. Therefore, it is important to study more than just the maximum temperature associated with heat wave events, as commonly done by forecasters and emergency managers (Bunting et al. IN PREP).

Beyond CHCI, the heat wave persistence data is a large contribution to the field as we can quantify human and environmental health impacts from long-term repeated heat wave exposure. Such data can be analyzed statistically in tandem with multiple datasets including demographics, soil moisture, urban extent, population, NDVI, and many more to fully develop our understanding of heat wave impacts. For instance, major single heat wave events across the U.S. and Europe have been linked to human health and mortality events. Now, with heat wave persistence, we can add to this body of literature and see not only how short-term exposure to extreme events impacts human health but how long-term repeated exposure impacts a system. Our results, in Section 3.4, highlight extreme spatial and temporal diversity in heat wave persistence. Heat-related deaths occur when a rapid rise in temperatures outpaces the body’s ability to cool itself (Habeeb et al. 2015). All heat wave variables have been studied in relation to their impacts on human health. For instance, heat wave duration has been shown to modify mortality rates (Kalkstein & Smoyer 1993). Longer heat waves have been noted to increase dangerous thermal exposure, particularly in urban areas (Hajat et al. 2002; Anderson & Bell 2009). Longer heat waves have also been shown to impact mortality rates in major cities such as Madrid and St. Louis (Smoyer 1998; Díaz et al. 2002). Timing of the event has shown to impact overall risk (Anderson & Bell 2011). Lastly, heat-related mortality increases during heat waves with greater intensity (Anderson & Bell 2009). Though all these studies highlight the impact of a single heat wave variable on mortality, they also note that one variable could not fully explain catastrophic heat wave impacts. There is no doubt that susceptibility to heat varies across the population and from region to region; therefore, with the CHCI index, we can more wholistically look at heat wave-related mortality rates and better pinpoint susceptibility by combining this data with demographic and health metrics. Additionally, with persistence, we can understand repeated exposure and its impacts.

4.5 Drawbacks in heat wave studies

The study of heat waves faces numerous challenges. In general, heat waves are defined as extended periods of extreme heat, though no consistent definition exists regarding the actual temperature threshold, metric, and event duration that definitively defines a heat wave. In this study, we utilized a standard definition for heat waves, using the climatological literature to guide us. A relative location-specific percentile-based threshold has been widely utilized across previous heat wave studies. However, differing heat wave definitions can result in inconsistent data and results. For example, research indicates that significant positive associations between heat waves and health outcomes (preterm birth and nonaccidental death) are more common when relative (rather than absolute) heat wave indices are used to define exposure (Kent et al. 2014). However, the approach employed in this study, using a percentile-based threshold of temperature, is common within climatological extreme studies, and therefore, the results highlight realistic heat wave patterns and impacts. We also do not consider humidity in our definition of heat waves. Humidity is known to negatively impact human comfort and amplify heat wave health impacts.

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Author contribution EB conceived the study and developed the methodology. DW led the data analysis. DW, EB, and DK led in writing and interpretation of results. EB and DK completed the edits and response to reviewers. NW assisted with the data analysis.

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Data availability The datasets generated during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval This original manuscript has not been submitted to another journal. The publication represents a single study that is free of fabrication or falsehoods.

Consent to participate and publish All authors have consented to this submission and to undertaking edits during the review process.

Competing interests The authors declare no competing interests.

References

Anderson BG, Bell ML (2009) Weather-related mortality: how heat, cold, and heat waves affect mortality in the United States. Epidemiol 20(2):205–213

Anderson BG, Bell ML (2011) Heat waves in the United States: mortality risk during heat waves and effect modification by heat wave characteristics in 43 U.S. communities. Environ Health Perspect. 119(2):210–218

Baldwin JW, Dessy JB, Vecchi GA, Oppenheimer M (2019) Temporally compound heat wave events and global warming: an emerging hazard. Earth's Futur 7(4):411–427

Barros VR, Field CB, Dokken DJ, Mastrandrea MD, Mach KJ, Bilir TE, ... White LL (2014) Climate change 2014 impacts, adaptation, and vulnerability Part B: regional aspects:working group II contribution to the fifth assessment report of the intergovernmental panel on climate change. In Climate Change 2014: Impacts, Adaptation and Vulnerability: Part B: Regional Aspects: Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press. pp 1–1820

Bunting EL, Southworth J, Herrero H, Waylen P (2018) Understanding long-term savanna vegetation persistence across three drainage basins in southern Africa. Remote Sens 10(7):1013

Cavole LM, Demko AM, Diner RE, Giddings A, Koester I, Schwenck SM, Yen NK, Zill ME (2016) Biological impacts of the 2013–2015 warm-water anomaly in the Northeast Pacific: winners, losers, and the future. Oceanogr 29(2):273–285

Chen Y, Li Y (2017) An inter-comparison of three heat wave types in China during 1961–2010: observed basic features and linear trends. Sci Rep 7(March):2–11

Cheng L, Hoerling M, Liu Z, Eischeid J (2019) Physical understanding of human-induced changes in U.S. hot droughts using equilibrium climate simulations. J Clin 32(14):4431–4443

Clark SS, Chester MV, Seager TP, Eisenberg DA (2019) The vulnerability of interdependent urban infrastructure systems to climate change: could Phoenix experience a Katrina of extreme heat? Sustain Resilient Infrastruct 4(1):21–35. https://doi.org/10.1080/23789689.2018.1448668

Cowan T, Hegerl GC, Colfescu I, Bollasina M, Purich A, Boschat G (2017) Factors contributing to record-breaking heat waves over the great plains during the 1930s Dust Bowl. J Climate 30(7):2437–2461. https://doi.org/10.1175/JCLI-D-16-0436.1

Daly C, Halbleib M, Smith JI, Gibson WP, Doggett MK, Taylor GH, Curtis J, Pasteris PP (2008) Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. Int J Climatol 28(8):2031–2064

Das PK, Podder U, Das R, Kamalakannan C, Rao GS, Bandyopadhyay S, Raj U (2020) Quantification of heat wave occurrences over the Indian region using long-term (1979–2017) daily gridded ($0.5° \times 0.5°$) temperature data—a combined heat wave index approach. Theor Appl Climatol. 142(1–2):497–511

Defne Z, Aretxabaleta AL, Ganju NK, Kalra TS, Jones DK, Smith KEL (2020) A geospatially resolved wetland vulnerability index: synthesis of physical drivers. PLoS One 15(1):1–27. https://doi.org/10.1371/journal.pone.0228504

DeGaetano AT, Allen RJ (2002) Trends in twentieth-century temperature extremes across the United States. J Clim 15(22):3188–3205. https://doi.org/10.1175/1520-0442(2002)015%3c3188:TITCTE%3e2.0.CO;2

Díaz J, Jordán A, García R, López C, Alberdi JC, Hernández E, Otero A (2002) Heat waves in Madrid 1986–1997: effects on the health of the elderly. Int Arch Occup Environ Health 75(3):163–170

Di Lorenzo E, Mantua N (2016) Multi-year persistence of the 2014/15 North Pacific marine heatwave. Nat Clim Chang 6(11):1042–1047

Dole R, Hoerling M, Perlwitz J, Eischeid J, Pegion P, Zhang T et al (2011) Was there a basis for anticipating the 2010 Russian heat wave? Geophys Res Lett 38(6):n/a-n/a

Fenner D, Holtmann A, Krug A, Scherer D (2019) Heat waves in Berlin and Potsdam, Germany – long-term trends and comparison of heat wave definitions from 1893 to 2017. Int J Climatol 39(4):2422–2437

Field CB, Barros V, Stocker TF, Dahe Q (ed) (2012) Managing the risks of extreme events and disasters to advance climate change adaptation:special report of the intergovernmental panel on climate change. Cambridge University Press

Frich P, Alexander LV, Della-Marta P, Gleason B, Haylock M, Tank Klein AMG, Peterson T (2002) Observed coherent changes in climatic extremes during the second half of the twentieth century. Clim Res 19(3):193–212

Guo Y, Gasparrini A, Armstrong BG, Tawatsupa B, Tobias A, Lavigne E, ... Tong S (2017) Heat wave and mortality: a multicountry, multicommunity study. Environ Health Perspect 125(8):087006

Habeeb D, Vargo J, Stone B (2015) Rising heat wave trends in large US cities. Nat Hazards 76(3):1651–1665

Hajat S, Armstrong B, Baccini M, Biggeri A, Bisanti L, Russo A, Paldy A, Menne B, Kosatsky T (2006) Impact of high temperatures on mortality: is there an added heat wave effect? Epidemiol 17(6):632–638

Hajat S, Kovats RS, Atkinson RW, Haines A (2002) Impact of hot temperatures on death in London: a time series approach. J Epidemiol Community Health 56(5):367–372

Hattis D, Ogneva-Himmelberger Y, Ratick S (2012) The spatial variability of heat-related mortality in Massachusetts. Appl Geogr 33(1):45–52. https://doi.org/10.1016/j.apgeog.2011.07.008

Hoerling M, Kumar A, Dole R, Nielsen-Gammon JW, Eischeid J, Perlwitz J et al (2013) Anatomy of an extreme event. J Climate 26(9):2811–2832. https://doi.org/10.1175/JCLI-D-12-00270.1
Jones B, O'Neill BC, Mcdaniel L, Mcginnis S, Mearns LO, Tebaldi C (2015) Future population exposure to US heat extremes. Nat Clim Chang 5(7):652–655
Kalkstein LS, Smoyer KE (1993) The impact of climate change on human health: some international implications. Experientia 49(11):969–979
Karl TR, Koss WJ (1984) Regional and national monthly, seasonal, and annual temperature weighted by area 1895–1983. Hist Climatol Ser. 4–3
Keellings D, Waylen P (2014a) Investigating teleconnection drivers of bivariate heat waves in Florida using extreme value analysis. Clim Dyn 44(11–12):3383–3391. https://doi.org/10.1007/s00382-014-2345-8
Keellings D, Bunting E, Engström J (2018) Spatiotemporal changes in the size and shape of heat waves over North America. Clim Change 147(1–2):165–178
Keellings D, Moradkhani H (2020) Spatiotemporal evolution of heat wave severity and coverage across the United States. Geophys Res Lett 47(9):1–9
Keellings D, Waylen P (2014b) Increased risk of heat waves in Florida: characterizing changes in bivariate heat wave risk using extreme value analysis. Appl Geogr 46:90–97. https://doi.org/10.1016/j.apgeog.2013.11.008
Kent ST, McClure LA, Zaitchik BF, Smith TT, Gohlke JM (2014) Heat waves and health outcomes in Alabama (USA): the importance of heat wave definition. Environ Health Perspect 122(2):151–158
Kloog I, Melly SJ, Coull BA, Nordio F, Schwartz JD (2015) Using satellite-based spatiotemporal resolved air temperature exposure to study the association between ambient air temperature and birth outcomes in Massachusetts. Environ Health Perspect 123(10):1053–1058
Kravchenko J, Abernethy AP, Fawzy M, Lyerly HK (2013) Minimization of heatwave morbidity and mortality. Am J Prev Med 44(3):274–282. https://doi.org/10.1016/j.amepre.2012.11.015
Lau NC, Nath MJ (2012) A model study of heat waves over North America: meteorological aspects and projections for the twenty-first century. J Climate 25(14):4761–4784. https://doi.org/10.1175/JCLI-D-11-00575.1
Lee M, Shi L, Zanobetti A, Schwartz JD (2016) Study on the association between ambient temperature and mortality using spatially resolved exposure data. Environ Res 151:610–617. https://doi.org/10.1016/j.envres.2016.08.029
Lopez H, West R, Dong S, Goni G, Kirtman B, Lee SK, Atlas R (2018) Early emergence of anthropogenically forced heat waves in the western United States and Great Lakes. Nat Clim Chang 8(5):414–420
Lorenz R, Jaeger EB, Seneviratne SI (2010) Persistence of heat waves and its link to soil moisture memory. Geophys Res Lett. 37(9):n/a-n/a
Lu Y, Kueppers L (2015) Increased heat waves with loss of irrigation in the United States. Environ Res Lett 10(6):064010
Marshall AG, Hudson D, Wheeler MC, Alves O, Hendon HH, Pook MJ, Risbey JS (2014) Intra-seasonal drivers of extreme heat over Australia in observations and POAMA-2. Clim Dyn 43(7–8):1915–1937. https://doi.org/10.1007/s00382-013-2016-1
Meehl GA, Tebaldi C (2004) More intense, more frequent, and longer lasting heat waves in the 21st century (80-). Science. 305(5686):994–997
Merte S (2017) Estimating heat wave-related mortality in Europe using singular spectrum analysis. Clim Change 142(3–4):321–330
Miller NL, Hayhoe K, Jin J, Auffhammer M (2008) Climate, extreme heat, and electricity demand in California. J Appl Meteorol Climatol 47(6):1834–1844
Miralles DG, Teuling AJ, van Heerwaarden CC, Vilà-Guerau de Arellano J (2014) Mega-heatwave temperatures due to combined soil desiccation and atmospheric heat accumulation. Nat Geosci 7(5):345–349. https://doi.org/10.1038/ngeo2141
Mishra V, Cherkauer KA (2010) Retrospective droughts in the crop growing season: implications to corn and soybean yield in the Midwestern United States. Agric for Meteorol 150(7–8):1030–1045. https://doi.org/10.1016/j.agrformet.2010.04.002
Mora C, Counsell CWW, Bielecki CR, Louis LV (2017) Twenty-seven ways a heat wave can kill you: deadly heat in the era of climate change. Circ Cardiovasc Qual Outcomes 10(11):1–3
Nairn JR, Fawcett RJB (2014) The excess heat factor: a metric for heatwave intensity and its use in classifying heatwave severity. Int J Environ Res Public Health 12(1):227–253

Peng RD, Bobb JF, Tebaldi C, McDaniel L, Bell ML, Dominici F (2011) Toward a quantitative estimate of future heat wave mortality under global climate change. Environ Health Perspect 119(5):701–706
Perkins-Kirkpatrick SE, White CJ, Alexander LV, Argüeso D, Boschat G, Cowan T, Evans JP, Ekström M, Oliver ECJ, Phatak A, Purich A (2016) Natural hazards in Australia: heatwaves. Clim Change 139(1):101–114. https://doi.org/10.1007/s10584-016-1650-0
Perkins SE (2015) A review on the scientific understanding of heatwaves-their measurement, driving mechanisms, and changes at the global scale. Atmos Res [internet] 164–165:242–267. https://doi.org/10.1016/j.atmosres.2015.05.014
Photiadou C, Jones MR, Keellings D, Dewes CF (2014) Modeling European hot spells using extreme value analysis. Clim Res 58(3):193–207
Russo S, Dosio A, Graversen RG, Sillmann J, Carrao H, Dunbar MB, Singleton A, Montagna P, Barbola P, Vogt JV (2014) Magnitude of extreme heat waves in present climate and their projection in a warming world. J Geophys Res Atmos 119(22):12500–12512
Schoof JT, Ford TW, Pryor SC (2017) Recent changes in U.S. regional heat wave characteristics in observations and reanalyses. J Appl Meteorol Climatol. 56(9):2621–2636
Schumacher DL, Keune J, van Heerwaarden CC, Vilà-Guerau de Arellano J, Teuling AJ, Miralles DG (2019) Amplification of mega-heatwaves through heat torrents fuelled by upwind drought. Nature Geosci 12(9):712–717. https://doi.org/10.1038/s41561-019-0431-6
Seneviratne SI, Donat MG, Mueller B, Alexander LV (2014) No pause in the increase of hot temperature extremes. Nat Clim Chang 4(3):161–163
Senkbeil JC, Saunders ME, Taylor B (2017) Changes in summer weather type frequency in eastern North America. Ann Am Assoc Geogr 107(5):1229–1245. https://doi.org/10.1080/24694452.2017.1295839
Sheridan SC, Kalkstein LS (2004) Progress in heat watch-warning system technology. Bull Am Meteor Soc 85(12):1931–1941. https://doi.org/10.1175/BAMS-85-12-1931
Singh S, Mall RK, Singh N (2021) Changing spatio-temporal trends of heat wave and severe heat wave events over India: an emerging health hazard. Int J Climatol 41(S1):E1831–E1845
Smoyer KE (1998) A comparative analysis of heat waves and associated mortality in St. Louis, Missouri - 1980 and 1995. Int J Biometeorol. 42(1):44–50
Tan J, Zheng Y, Song G, Kalkstein LS, Kalkstein AJ, Tang X (2007) Heat wave impacts on mortality in Shanghai, 1998 and 2003. Int J Biometeorol 51(3):193–200
Thornton PE, Thornton MM, Mayer BW, Wilhelmi N, Wei Y, Devarakonda R, Cook RB. 2014. Daymet: daily surface weather data on a 1-km grid for North America, version 2. [Internet]. Oak Ridge, TN (United States). https://www.osti.gov/biblio/1148868-daymet-daily-surface-weather-data-km-grid-north-america-version
Tsai H, Southworth J, Waylen P (2014) Spatial persistence and temporal patterns in vegetation cover across Florida, 1982–2006. Phys Geogr 35(2):151–180. https://doi.org/10.1080/02723646.2014.898126
Vanos JK, Kalkstein LS, Sanford TJ (2015) Detecting synoptic warming trends across the US Midwest and implications to human health and heat-related mortality. Int J Climatol 35(1):85–96. https://doi.org/10.1002/joc.3964
Waylen P, Southworth J, Gibbes C, Tsai H (2014) Time series analysis of land cover change: developing statistical tools to determine significance of land cover changes in persistence analyses. Remote Sens 6(5):4473–4497
World Meteorological Organization, World Health Organization. 2015. Heatwaves and health: guidance on warning-system development. [place unknown]. http://www.who.int/globalchange/publications/WMO_WHO_Heat_Health_Guidance_2015.pdf
Wreford A, Neil AW (2010) Adaptation in agriculture: historic effects of heat waves and droughts on UK agriculture. Int J Agric Sustain 8(4):278–289
Zhao L, Oppenheimer M, Zhu Q, Baldwin JW, Ebi KL, Bou-Zeid E, Guan K, Liu X (2018) Interactions between urban heat islands and heat waves. Environ Res Lett. 13(3):034003