BAMS Article

Spatial Analysis of United States National Weather Service Excessive Heat Warnings and Heat Advisories

David M. Hondula, Samuel Meltzer, Robert C. Balling Jr., and Paul Iñiguez

ABSTRACT: Public heat alerts are important risk communication tools, but there has been no systematic analysis of how frequently they are issued or how patterns in alert frequency relate to regional climatology or heat–health impacts. We compiled and analyzed all excessive heat warnings and heat advisories (collectively, heat alerts) issued by the U.S. National Weather Service for 2010–19. Heat alert frequency was correlated to climatological indicators derived from reanalysis data aggregated to Weather Forecast Office (WFO) polygons and to estimates of heat-attributable mortality for 134 metropolitan areas. The type of heat alerts used and the frequency with which they were issued were highly variable. Across 77% of the country, heat advisories were the primary product issued. The median location experienced 2.3 heat alert days per year. Regions with the highest frequency (approaching 25 heat alert days per year) included the southern Midwest and Great Plains, as well as the desert Southwest. The 95th-percentile daily maximum heat index was the climatological indicator most strongly correlated with heat alert frequency across all WFOs ($r = 0.71$). Locations that issued heat alerts more frequently than would be expected based on climatology were primarily located along the Pacific coast; those that issued heat alerts less frequently than expected were in southern Texas and southern Florida, the latter of which includes multiple cities with high rates of heat-attributable mortality. Our results suggest that the public may be receiving mixed signals about the severity of the heat hazard, with some hotter locations particularly underserved by heat risk messaging.

KEYWORDS: Extreme events; Communications/decision making; Emergency preparedness; Geographic Information Systems (GIS); Health; Societal impacts

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Weather alerts (including advisories, watches, and warnings) are important risk communication tools widely used by meteorological agencies to notify the public of the onset of dangerous conditions. Alerts are intended to encourage protective behavior (e.g., evacuation, seeking shelter, avoiding driving, wearing appropriate clothing) for the public at large and for institutions and organizations that may play a role in preparing for or responding to a dangerous meteorological event. There is clear evidence that weather alerts are effective in triggering behavior change by organizations and individuals (Liu et al. 1996; Balluz et al. 2000; Sheridan 2007; Montz et al. 2015), and several case studies suggest that alerts have helped prevent injuries and deaths (Ebi et al. 2004; Parker et al. 2007; Simmons and Sutter 2008). There is also evidence that the effectiveness of alerts depends on a wide variety of factors, including message content, cultural context, delivery channels, and frequency of use (Phillips and Morrow 2007; Perry et al. 2013; Perreault et al. 2014; Weyrich et al. 2020; Kreibich et al. 2021). In this manuscript, we investigate the last of those factors, frequency, and how the frequency with which official public alerts are issued for one hazard type, extreme heat, varies across the United States. Knowledge of spatial patterns in alert frequency may be useful to scholars investigating risk perceptions and health impacts associated with meteorological hazards, as well as practitioners involved in the design, implementation, and evaluation of weather alert systems.

Extreme heat is one of the most dangerous meteorological hazards for public health. Scholars estimate that the annual attributable mortality to heat in the United States exceeds 5,000 cases (Weinberger et al. 2020). A more conservative assessment by the U.S. Centers for Disease Control and Prevention, based on coded causes of death, identifies approximately 700 heat-related deaths per year, exceeding the death toll of all other weather hazards combined with the exception of extreme cold (Berko et al. 2014). More generally, heat creates illness, discomfort, stress, and anxiety for many people (Howe et al. 2019; Khare et al. 2015; Knowlton et al. 2011; Petitti et al. 2016), and strains critical infrastructure systems including electricity, water, and transportation (Chapman et al. 2013; Clark et al. 2019). Improving societal preparedness for extreme heat is increasingly prioritized by researchers and practitioners, given large projected increases in the public health impacts of extreme heat associated with continued global and urban warming and demographic change (Hondula et al. 2015; Petkova et al. 2017; Keith et al. 2019).

Heat alerts are perceived to be a cornerstone of an effective multisector response to extreme heat events (Pascal et al. 2006; Toloo et al. 2013a,b). Alerts not only communicate risk and encourage specific actions to the public at large, but also in many cases trigger particular actions by public and private sector organizations. The available evidence suggests that heat alerts and the protective actions coupled to them are effective in raising awareness, promoting behavioral changes, and/or protecting public health (Sheridan 2007; Ebi et al. 2004; Toloo et al. 2013a; Lefevre et al. 2015; Weinberger et al. 2018). However, the evidence base concerning heat alert effectiveness is relatively limited, due in part to the difficulty in establishing a counterfactual (Toloo et al. 2013b; Boeckmann and Rohn 2014).

In the United States, the National Oceanic and Atmospheric Administration's National Weather Service (NWS) is the lead agency for issuing heat alerts to the public. The requisite weather conditions to trigger an alert are highly variable from jurisdiction to jurisdiction (Hawkins et al. 2017). While this variability may present challenges with respect to operations and public interpretation, it is also consistent with international recommendations that "(heat–health alert systems) should consider local meteorology, demographics, and urban structure," and that "one-size-fits-all systems may not properly accommodate all locations, especially if developed within countries that span different cultural and climate zones" (McGregor et al. 2015). There are several conceptual bases that motivate tailoring heat alert criteria at the local scale. One is the well-established notion that certain impacts of heat occur *relative* to each location's underlying climate: the same ambient air temperature produces differential societal impacts in Minneapolis versus Phoenix, for example (following Curriero et al. 2002; Anderson and Bell 2009). Second is the interest to couple alert criteria to impact data. Different people and populations have varying sensitivity and exposure to heat based on underlying demographic and infrastructure factors (Anderson and Bell 2011). These differences could motivate the application of different thresholds even among localities with similar climates, if societal impacts in one location become apparent at lower (or higher) temperatures than another.

Given that there are many different variables to consider when setting heat alert criteria, and that there is no national harmonized heat alert protocol, it is perhaps unsurprising that there is a diverse patchwork of alert criteria in effect across the United States. Individual NWS Weather Forecast Offices (WFOs) have independent authority to set alert criteria, and a 2013 survey of WFOs revealed that approximately half had developed local policy to do so (Hawkins et al. 2017). This approach is consistent with the national policy directive from the NWS regarding nonprecipitation weather products, which states:

> The Excessive Heat Warning/Heat Advisory criteria are highly variable in different parts of the country due to climate variability and the effect of excessive heat on the local population. WFOs are strongly encouraged to develop local criteria in cooperation with local emergency and health officials, and/or utilize detailed heat/health warning systems based on scientific research. (NWS 2019, p. 7)

The consequence of the resulting patchwork approach in terms of the frequency with which the public is exposed to heat products from the NWS is currently unknown. A national perspective on the current use of heat products could be useful for crafting guidance as alert systems continue to evolve, particularly with projections for increasing heat–health impacts in the coming decades. As such, our research objective was to assess spatial variability in the use of heat products issued by NWS WFOs in the United States. We ask: How often are heat alerts in effect, how does their frequency spatially vary, and how does their frequency relate to climate and heat–health indicators?

Methods

Data sources. Archived NWS excessive heat warnings and heat advisories were obtained from the Iowa State University Mesonet (Iowa State University 2021). We define a "heat alert" (HA) as *either* an excessive heat warning or a heat advisory issued for a given location. "Heat alert" is not an official term or product issued by the NWS, but is applied in this manuscript to reflect a combination of two NWS products. We excluded excessive heat watches (another product that NWS WFOs can issue) from this study, because they are typically issued directly in advance of an excessive heat warning, and thus would be largely redundant. There were very few cases where heat advisories were issued in advance of excessive heat warnings and subsequently upgraded to the latter.

We downloaded all HAs for the period 2010–19 for the entire United States; no HAs were issued in Hawaiʻi or Alaska during that time frame and thus the remainder of the analysis is focused on the contiguous 48 states. The Iowa State University Mesonet provides boundary files (shapefile format) for each HA issued by an NWS WFO; there is a unique record for each individual forecast zone for which an HA is issued. A single HA issued for 10 forecast zones would thus result in 10 different records in the Iowa State Archive; we define each of these instances as a zonal heat alert (ZHA). Attributes included for each ZHA include the start and end time, issuing WFO, and the forecast zone name. Start and end times were based on the "INIT_ISS" and "EXPIRED" fields in the Iowa State database. We calculated HA duration as the difference (in decimal days) between the start and end time for each HA. HA duration (in days per year) is the primary variable for this analysis rather than HA counts, because HAs can vary considerably in duration. Boundary files for NWS WFO service areas (county warning areas) and regions were downloaded from the NWS website (NWS 2021a).

Daily historical weather data for the period 2010–19 were obtained from the U.S. National Centers for Environmental Prediction North American Regional Reanalysis (NARR) gridded dataset (Mesinger et al. 2006). We selected a gridded product to have access to spatially consistent and complete observations over the contiguous United States. NARR data are available at 3-hourly time steps over a grid with a spatial resolution of approximately 32 km. Critically, NARR data include 3-hourly estimates of both air temperature and relative humidity, from which we were able to derive 3-hourly heat index estimates. Heat index is a combined temperature–humidity metric that is used as the basis for issuing warnings and advisories at many NWS WFOs (Hawkins et al. 2017). We used the monolevel data products for air temperature at 2 m and relative humidity at 2 m. The heat index was calculated using the *weathermetrics* package in R (Anderson et al. 2013). We extracted daily maximum heat index and air temperature from the 3-hourly observations for the months of June–August (JJA) and then calculated the 50th, 90th, 95th, and 99th percentiles of JJA maximum temperatures and heat indices as indicators of the severity of heat experienced at different locations around the United States. We additionally calculated the difference between the 99th and 90th percentiles of JJA maximum temperatures and heat indices to assess differences in the range of the upper portion of the temperature distribution from one location to another. Collectively, these 10 metrics are termed "climate indicators" for the remainder of the analysis.

A heat–health indicator was extracted from a published international analysis of temperature-attributable mortality (Gasparrini et al. 2015). Heat-attributable mortality is a statistically derived estimate of the fraction of all deaths (from all nonexternal causes) in an area that occurred prematurely as a consequence of high temperatures. The calculation of heat-attributable mortality does not rely on direct attribution of individual deaths to heat exposure as recorded on death certificates or vital registries, which can vary widely from jurisdiction to jurisdiction. Instead, heat-attributable mortality is calculated using time series methods that attempt to estimate how many additional deaths occurred on days with temperatures above a locally defined temperature of minimum mortality, accounting for long-term and seasonal variations in mortality. The Gasparrini et al. (2015) estimates were based on 22 years (1985–2006) of mortality records analyzed for county or multicounty areas that comprise 134 metropolitan areas across the United States; the geographic definitions for these areas were further detailed by Zanobetti et al. (2013). Deaths linked to external causes, such as intentional and unintentional injury, poisoning, drug overdose, and complications of medical care, were excluded from the mortality data used by Gasparrini et al. (2015) and are thus not reflected in the estimates used in this study.

Data processing. The forecast zones for which HAs are issued are subject to change over time as the NWS updates its forecasting approach. As such, there is no single, temporally consistent, spatial boundary file for tabulating HAs over the decade we examined. We generated an equally spaced point mesh over the contiguous 48 states at 0.25° × 0.25° resolution; the resultant grid contained 81,874 points. We then applied a spatial join to calculate the sum of all HA durations over the study period for each point in the mesh.

We compared HAs to climatological indicators at the WFO scale, taking the spatial average of all HA and/or climate data that fell within each WFO boundary. For the health indicator, we took to the spatial average of all HA data that fell within the county or multicounty area that comprised each metropolitan area and extracted the estimate of heat-attributable mortality directly from the literature.

Analysis. Our analysis consisted of three major components: descriptive statistics, spatial hotspot identification, and comparisons to the climate and health indicators. We calculated a wide range of descriptive statistics concerning HAs at the scale of the original point mesh and for WFOs, including the average annual number of HA days, which serves as the primary dependent variable for this study.

We applied a spatial hotspot (clustering) technique to identify regions of the country with relatively high and low average annual HA frequency. The hotspot analysis for the heat alert counts is based on the calculation of the Getis-Ord Gi* statistic (Getis and Ord 1992; Ord and Getis 1995) at each of the 81,874 grid points. The statistic is similar to a locally generated z score along with the associated p value that allows statistical significance to be attached to areas of relatively high or low heat alert counts.

Comparisons with climate and health indicators were completed using Spearman rank order correlations, owing to nonnormality in the HA data. For the WFO-based climatological analysis, we calculated Spearman correlations between HA frequency and the 10 climate indicators (50th-, 90th-, 95th-, and 99th-percentile heat index and air temperature, as well as the difference between the 99th and 90th percentiles for both heat index and air temperature). We calculated correlations at the national scale, using all WFOs, as well as within each of the four NWS regions in the contiguous United States (Central, Eastern, Southern, and Western), to determine if there was geographic variability in the relationship between climate indicators and HA frequency. For both approaches (WFO and metro areas), we identified locations that issued HAs relatively frequently or infrequently given their climatology or heat–health burden based on the difference in ranked climate or health indicators and HA frequency. Out of the 10 climate indicators that we used, we conducted the rank comparison using the single indicator that had the highest correlation with HA frequency; the selected climate indicator might vary between regions or scales of analysis.

Results

Heat alert descriptive statistics. There were 111,963 unique ZHAs in the contiguous United States over the period 2010–19. heat advisories accounted for approximately 85% of all ZHAs. Across all ZHAs, the median duration was 1.16 days, with an interquartile range of 0.65–2.0 days. The median excessive heat warning (2.12 days) was nearly twice as long as the median heat advisory (1.14 days). The longest ZHAs in the record spanned 3–4 weeks and were issued for locations in the south-central United States associated with the July–August 2011 heat wave. 97.5% of the ZHA days in the study period occurred in the months of June–August, with July accounting for 51.9% of all ZHA days alone. May, September, and October accounted for the remaining 2.5% of ZHA days.

Spatial analysis of heat alerts. Using an equally spaced point mesh, we found that the median location in the contiguous United States experienced 2.3 HA days per year over the

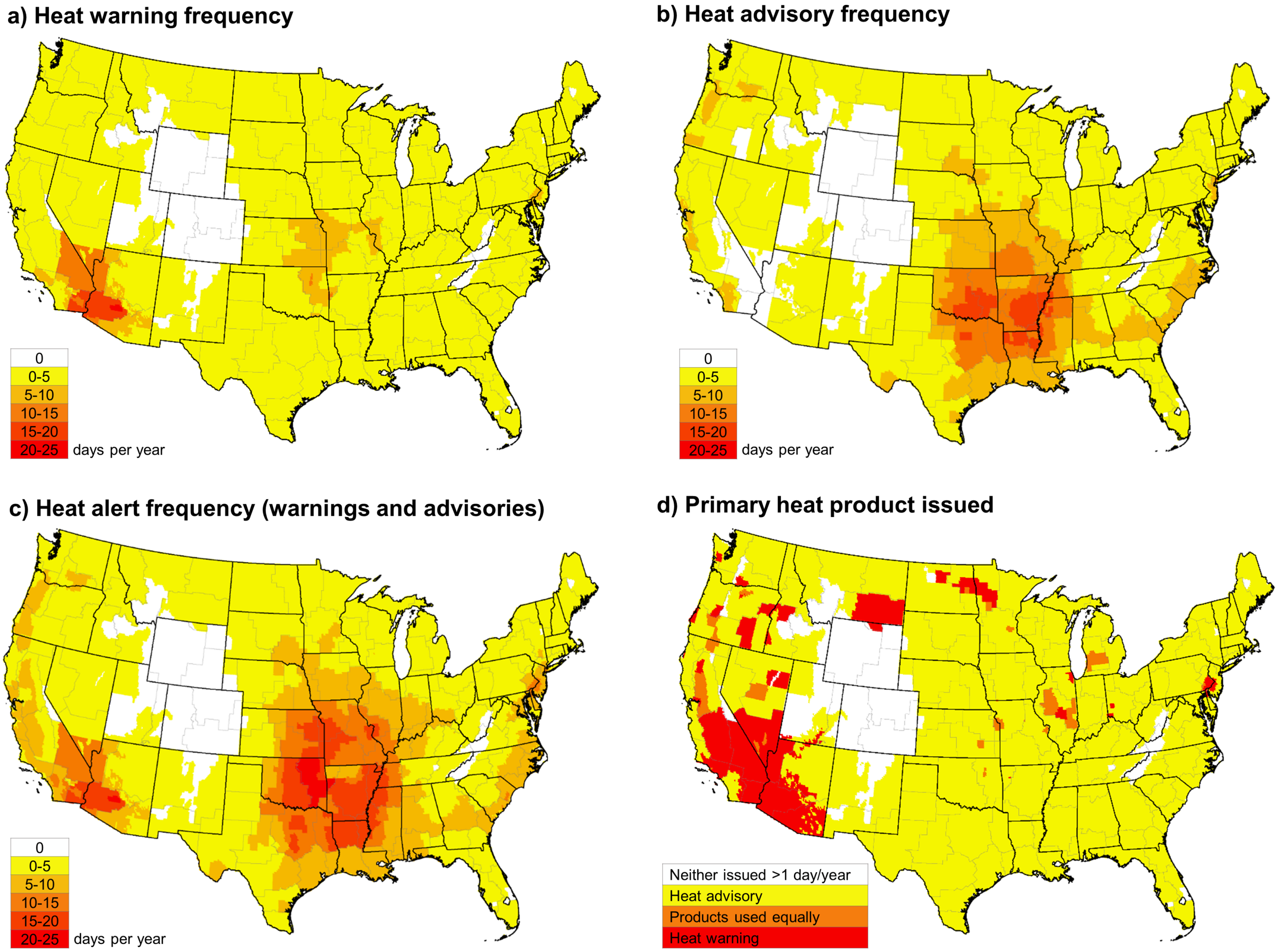

Fig. 1. Frequency of U.S. National Weather Service (a) heat warnings, (b) heat advisories, and (c) heat alerts by location, 2010–19. Heat alerts include heat warnings and heat advisories. (d) The primary type of heat product issued over the same time period. The faint gray lines show the boundaries of National Weather Service Weather Forecast Offices.

study period. HA frequencies varied considerably across the country: 12.4% of the study area had HAs in effect for less than 1 day per year over the decade (including 12.1% with exactly zero HAs), whereas approximately 12.7% of the study area averaged more than 10 HA days per year (Fig. 1). The 99th percentile of HA duration was 18.9 days per year. The locations with the highest averages were located about 60 km south of Tulsa, Oklahoma, and had HAs in effect for 24.9 days per year. Across 77% of the country, heat advisories were the primary product issued, as compared to only 8.5% of the country where excessive heat warnings were the primary product issued. The two products were used in approximately equal proportions in 1.7% of the study domain (see Fig. 1d).

Hotspot analysis revealed spatially continuous clusters of points with relatively higher HA frequencies (Fig. 2). There were two large regions identified as hotspots: one that includes much of the southern Midwest and Great Plains, spanning across parts of the Sun Belt to include the southern Atlantic Coast, and a second that encompassed parts of the desert Southwest in Arizona and California. Additional smaller hotspots were identified in the Philadelphia–New York City metropolitan areas, southwestern Texas, Minneapolis, valley locations along the Pacific coast, and along the Oregon–Washington border. Cold spots—locations with relatively lower HA frequencies—included much of the northern tier of the United States, the interior West, Appalachia, much of New England, most of Florida, and parts of Texas.

Heat alert hot and cold spots

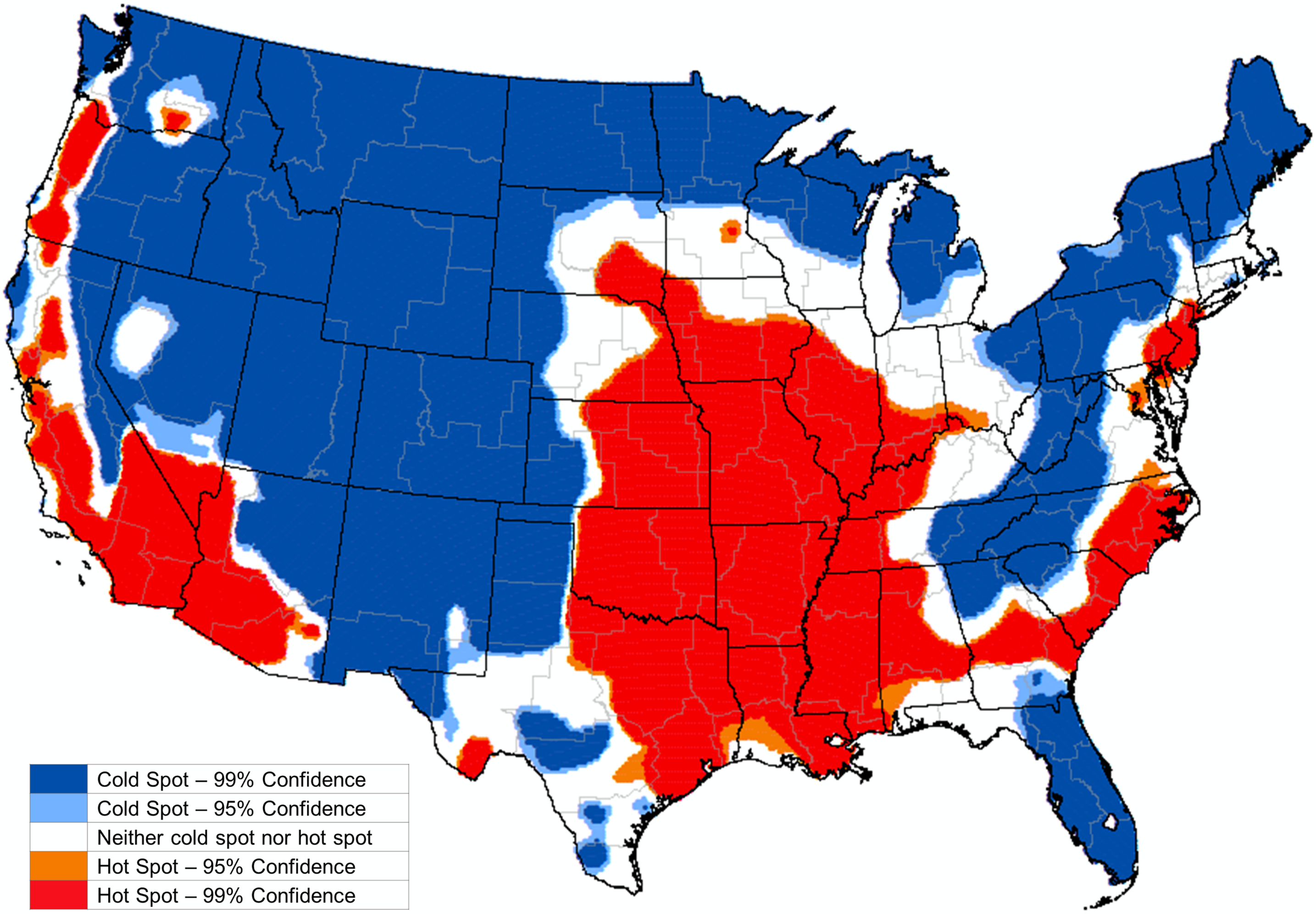

Fig. 2. Spatial hotspot analysis of U.S. National Weather service heat alerts, 2010–19. Hotspots are locations where high values for heat alert frequency are spatially clustered. Heat alerts include heat warnings and heat advisories. The faint gray lines show the boundaries of National Weather Service Weather Forecast Offices.

Comparisons with climate and health indicators.

Climate indicators. We found moderate to high positive correlations between indicators of summer heat and HA frequency for the 116 WFOs in the contiguous United States (Table 1, Fig. 3). At the national scale, HA frequency was more closely correlated with daily maximum heat index than daily maximum air temperature. The single metric most closely correlated with HA frequency at the national scale was the 95th-percentile daily maximum heat index ($r = 0.71$).

Despite the relatively high correlation between the 95th-percentile daily maximum heat index and HA frequency across the country, there were numerous cases where the rank of a particular WFO with respect to HA frequency considerably differed from its rank with respect to climatology (Fig. 3). Nearly all of the WFOs that issued HAs more frequently than the national pattern would suggest were located in the western United States. The two WFOs with the largest rank difference in this regard were San Diego, CA (SGX), which covers southern coastal California, and Portland, OR (PQR), which covers much of western Oregon and southwestern Washington. Locations in the SGX forecast zone averaged approximately 9 HA days per year, which ranked 15th nationally. But the 95th-percentile heat index in the SGX forecast zone, 93°F (~34°C), ranked 86th. PQR had one of the lowest 95th-percentile heat indices of all WFOs, 85°F (~28°C), which ranked 110th. Yet locations

Table 1. Spearman correlation coefficients for the association between U.S. National Weather Service heat alert frequency and several climate and heat–health indicators, as measured for Weather Forecast Offices (climate indicators), and 134 metropolitan areas (heat–health indicator).

Metric	Percentile	National	Central	Eastern	Southern	Western
Heat index	50th	0.63	0.93	0.72	0.58	0.50
	90th	0.70	0.96	0.81	0.72	0.57
	95th	0.71	0.95	0.84	0.72	0.60
	99th	0.68	0.84	0.84	0.76	0.62
	99th–90th	0.14	0.12	−0.28	0.40	−0.06
Air temperature	50th	0.53	0.61	0.67	0.40	0.46
	90th	0.57	0.63	0.69	0.46	0.55
	95th	0.59	0.66	0.72	0.49	0.56
	99th	0.61	0.68	0.73	0.51	0.57
	99th–90th	0.38	0.53	0.28	0.70	0.22
Heat-attributable mortality	—	−0.04	0.09	0.16	−0.07	−0.27

in this forecast zone, on average, had 5.1 HA days per year, ranking 39th. At the other end of the spectrum, many of the WFOs that issued HAs less frequently than the national pattern would suggest were located in the south-central and southeastern United States, in locations with relatively high heat indices. The largest difference was observed for the Melbourne, FL (MLB), forecast zone along the Atlantic coast, which had the 30th-highest heat index (108°F, ~42°C) but had only 0.15 HA days per year, ranking 110th. The adjacent Miami–South Florida (MFL) and Tampa Bay, FL (TBW), forecast zones had similar rankings for both heat index and HA frequency.

At the regional scale, correlations between climate indicators and HA frequency were also moderate to high (Table 1, Fig. 4). In all regions, the highest correlations were observed using upper-tail measures of daily maximum heat index. In the Central region, the correlation

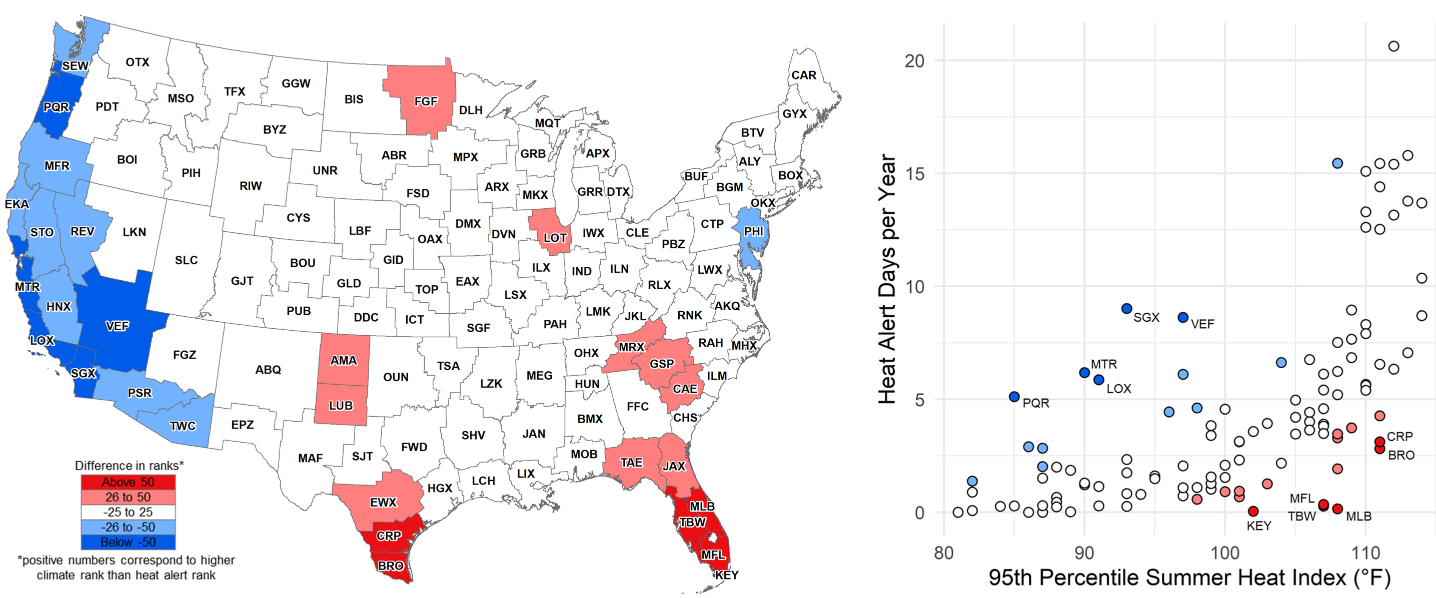

Fig. 3. Comparisons of 95th-percentile summer heat index and heat alert frequencies for U.S. National Weather Service Weather Forecast Offices (WFOs). (left) Map of WFOs with large differences between their rank with respect to heat index and their rank with respect to heat alert frequency. Red colors indicate WFOs that issue heat alerts relative infrequently given their climate; blue colors indicate WFOs that issue heat alerts relatively frequently given their climate. (right) Scatterplot illustrating the relationship between 95th-percentile summer heat index and heat alert frequency for all WFOs; the color scale in the scatterplot matches the map. WFOs with a difference in rank of ±50 are labeled on the scatterplot.

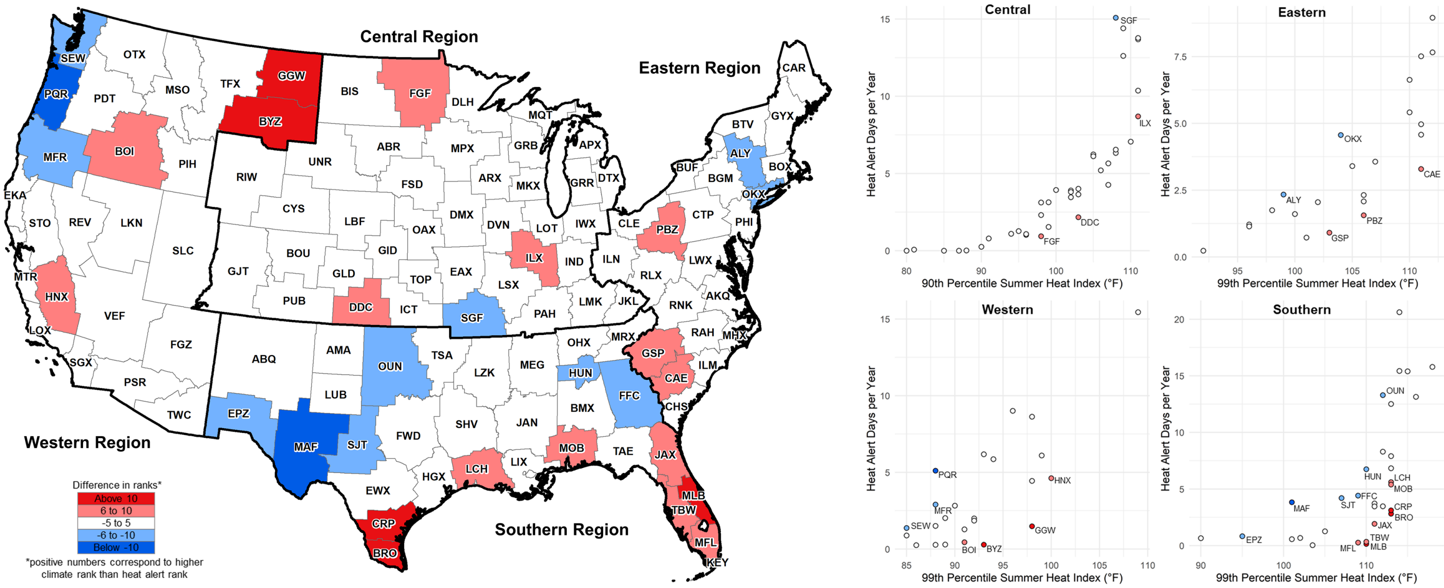

Fig. 4. Comparisons of summer heat indices and heat alert frequencies for U.S. National Weather Service Weather Forecast Offices (WFOs), disaggregated by region. The figure conventions are as in Fig. 3, but the specific heat index percentile used to rank WFOs varies between the four National Weather Service regions, and all ranks and differences in ranks are calculated within each region. WFOs with a region-specific difference in rank of ±5 are labeled on the scatterplots.

between the 90th-percentile daily maximum heat index at HA frequency was 0.96, the highest observed for any metric and region in this study. The strongest correlation for all other regions was with the 99th-percentile daily maximum heat index. Correlations based on the heat index or air temperature were fairly similar the Western region, but modestly different elsewhere. The difference between the 99th- and 90th-percentile heat metrics was generally not well correlated with HA frequency, with the exception of the Southern region, where the air temperature difference was more closely correlated with HA frequency than any of the daily maximum air temperature percentiles.

The within-region analysis revealed a different set of WFOs that had large differences in rankings based on heat index and HA frequency than the national analysis (Fig. 4). In the Eastern region and Central region, no WFOs differed in rank based on heat index and HA frequency by 10 or more.

The Southern and Western regions had forecast zones with larger differences in ranks. As was the cases in the national analysis, forecast zones in southern Florida and Texas also emerged as having few HA days given their heat index (relative to WFOs in the Southern region), and the PQR forecast zone in western Oregon issued HAs more frequently than the Western regional pattern in heat index suggested. Also in the West, two forecast zones in eastern Montana [Billings (BYZ) and Glasgow (GGW)] were ranked among the 10 hottest with respect to the 99th-percentile heat index, but were among the 10 lowest with respect to HA frequency.

Health indicator. There was a weak negative correlation between HA frequency and heat-attributable mortality across the 134 metropolitan areas included in this study ($r = -0.04$). Correlations were also low when stratifying metropolitan areas based on the four NWS regions, but the sign of the correlation varied by region (see Table 1).

When considering all 134 metropolitan areas, there were two regional clusters of cities where HAs were issued relatively infrequently given their heat-attributable mortality: one located across parts of the northeast extending into the upper Midwest, and a second located in central and southern Florida (Fig. 5). The cities with the largest positive difference in their HA frequency rank and their heat-attributable mortality rank were all located in south

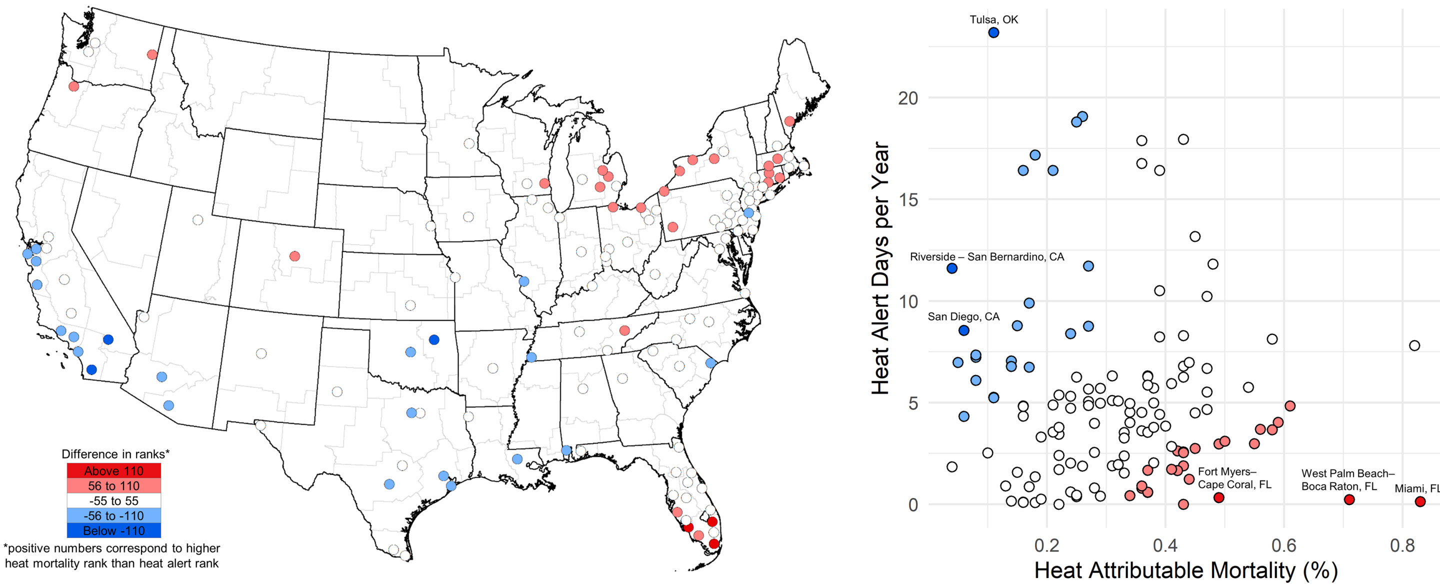

Fig. 5. Comparisons of heat-attributable mortality and heat alert frequencies for 134 metropolitan areas in the United States. The figure conventions are as in Fig. 3, but ranks are calculated for individual metropolitan areas. Metropolitan areas with a difference in heat-attributable mortality rank and heat alert frequency rank of ±110 are labeled on the scatterplot. NWS Weather Forecast Office boundaries are shown with faint gray lines.

Florida: Miami, West Palm Beach–Boca Raton, and Fort Myers–Cape Coral. Miami had the highest heat-attributable mortality of any city included in this study (0.81%) but had HAs in effect for only 0.13 days per year, which ranked 129th. West Palm Beach–Boca Raton had the second highest heat-attributable mortality (0.71%) and HAs in effect similarly infrequently (0.23 days per year, ranking 127th).

Conversely, there were two clusters of cities where HAs were issued relatively abundantly given heat-attributable mortality. The first included many cities in California and extended into Arizona. The second included cities in parts of the south-central United States and western reaches of the coast of the Gulf of Mexico. In the former, Riverside–San Bernardino, California, was tied for the lowest heat-attributable mortality of the 134 cities included in the study (0.04%) but issued the 14th-most HA days per year (11.6). In the south-central cluster, Tulsa, Oklahoma had the largest negative difference between HA frequency rank and heat-attribute mortality rank. Locations in Tulsa averaged 23.2 days per year with a HA in effect (ranking 1st) with 0.11% of mortality attributed to heat (ranking 124th).

Discussion

Issuance of excessive heat warnings and heat advisories varies considerably across the United States, and consequently people across the country have very different experiences with respect to how their local NWS office communicates alerts for one of the nation's deadliest weather hazards. This finding supports and complements previous work demonstrating that "various methodologies are used to develop criteria for issuing heat products" across NWS WFOs (Hawkins et al. 2017). However, to the best of our knowledge, our results provide the first quantitative evidence concerning the manifestation of those variations in terms of the frequency with which warnings and advisories are communicated to the public.

Our analysis revealed that product issued most often—an excessive heat warning or heat advisory—varied across the country. Heat advisories were the dominant product across much of the country, with exceptions in the southwestern United States, and a few isolated other locations. In NWS directives, a warning is issued when "a hazardous weather event is occurring, is imminent, or has a very high probability of occurrence" and "conditions pose a threat to life or property." Conversely, an advisory is issued "for less serious conditions that cause significant inconvenience, and if caution is not exercised, could lead to situations that may threaten life and/or property" (NWS 2019). The tendency to use warnings instead of advisories in the hottest part of the country, the desert southwest, may align with the severity of heat-related risks experienced there. The otherwise inconsistent pattern across the rest of the country is likely driven by WFOs working to implement national policy with partners at the city, county, and state level. We hypothesize that these collaborative networks (which include WFO staff) influence local HA policy (including product choice), and that these networks are highly variable across WFOs with respect to their constituents, organizational structures, perceptions of community heat risk and impacts, and domains of expertise. A systematic survey of WFOs that builds upon the work of Hawkins et al. (2017) could measure different factors that influence local HA policy, including any role of external partners.

The mixture of heat products with different names has contributed to public confusion (Hawkins et al. 2017). At the writing of this manuscript, the NWS was undertaking a national hazard simplification process that is expected to change current "advisory" products to "plain language headlines." Social science research is needed to create useful guidance for the WFOs that serve the vast majority of the country where heat advisories have historically been the primary product issued. Offices that frequently issue heat advisories will be especially impacted by this change and will need to consider the implications concerning public risk perception and adoption of protective behaviors (following Adame and Miller 2015; Morss et al. 2018).

Beyond the differences in the use of warnings versus advisories, we found many cases where places with seemingly similar summer weather had vastly different frequencies in the use of either product. We also found that there were many places that were either among the hottest in the country, and/or had a higher rate of heat-attributable mortality, that issued HAs quite rarely. Importantly, these findings do not provide any evidence regarding the (in) effectiveness of (not) issuing heat warnings; a different study design would be required to explore those relationships. We did not develop an a priori hypothesis about how the national pattern in HA frequency might vary across space, nor is it clear from prior research what an optimal pattern would be. It is known that there is city-to-city and region-to-region variability in the specific environmental conditions that lead to elevated heat–health risks and how severe those risks are. This variation emerges as a result of physiological and behavioral acclimatization and underlying social vulnerabilities and adaptive capacities. As such, hotter locations do not necessarily demand more frequent HAs than cooler ones (e.g., Kalkstein and Davis 1989; Robinson 2001; Anderson and Bell 2011; Kent et al. 2014).

In addition to exploring how and why local variations in HA policy emerge, future research should investigate the consequences of spatial variability in HA frequency on public risk perception related to heat, protective actions triggered by HAs at scales ranging from individuals to communities and regions, and subsequent impacts on health and quality of life. We did not observe any qualitative similarity between the spatial pattern in NWS HAs and the community- and state-level heat risk perception estimates provided by Howe et al. (2019), although we acknowledge that there are many variables beyond NWS HAs that influence heat risk perception (Hass et al. 2021). One surprising comparison between our study and the work of Howe et al. (2019) is that some of the highest heat risk perception indices in the Howe et al. study were observed along the Texas–Mexico border, one of the relatively hot regions where we found particularly low HA frequencies. This could imply that local forecasters do not perceive that additional alerts would be effective in triggering protective actions, potentially as a consequence of the relative frequency with which hot conditions are observed and the possibility of warning fatigue. Learning the precise role of the NWS and its heat products in influencing community heat risk perception, compared to services and products from other important actors and institutions, could reveal new opportunities for collaboration and coordination.

No estimates of the effect of NWS HAs on health impacts were available for the exact time period of this study, although Weinberger et al. (2018) found that Philadelphia was the only one of 20 cities they examined where NWS HAs were associated with a statistically significant reduction in mortality. Philadelphia has a comparatively long history of investment in heat-related risk communication (e.g., Kalkstein et al. 1996), and perhaps as a consequence, was one of the cities in our study that issued the most HAs relative to its summer climate. Other research has found that heat–health impacts begin to be observed at lower temperatures than thresholds for NWS HAs and suggested that issuing alerts more frequently could reduce the public health burden of extreme heat (e.g., Wellenius et al. 2017; Adeyeye et al. 2019).

We acknowledge that it is not inherently preferable to issue more or fewer alerts, nor is there any inherent disadvantage to local autonomy in setting warning and advisory thresholds. Local forecasters have the best opportunity to understand the context and culture of their constituents, especially with respect to risk perception around societal impacts of extreme heat. However, given that heat–health impact data are inconsistently collected and reported across the country, and that heat risk perception research is relatively scarce (but see Howe et al. 2019; Hass et al. 2021), local forecasters may not yet have access to the full suite of information that would help them implement more customized, Impact-Based Decision Support Services related to heat that best meet community needs. Indeed, the 2019–22 NWS Strategic Plan specifically calls for "incorporating social science research" to "make forecasts more ... actionable, accessible, and consistent" (NWS 2020). New research that can complement our findings and support national-scale heat risk communication improvements would build knowledge about how NWS HAs impact risk perception, subsequent behaviors, and societal impacts.

Local and national NWS guidelines related to HAs evolve over time, and our results are only reflective of the guidance in place during the period 2010–19. Guidelines and policies for issuing HAs changed in some WFOs over that decade and will likely continue to change. For example, certain WFOs in the NWS Western Region started using the NWS Experimental HeatRisk product for HA decision support as early as 2015, which provides time-of-year and location-specific contextualization of forecast temperatures against historical climatology and heat–health impacts (NWS 2021b). More recently, HAs were issued in the Denver metropolitan area in summer 2021, believed to be the first on record, coinciding with a record-setting heat event (Spears 2021). We anticipate and recommend that heat alert guidance in the United States continues to evolve as further scientific advances are made, particularly concerning the efficacy of different approaches for risk communication. Outside of the United States, other indices used to trigger heat warning systems and communicate heat risks to the public include the Humidex (Henderson et al. 2020), Universal Thermal Comfort Index (Di Napoli et al. 2019), and Excess Heat Factor (Nairn et al. 2018). These and other models should continue to be explored and evaluated. Relatedly, there is recent interest in exploring the feasibility of implementing "hyperlocal" HA systems at scales ranging from neighborhoods to individual buildings that account for fine-scale variability in climate conditions and social vulnerabilities, particularly within cities (e.g., Hondula et al. 2018; Gustin et al. 2020; McElroy et al. 2020). We observed considerable variability in HA frequency at spatial scales finer than WFOs (see Fig. 1) and recommend additional research exploring how those spatial patterns relate to indicators of exposure and risk.

We conducted our analysis at two different spatial scales to leverage available weather and health data as best as possible. However, significant spatial variability in summer weather exists in some of the WFOs included in our study, particularly in some coastal and/or more topographically varying locations, and those with large urban heat island effects, and this variability may not be well represented in the gridded climate data we used. Further analysis based on weather station data would provide a useful complement to this study, in the light of previous findings regarding limitations of gridded datasets at the upper end of the temperature distribution (Sheridan et al. 2020). Other study limitations include the use of a relatively narrow set of simple metrics for climate indicators, and the use of heat-attributable mortality (from only one study, with health data that precede those gathered for HAs) as a representation of heat–health impacts. Notably, the heat-attributable mortality estimates are calculated from all days above a locally defined minimum mortality temperature, rather than an upper-tail metric such as the 95th- or 99th-percentile temperature. As such, the city-specific heat-mortality estimates span a wide conceptual range for heat that may not be well-aligned with the traditional advisory and warning paradigm (e.g., the minimum mortality temperature for Miami is the 39th percentile, whereas for San Diego it is the 96th percentile). Furthermore, spatial patterns in heat-related morbidity and other adverse health effects associated with heat exposure could differ from those for heat-related mortality, owing to differences in the demographic characteristics of the impacted populations, and the varied accessibility of healthcare services. Future research could more deeply explore these choices to build a more comprehensive understanding of the intersection of HAs, climate, and health.

Conclusions

The primary risk communication product issued by the United States NWS for one of the nation's deadliest weather hazards, extreme heat, was applied in widely different manners across the country over the period 2010–19. Heat alerts were typically made in the form of heat advisories, rather than excessive heat warnings, which presents a communication challenge in the coming years as the NWS proposes to convert current advisory products to plain language headlines. We observed a high degree of spatial variability in heat alert frequency: while the median location in the country experienced 2.3 heat alert days per year, some experienced zero, while others experienced nearly 25. The locations with the most frequent heat alerts included much of the south-central United States, the desert Southwest, the interior valleys of the West Coast, and parts of the coastal mid-Atlantic. Heat alerts were issued infrequently throughout much of the Mountain West, northern tier of the country, New England, Appalachia, and in parts of Florida and Texas. Heat alert frequency was more closely correlated with climate metrics based on daily maximum heat index than those based on daily maximum air temperature. Despite the generally moderate to high correlations between climate indicators and heat alert frequency, there were some locations that ranked much lower with respect to heat alert frequency than heat index, particularly in Florida and Texas. Furthermore, the spatial pattern in heat alerts was not correlated with heat-attributable mortality, suggesting that the current approach may not well align with heat–health risk. As communities all across the United States face a future with more frequent, intense, and long-lasting heat events, more social science research is urgently needed to determine how well the current approach to issuing heat alerts is meeting public needs, and how it can be improved.

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Data availability statement. All data analyzed in this study are openly available at locations cited in the reference section.

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