

Diverse Characteristics of U.S. Summer Heat Waves

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ABSTRACT

Heat waves are climate extremes having significant environmental and social impacts. However, there is no universally accepted definition of a heat wave. The major goal of this study is to compare characteristics of continental U.S. warm season (May–September) heat waves defined using four different variables—temperature itself and three variables incorporating atmospheric moisture—all for differing intensity and duration requirements. To normalize across different locations and climates, daily intensity is defined using percentiles computed over the 1979–2013 period. The primary data source is the U.S. Historical Climatological Network (USHCN), with humidity data from the North American Regional Reanalysis (NARR) also tested and utilized. The results indicate that heat waves defined using daily maximum temperatures are more frequent and persistent than when based on minimum temperatures, with substantial regional variations in behavior. For all four temperature variables, heat waves based on daily minimum values have greater spatial coherency than for daily maximum values. Regionally, statistically significant upward trends (1979–2013) in heat wave frequency are identified, largest when based on daily minimum values, across variables. Other notable differences in behavior include a higher frequency of heat waves based on maximum temperature itself than for variables that include humidity, while daily minimum temperatures show greater similarity across all variables in this regard. Overall, the study provides a baseline to compare with results from climate model simulations and projections, for examining differing regional and large-scale circulation patterns associated with U.S. summer heat waves and for examining the role of land surface conditions in modulating regional variations in heat wave behavior.

1. Introduction

At first glance, the physical characteristics of heat waves would seem to be self-evident: extreme daily air temperature anomalies that exceed specified magnitude and duration criteria. These definitional criteria, however, are subjective and often chosen with a particular impact in mind (e.g., [McGregor 2015](#); [Barnett et al. 2010](#); [White et al. 2006](#); [Schlenker and Roberts 2009](#)). The physical characteristics of heat waves can in fact be rather nuanced. For example, the specific variable examined may be the maximum, minimum, or mean daily temperature and atmospheric humidity (and other factors, such as solar radiation) may or may not also be

included in the definition of a heat wave [see the review by [Souch and Grimmond \(2004\)](#) and references therein]. In addition, while a clear expectation of a warming climate is for heat waves to become more frequent and intense ([Melillo et al. 2014](#)), future heat wave characteristics will not necessarily change in a synchronous fashion given their multiple definitions.

In this paper heat waves are viewed from a physical climate perspective, with emphasis on the geographical distribution of their occurrence and persistence characteristics, and the sensitivity of these attributes to the criteria used to define them. The geographic domain considered is the conterminous United States and the focus is on the warm season (May–September 1979–2013). Previous work has generally addressed the various attributes of U.S. summer heat waves in a piecemeal fashion. For example, some studies have focused on the

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sensitivity of specific heat-related outcomes to differing temperature threshold exceedance criteria (Anderson and Bell 2011; Barnett et al. 2010; Peterson et al. 2008). Other studies have emphasized the need to include surface humidity and advocate for the use of heat indices (McGregor 2015; Sheridan and Kalkstein 2004; Robinson 2001; Kalkstein and Valimont 1986; Steadman 1984, 1979) rather than temperature alone. Regional variations in heat wave occurrence have been addressed to varying degrees in these and other studies. The geographical distribution of the persistence characteristics of heat waves has received even less attention, with studies tending to emphasize temporal trends in extreme daily temperatures, heat indices, or associated surface humidity (Peterson et al. 2008; Brown and DeGaetano 2013; Robinson 2000; Kunkel et al. 1999; Gaffen and Ross 1998, 1999). A recent study by Smith et al. (2013) takes a broader view of U.S. heat waves by examining the geographical distribution of trends and average heat wave occurrence for 15 heat wave indices. These indices included the maximum, minimum, and mean daily temperature as well as humidity. Consideration of varying magnitude criteria was implicit in the study, as it is included in the index definition. That is, several of the 15 indices used differ only in the intensity level used to define them (e.g., the maximum daily temperature exceeding the 90th vs the 95th percentile in the historical distribution). The persistence characteristics of heat waves were not explicitly examined in the study.

The motivation for this paper is to build upon these and other results by undertaking a more thorough analysis of the geographical distribution and regional persistence characteristics of heat waves and their sensitivity to heat wave definition. Different daily temperature variables, temperature thresholds, and duration criteria are considered in the analysis, with subseasonal variations in heat wave behavior also examined. The covariability of warm season humidity and temperature is explored before examining the persistence characteristics of three widely used heat indices that include both surface temperature and humidity in their formulation. These results are then contrasted with those for the temperature-only heat wave definitions. This study represents part of a larger effort to investigate U.S. summer heat wave characteristics, temporal evolution, trends, and projected changes. The current study will thus provide a set of baseline analyses before climate model simulations and projected changes in U.S. summer heat wave occurrence are considered.

The paper is organized as follows. The datasets and basic methodological approaches used are described in section 2. Section 3 first examines the temporal variability

and covariability among several of the heat wave variables used in the study before considering the geographical distribution and regional persistence characteristics of heat waves. Differing behavior between daily maximum and minimum temperature variables is considered in section 4, with a brief discussion and the main conclusions of the study provided in section 5.

2. Data and methodology

a. Data

The study utilizes three main observational and reanalysis datasets. The primary dataset consists of daily maximum, minimum, and mean temperatures for 1218 stations across the United States as contained in the United States Historical Climatology Network (USHCN; Menne et al. 2015). Although some of these stations have records dating to the early part of the twentieth century, the period 1979–2013 is emphasized here. Various data quality control flags are included in the USHCN dataset; their use in quality control analysis is described in section 2b. A second, and much smaller, set of station data consists of daily maximum and minimum values of apparent temperature T_a computed for 187 stations located across the United States (NCDC 2011) over the period 1948–2015. These are first-order stations that have observed humidity as well as temperature data (more on this in section 2c). The third dataset is the North American Regional Reanalysis (NARR; Mesinger et al. 2006). The NARR data are based on an observational data assimilation system built around the Eta forecast model and consist of gridded values at 32-km spatial resolution. The variables used from this dataset are 3-hourly values of air temperature, specific humidity, and relative humidity at 2 m above ground level covering the period 1979–2014. Daily maximum and minimum temperatures are computed from the 3-hourly values, with the specific humidity at the time of the maximum and minimum temperature also identified. The atmospheric vapor pressure was computed at 3-hourly intervals using the relative humidity and temperature data. The availability of surface humidity in NARR allows for substantially greater spatial detail in analyses of T_a (and other indices) than the 187 locations where station humidity data is available. To accomplish this, “hybrid” station T_a values are computed using NARR humidity and USHCN-based station temperature with results compared to those using the 187-station dataset. The NCEP–DOE AMIP II reanalysis (Reanalysis-2; Kanamitsu et al. 2002) product is used to compute the transient eddy transports discussed in section 3c.

b. Quality control of USHCN data

The USHCN daily station data come with quality control indicators for each day's data. For most days, no quality control flag is present and the datum is deemed to be good by the developers. For some days, however, quality control flags of various types appear. Here, individual cases of data accompanying each of the quality control flags were examined to determine whether the data accompanied by that particular flag type should generally be rejected, or alternatively accepted. For most flag types, the flag was indeed sometimes found to indicate potentially bad data. Such quality control flags include, for example, poor spatial consistency, extreme outlier (more than five standard deviations from mean), data duplication from other years or months, zeros, poor temporal consistency, and others. One data flag, however, indicative of internal consistency, was not found to be associated with questionable data in approximately 10 cases checked. That is, the authors judged that the behavior during the days surrounding this flag was reasonable. Therefore, this particular flag was ignored, while the data accompanied by all other quality control flag types were replaced as missing.

An important factor not accounted for in the version of the USHCN daily data used here is a systematic temperature bias associated with changes in the time of observation. Over the course of our study period there has been a continual and substantial shift toward taking observations in the morning (LST) rather than afternoon, which introduces a temporally increasing cold bias in the temperature data (Vose et al. 2003; Menne et al. 2009). This bias is not seen as being prohibitive in examining the spatial variability of heat waves, but could reduce the magnitude of the positive temporal trends in heat wave frequency that are discussed in section 4.

c. Calculation of apparent temperature, equivalent temperature, and heat index

In addition to examining temperature variables alone in the analysis, three heat indices are also considered that incorporate atmospheric humidity in various forms. These include T_a , the equivalent temperature T_{eq} and a heat index HI used by the U.S. National Weather Service (NWS). These three indices were chosen because they are all in widespread use and each index has a different functional sensitivity to atmospheric moisture (more on the latter will be presented in sections 3b and 4).

For consistency with the 187-station dataset of daily T_a , the same formula for computing the index is used when incorporating the NARR data. Its computation utilizes the linear regression results of Steadman (1984):

$$T_a = -1.3 + 0.92T + 2.2e, \quad (1)$$

where T_a is the apparent temperature ($^{\circ}\text{C}$), T is the ambient temperature ($^{\circ}\text{C}$), and e is the vapor pressure (kPa). An expression for T_{eq} may be derived from the moist enthalpy of the air (e.g., Fall et al. 2010) and written as

$$T_{eq} = T + L_v q / C_p, \quad (2)$$

where T_{eq} (K) is the equivalent temperature [$T_{eq} = H / C_p$, where H is the specific enthalpy (J kg^{-1}) and C_p is the specific heat of air at constant pressure ($\text{J kg}^{-1} \text{K}^{-1}$)], T is the air temperature (K), L_v is the latent heat of vaporization (J kg^{-1}), and q is the specific humidity (dimensionless). As will be shown, T_{eq} is affected much more strongly by humidity than is T_a . The third index used is the HI from the NWS. The HI is computed using 2-m temperature and relative humidity as inputs (Rothfus 1990) and is based on a multiple regression fit to the heat index of Steadman (1979), the latter which included several other variables (wind, solar radiation, etc.). The index has nine terms:

$$\text{HI} = c_0 + c_1 T + c_2 \text{RH} + c_3 \text{TRH} + c_4 T^2 + c_5 \text{RH}^2 + c_6 T^2 \text{RH} + c_7 \text{TRH}^2 + c_8 T^2 \text{RH}^2, \quad (3)$$

where HI is the heat index ($^{\circ}\text{F}$), T is the temperature ($^{\circ}\text{F}$), and RH is the relative humidity (%). The coefficient values are $c_0 = -42.379$, $c_1 = 2.04901523$, $c_2 = 10.14333127$, $c_3 = -0.22475541$, $c_4 = -6.83783 \times 10^{-3}$, $c_5 = -5.481717 \times 10^{-2}$, $c_6 = 1.22874 \times 10^{-3}$, $c_7 = 8.5282 \times 10^{-4}$, and $c_8 = -1.99 \times 10^{-6}$. If the RH is less than 13% and the temperature is between 80° and 112°F , then the following adjustment is subtracted from HI:

$$\text{A1} = \frac{13 - \text{RH}}{4} \sqrt{\frac{17 - |T - 95|}{17}}. \quad (4)$$

Additionally, if RH is greater than 85% and the temperature is between 80° and 87°F , then the following adjustment is added to HI:

$$\text{A2} = \frac{\text{RH} - 85}{10} \left(\frac{87 - T}{5} \right). \quad (5)$$

Finally, if the temperature is less than 80°F a simpler formula is applied to calculate the overall index:

$$\text{HI} = 0.5[T + 61.0 + 1.2(T - 68.0) + 0.094\text{RH}]. \quad (6)$$

When used in this study, the index was first converted to degrees Celsius $\{T(^{\circ}\text{C}) = [T(^{\circ}\text{F}) - 32]/1.8\}$.

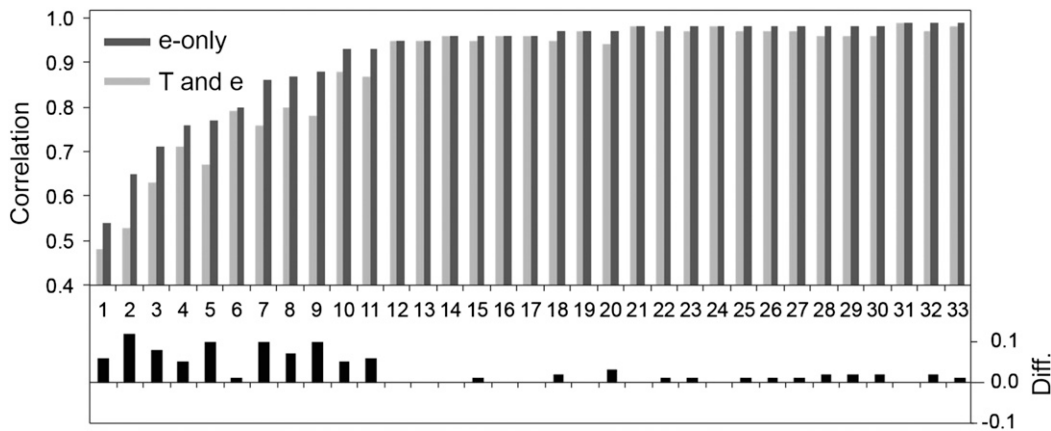


FIG. 1. (top) The temporal correlation of daily values of T_a computed at 33 first-order stations when using both temperature and vapor pressure from NARR (light gray bars) and USHCN temperature data and NARR humidity data (dark gray bars). (bottom) The difference in correlation values at each station is shown by the solid black bars.

d. Comparisons of station T_a with USHCN plus NARR

As this study emphasizes results based on the USHCN station temperature dataset, a method was needed to include atmospheric humidity to compute T_a , T_{eq} , and HI. As the USHCN only contains daily temperatures, the moisture field from the NARR dataset was used. To see how well the NARR data performs, correlations were computed between the daily maximum values of T_a for 33 of the 187 first-order stations (NCDC 2011) and those based on 1) NARR daily maximum temperature and humidity at the nearest grid point and 2) USHCN temperature and NARR humidity at the nearest grid point. The 33 USHCN stations used for this purpose were selected for being less than 10 km away from the first-order station they are being compared with. Correlations were computed based on daily July values for seven arbitrarily selected years as having above-average heat wave activity (1980, 1983, 1988, 1998, 1999, 2011, and 2012). The results are summarized in Fig. 1, where correlations are ranked from lowest to highest. For the vast majority of the stations, correlations exceed 0.9 and are higher when using USHCN temperature plus NARR humidity than using both temperature and humidity from NARR. The largest determinant of difference in the correlations in Fig. 1 is the distance between the stations being compared (not shown). Overall, the results suggest that the NARR humidity field is a very reliable surrogate for station humidity.

e. Calculation of percentiles

For a given temperature variable, its percentile value is first determined for each single date, with respect to the number of years in the dataset (35 yr). Here, dates

span 153 days from 1 May to 30 September and, given the finite record length, results are somewhat jumpy over adjacent dates due to sampling variability. Therefore, a second step is to temporally smooth the daily results using a fourth-degree polynomial function. The following describes the two steps further. Let us call the needed percentile P (here, we let P have the four values of 80, 85, 90, and 95). We have a given number of years, called nyr . For calculations involving the NARR data, $nyr = 35$ yr because the year range is 1979–2013; for calculations using only USHCN data, nyr can assume larger values. For a given date, the years for nyr are ordered from 1 (the lowest; i.e., the coldest) to nyr (the highest; i.e., the warmest). Note that there will be ties. Then, to get the value of the variable corresponding to percentile P , we define the desired rank as $0.01Pnyr + 0.5$. For example, if there are 100 years and we want the 90th percentile ($P = 90$), then we have $0.9 \times 100 + 0.5 = 90.5$. The value of the variable is then halfway between the 90 lowest values and the 10 highest values (i.e., halfway between the 10th highest value and the 11th highest value). For any rank fraction, the answer is a weighted average of one of the observed values and the observed value of an adjacent rank. In this simple example, the two weights are both 0.5.)

To temporally smooth the resulting values, a polynomial fit is applied to the 153-day series of raw percentile results. A fifth-order polynomial (containing the mean as well as terms in x , x^2 , x^3 , and x^4 , where x is the day number of the series) is used, as it was found to produce a realistic fit for the more common climatological patterns—a series having a broad maximum in the second half of July, and rough symmetry between the decreasing rate of warming in May and June and the increasing rate of cooling in late August and September.

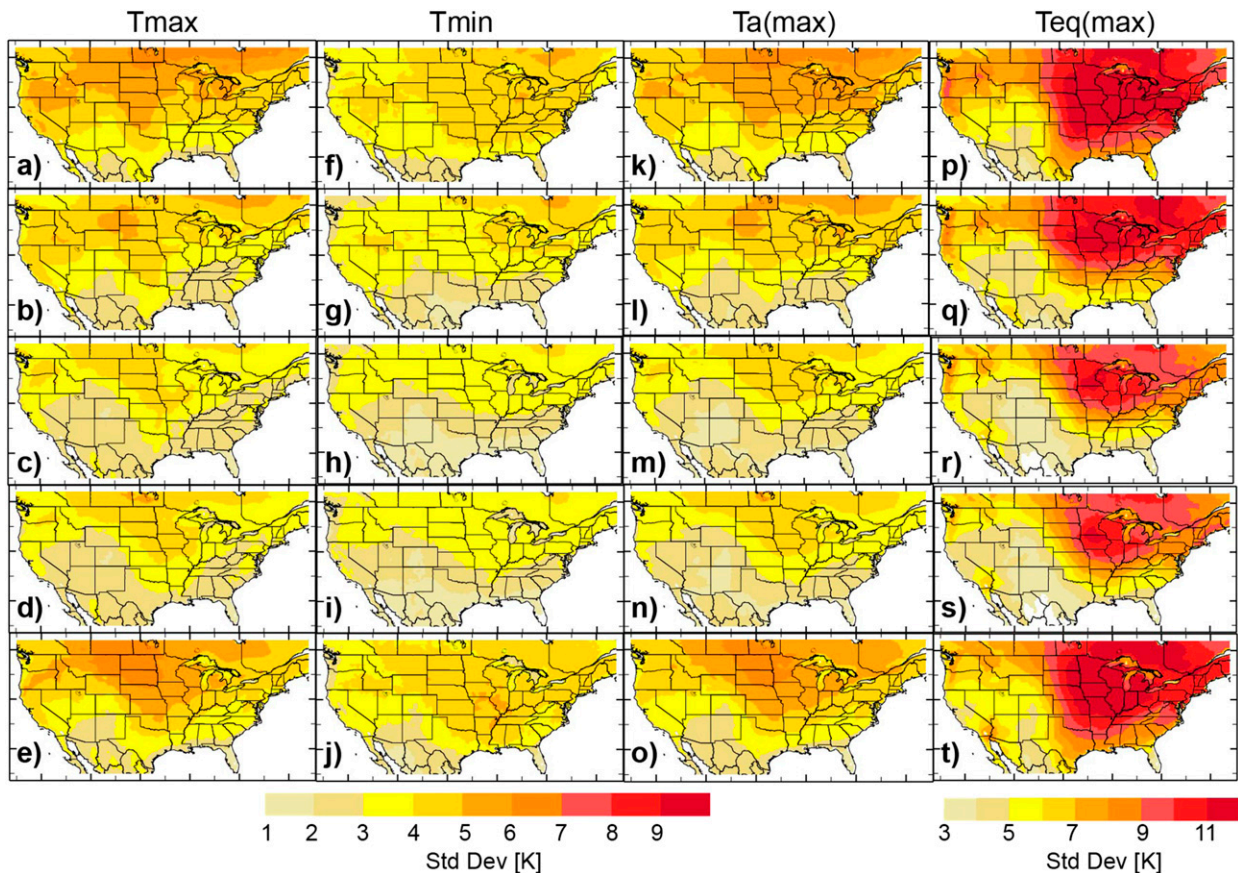


FIG. 2. Standard deviation (K) of daily values of four temperature variables used in the study based on the NARR data (1981–2010) and as a function of warm season month. (a)–(e) T_{\max} for May–September, (f)–(j) T_{\min} , (k)–(o) $T_{a(\max)}$, and (p)–(t) $T_{eq(\max)}$.

It also served to fit stations having irregular but climatologically meaningful features, such as west coast stations that have temporary drops in temperature in June due to the onset of strong sea breezes and fog as inland regions rapidly increase in daily temperature. The fifth-order fit is not found to result in spurious variations due to overfitting.

f. Heat wave definition

Heat waves are defined using varying temperature exceedance thresholds and duration criteria as in previous work (Lyon 2009). Temperature and temperature index values exceeding the 80th, 85th, 90th, and 95th percentiles are considered. While the lower thresholds may not appear to represent “extreme” conditions, other studies have found, for example, that summer T_a values exceeding the 85th percentile are closely correlated with increased human mortality rates in the United States (Kalkstein and Davis 1989). The required duration for a heat wave was allowed to vary between 1 and 7 consecutive days, with both sets of criteria applied to

define heat waves using daily maximum and minimum values of temperature, T_a , T_{eq} , and HI.

3. Results

a. Temporal variability and covariability of heat wave variables

To first provide some context for the subsequent analysis of heat wave characteristics, we begin by examining the temporal variability and covariability of several of the variables used in the study, emphasizing regional variations and their evolution during the warm season. The standard deviation of daily departures of T_{\max} and T_{\min} and daily maximum T_a and T_{eq} from their 35-yr average value based on the NARR data (only) are shown in Fig. 2, by month, from May to September. Across the United States the variability of all variables decreases from May to July and August before increasing again in September. With the exception of T_{eq} , to first order, variability also increases moving from south to north across the country. The spatial patterns

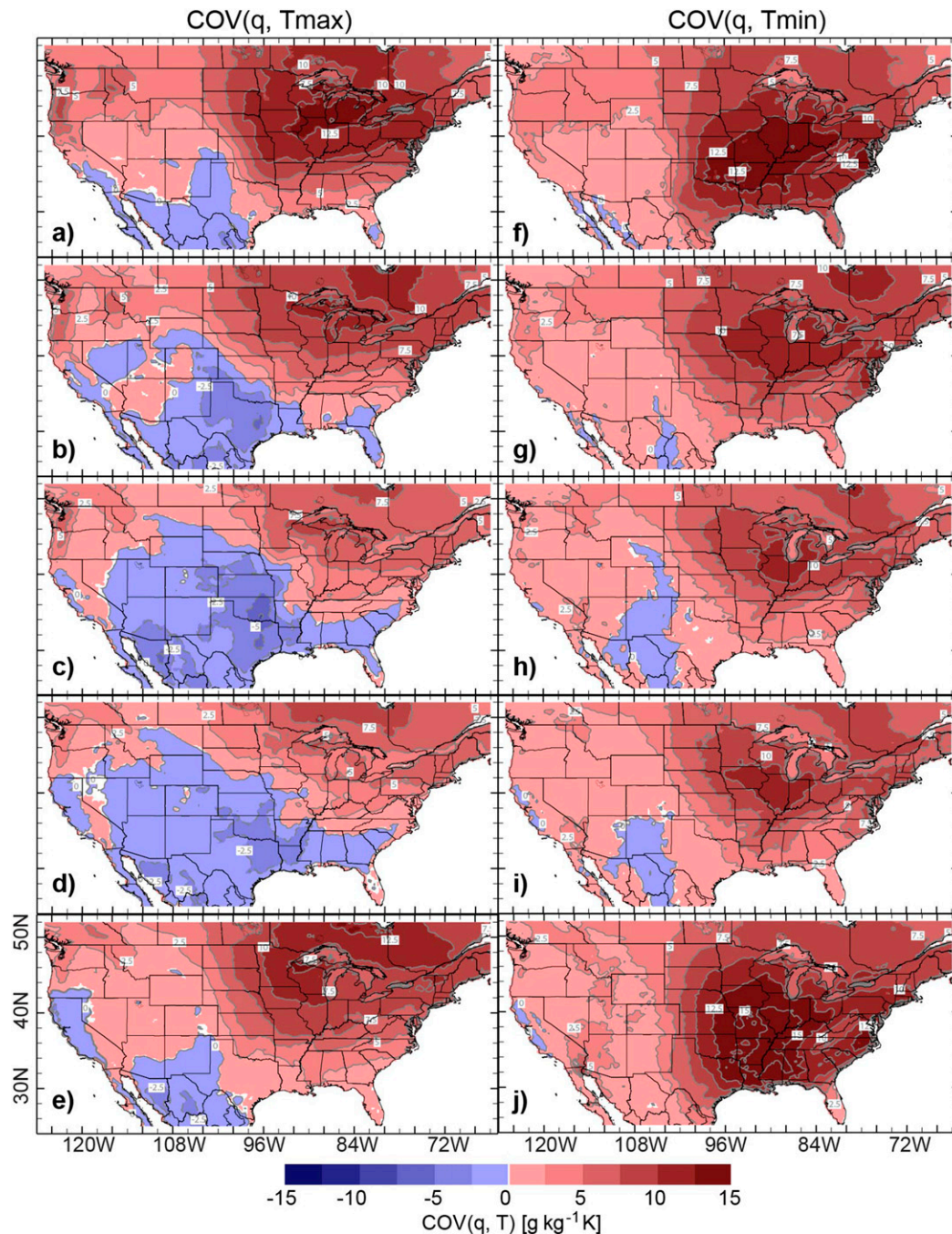


FIG. 3. The covariance of daily (a)–(e) maximum and (f)–(j) minimum values of specific humidity and surface temperature ($\text{g kg}^{-1} \text{K}$) for May–September based on NARR data.

for the standard deviation of daily $T_{a(\max)}$ are very similar to those for T_{\max} , indicating the dominance of temperature variability over humidity for this index. Conversely, the variability of $T_{\text{eq}(\max)}$ is dominated by the contribution from specific humidity as reflected by the maximum values in the eastern United States. The southern edge of this maximum area moves northward

as the summer progresses, placing its center in the Midwest in midsummer.

The covariance (chosen instead of correlation in order to retain physical units) between daily q and daily T_{\max} and T_{\min} is shown in Fig. 3, again from May to September. There are marked differences in behavior for the two temperature variables. For T_{\max} , negative

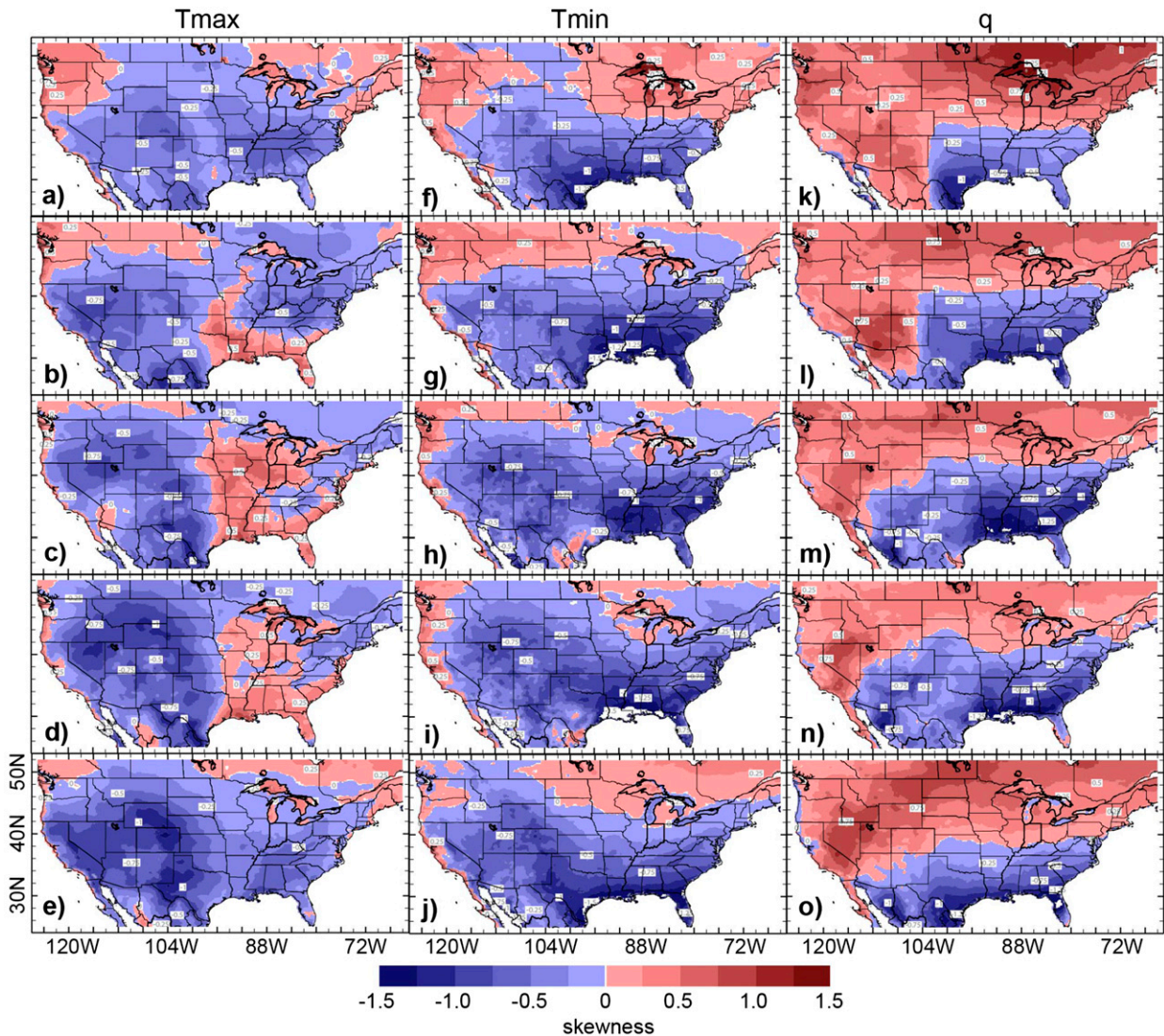


FIG. 4. Skewness of daily values of (a)–(e) T_{\max} and (f)–(j) T_{\min} for May–September and (k)–(o) daily mean specific humidity based on the NARR data.

covariance values develop across the southern and southwestern portions of the United States as the summer season progresses. Positive covariance values are seen elsewhere, reaching a maximum over the upper Midwest and retreating northward as the summer season advances. In contrast, the covariance between q and T_{\min} is generally positive across all of the United States during each month. The covariance is largest in the eastern United States, although the local maxima are located considerably farther south than the positive covariance of q and T_{\max} . One possible physical explanation for the more widespread, positive covariance of q and T_{\min} as compared to that for q and T_{\max} is the greater influence of radiative cooling on T_{\min} versus T_{\max} . Higher (lower) q is associated with elevated

(reduced) T_{\min} as a result of greater (less) downwelling thermal radiation, whereas T_{\max} is more closely tied to variations in solar radiation and temperature advection.

Finally, Fig. 4 shows the skewness of daily T_{\max} , T_{\min} , and q , again from NARR and by month. Given sampling variability, even a normally distributed variable will likely exhibit skewness values different from zero. As there are roughly 1000 daily observations used to compute the skewness values in Fig. 3 ($30 \text{ days month}^{-1} \times 35 \text{ yr}$), Monte Carlo methods were used to determine the range in skewness values expected by chance. To do so, the skewness of 500 sets of 1000 normally distributed random numbers was computed, with values larger than ± 0.17 found to occur less than 5% of the time, thus indicating the 95% confidence limits. For both T_{\max} and

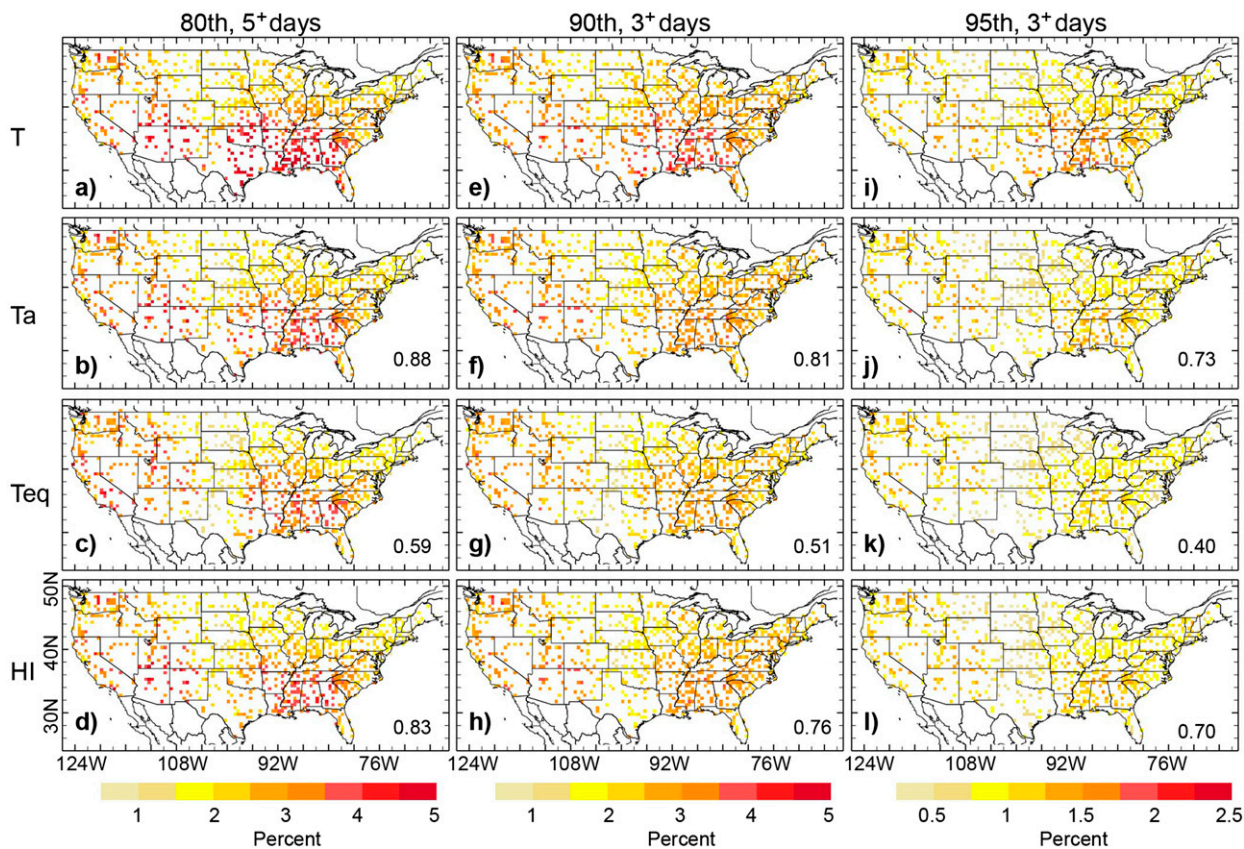


FIG. 5. The percent occurrence of total heat wave days (1979–2013) defined using daily maximum values of four different temperature variables and as a function of different definitional criteria. Results for daily variables exceeding the 80th percentile for at least 5 consecutive days shown for (a) T , (b) T_a , (c) T_{eq} , and (d) HI; for the 90th percentile and 3 or more days for (e) T , (f) T_a , (g) T_{eq} , and (h) HI; and the 95th percentile for 3 or more days in (i) T , (j) T_a , (k) T_{eq} , and (l) HI. The pattern correlations with T are shown at the bottom right in (b)–(d), (f)–(h), and (j)–(l).

T_{min} Fig. 3 shows that skewness tends to be negative across much of the country. For T_{max} , skewness generally has greater negative skewness in the western United States while for T_{min} the largest negative values are seen across the south and southeast. The specific humidity q shows negative skewness values across the southeast, extending to the southwestern United States over the course of the summer and in conjunction with the North American monsoon system. Positive skewness is seen elsewhere, generally largest in the western part and the northern tier of the United States, suggesting that in those locations advection can occasionally bring higher q values to these otherwise comparatively less humid areas.

Taken together, Figs. 2–4 indicate clear and substantial differences in the variability and covariability of the variables included in the definition of U.S. summer heat waves. These will serve as a backdrop for the analyses provided in the following sections that examine the behavior of specific heat wave characteristics, including

their geographical location, frequency of occurrence, and persistence characteristics. Emphasis will be on behavior at the USHCN stations, including a hybrid combination of USHCN temperature data with NARR humidity to compute T_a , T_{eq} , and HI.

b. Geographic distribution of heat wave frequency of occurrence

For all four temperature variables, the frequency of occurrence of heat waves was evaluated at each station location using the 80th, 90th, and 95th percentiles for threshold criteria, and minimum durations of 5, 3, and 3 days for each threshold, respectively. For this purpose, a “heat wave day” was defined as a member of a string of consecutive days in which the daily temperature has met or exceeded the threshold criterion for at least the minimum duration. For example, if the daily temperature exceeded the 90th percentile for 4 consecutive days at a given station, that event would represent two heat wave days, because the third and fourth day

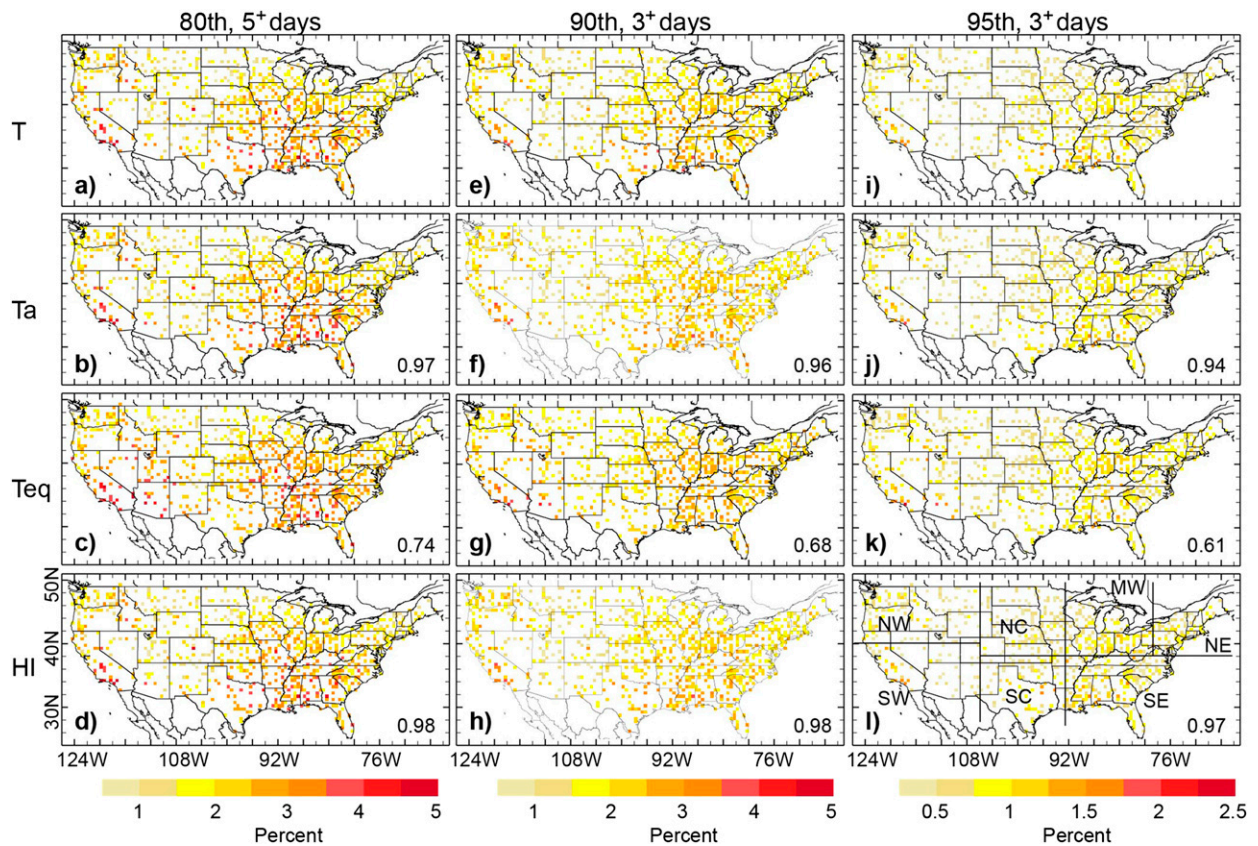


FIG. 6. As in Fig. 5, but for daily minimum values of the four temperature variables.

met the requirement for at least 3 days at the 90th percentile. The first two days are not included because we are interested in differences in duration among heat wave events and definitional criteria (e.g., the first two days would be in common among all events when a 3-day minimum duration is specified). Of course, for impact studies, the first few days of a heat wave can be quite important in determining outcomes, such as on human health (Semenza et al. 1996). If the temperature exceeded the 90th percentile for only two days, neither day would be considered a heat wave day. For each station and temperature variable, the fraction of heat wave days in each month between May and September 1979–2013 was computed. These results were analyzed for each month separately and for the warm season as a whole, with both daily maximum and minimum temperatures considered.

For daily maximum values, Fig. 5 shows the percent of all warm season days across all 35 years that were identified as heat wave days for each variable and the three sets of intensity and duration criteria. Naturally, the number of heat wave days decreases as the intensity threshold becomes higher. Generally speaking, Fig. 5 reveals that the highest frequency of heat wave days for

daily maximum values tends to occur in the southeastern and southwestern United States for all temperature variables and intensity thresholds, with a relative minimum in the north-central United States. There are, however, notable differences in the spatial distributions between the temperature variables. As one measure of these differences, pattern correlations between the percent occurrence of maximum values of T_a , T_{eq} , and HI with T were computed and are displayed in the bottom right of each panel in Fig. 5. The pattern correlations are higher for T_a and HI than for T_{eq} , with values typically in the range of 0.7–0.8 for the former and 0.4–0.6 for the latter. The fact that the lowest pattern correlation is with T_{eq} is likely associated with this variable's strong sensitivity to humidity compared with the other variables (cf. Fig. 2). All of the pattern correlations also decrease for the more intense events. This decrease may just represent the influence of sampling variations as there are, by definition, fewer intense events, which reduces the overall sample sizes being evaluated.

The results for daily minimum temperature are shown in Fig. 6. The first feature that stands out is that the overall frequency of heat wave days for daily minimum temperatures is less than that for daily maximum values

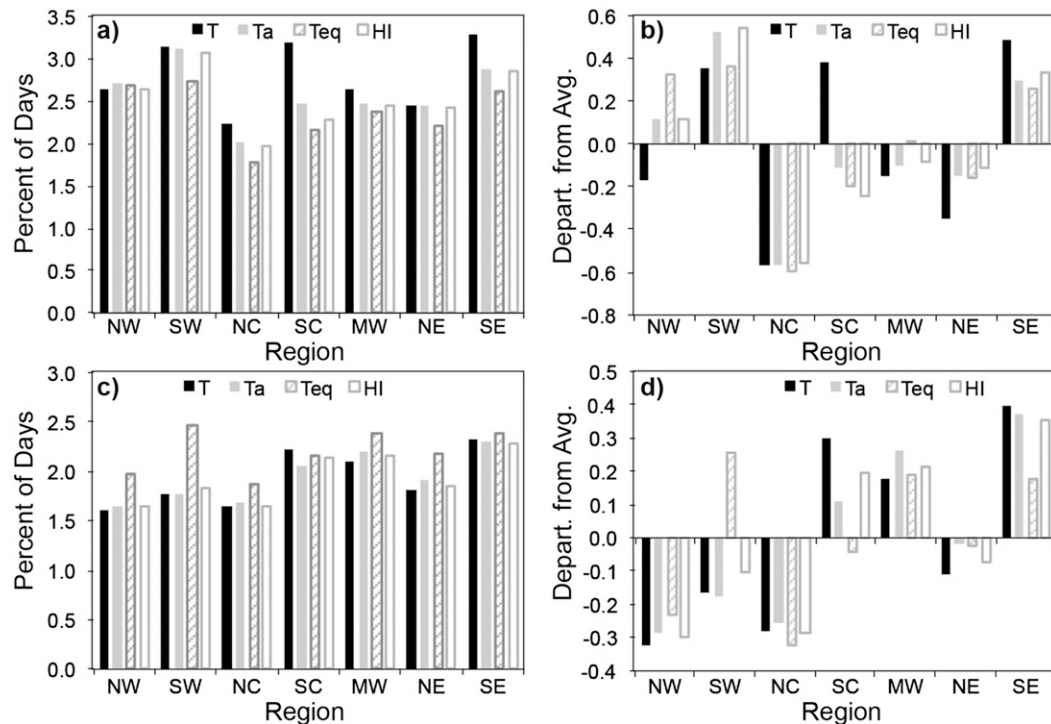


FIG. 7. (a) Median values of the percent occurrence of heat wave days (events exceeding the 90th percentile for 3 or more days) for all years based on daily maximum values of the four temperature variables and computed for the different regions of the United States: NW, SW, NC, SC, MW, NE, and SE. (b) Differences in percentage from the average across all regions. (c),(d) As in (a),(b), but for daily minimum values of the temperature variables.

across all four variables. The pattern correlations with T_{\min} for the variables that include moisture are also much higher than those for T_{\max} . The spatial distributions of heat wave frequency also show some departures from those seen for daily maximum temperatures. Heat wave frequency is still comparatively higher in the southeastern United States relative to other regions, but this regional maximum now extends northward into the Midwest. Heat wave frequency in the southwestern United States is generally lower than that seen for daily maximum temperatures. Overall, the higher frequency in the eastern United States is consistent with the observation that daily minimum temperatures across variables are more closely associated with humidity than daily maximum values (cf. Fig. 3). To synthesize the results for both daily maximum and minimum values, the country was arbitrarily divided into seven coherent U.S. geographic regions: the Northwest (NW), Southwest (SW), North Central (NC), South Central (SC), Midwest (MW), Northeast (NE), and Southeast (SE). These regions are outlined in Fig. 6l.

Figure 7 shows the median frequency of heat wave day occurrence based on events exceeding the 90th percentile for 3 or more days for all four variables and across all stations in each U.S. region. Regional departures from

the national average are also displayed in the right panels. Figures 7a,b (Figs. 7c,d) show daily maximum (minimum) temperatures. For maximum values, Fig. 7b confirms that the SE and SW regions have comparatively higher occurrence of heat waves during 1979–2013. An interesting exception is for the SC region, where heat wave frequency based on daily maximum temperature (i.e., no humidity included) is also higher than the national average. The NC region has the lowest frequency of heat waves. For minimum daily temperatures, Fig. 7d again reveals that SE and MW regions generally have a higher frequency of occurrence, with the lowest occurrence again in NC and now in NW as well. An interesting exception is the SW region, where heat waves based on T_{eq} show a high rate of occurrence relative to the national average. As T_{eq} is most strongly related to humidity, this would seem consistent with the increase of humidity during the North American monsoon, when daily maximum temperatures are reduced by increased cloudiness while minimum values increase with increased humidity.

An analysis of heat wave frequency using daily data for individual warm season months was also conducted in an attempt to discern if there were notable, coherent spatial variations in the occurrence of heat waves on the

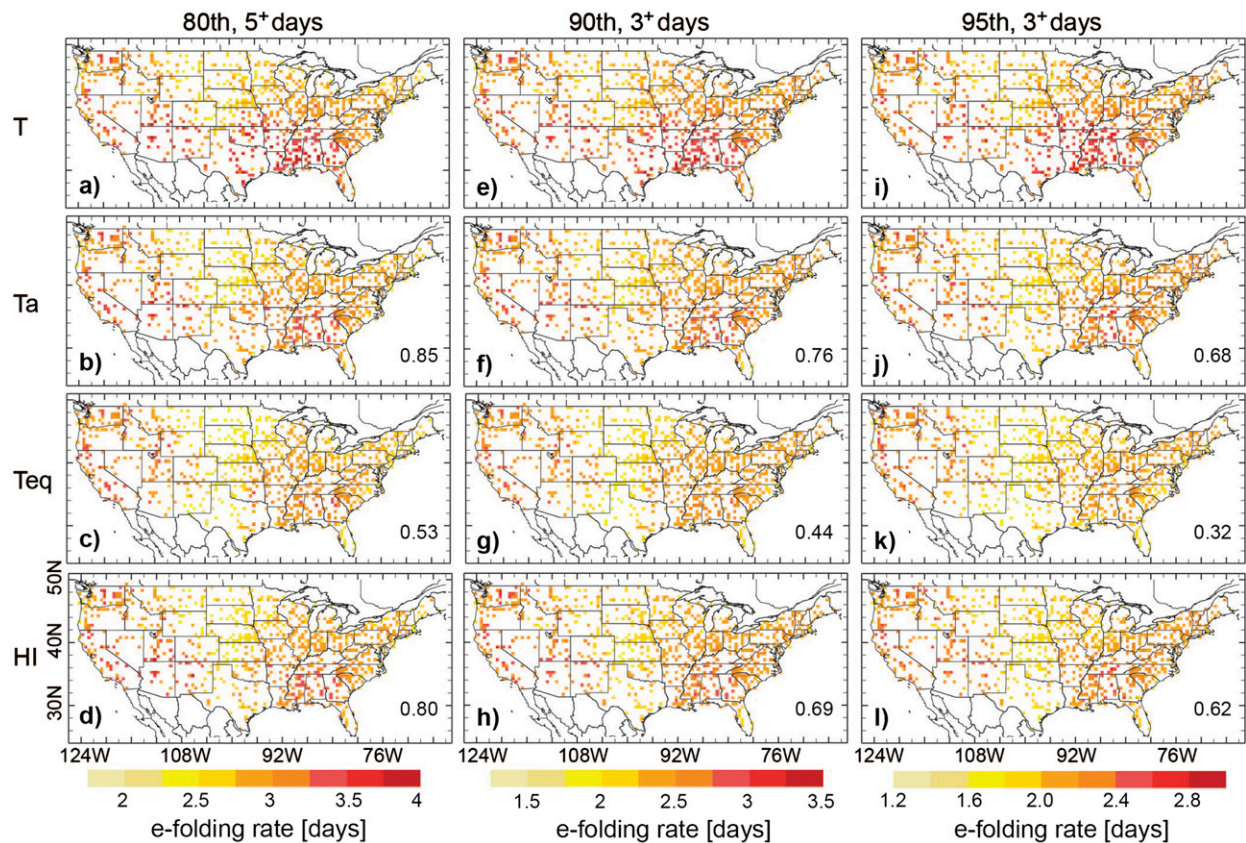


FIG. 8. As in Fig. 5, but for daily maximum temperature variables but for the e -folding time (days) for heat wave events.

subseasonal time scale. These analyses (not shown) did not identify any consistent differences in behavior during the evolution of the warm season, although this result is likely sensitive to a small sample size as only 35 years of data are available to analyze.

c. Regional persistence characteristics

In addition to regional variations in heat wave frequency, different measures of persistence of heat wave events were assessed. The fundamental question here is the degree to which the frequency of heat wave days is related to their persistence characteristics. For example, does a high frequency of occurrence of heat wave days in a particular region arise from longer-lasting individual heat wave events, or just more frequent heat wave events of shorter duration? For this analysis, at each station the cumulative number of heat wave days equaling or exceeding a given duration was computed. The cumulative number of heat wave days will drop off more quickly as a function of duration at locations where short duration heat waves prevail relative to locations having more protracted heat wave events. The e -folding time represents the amount of time required

for the cumulative frequency of heat wave days to drop by a factor of $1/e$ (0.368) from the cumulative single heat wave day frequency. To calculate the e -folding time, a polynomial was fit (using a sixth-order polynomial and including terms up to x^5 , where x is the duration in number of days) to the cumulative frequencies of occurrence of heat wave days for each number of days' duration. For example, if the cumulative percentage frequencies of occurrence of 90th-percentile heat waves lasting for at least 1, 2, 3, 4, and 5 days is 10.0%, 5.53%, 3.25%, 2.02%, and 1.21%, respectively, then the number of days required for the smoothed curve to drop to 3.68 (the e -folding time) is calculated at 2.76 days.

The e -folding time of daily maximum temperature variables is provided in Fig. 8. As expected, the e -folding rate is shorter (longer) for heat waves defined using a higher (lower) intensity threshold. The overall spatial patterns for persistence, however, are very similar to those for heat wave frequency, with higher values in the SE and SW regions, for example. Also plotted in Fig. 8 are the pattern correlations between the variables that include humidity with maximum temperature. They tend to be somewhat lower for e -folding time than for

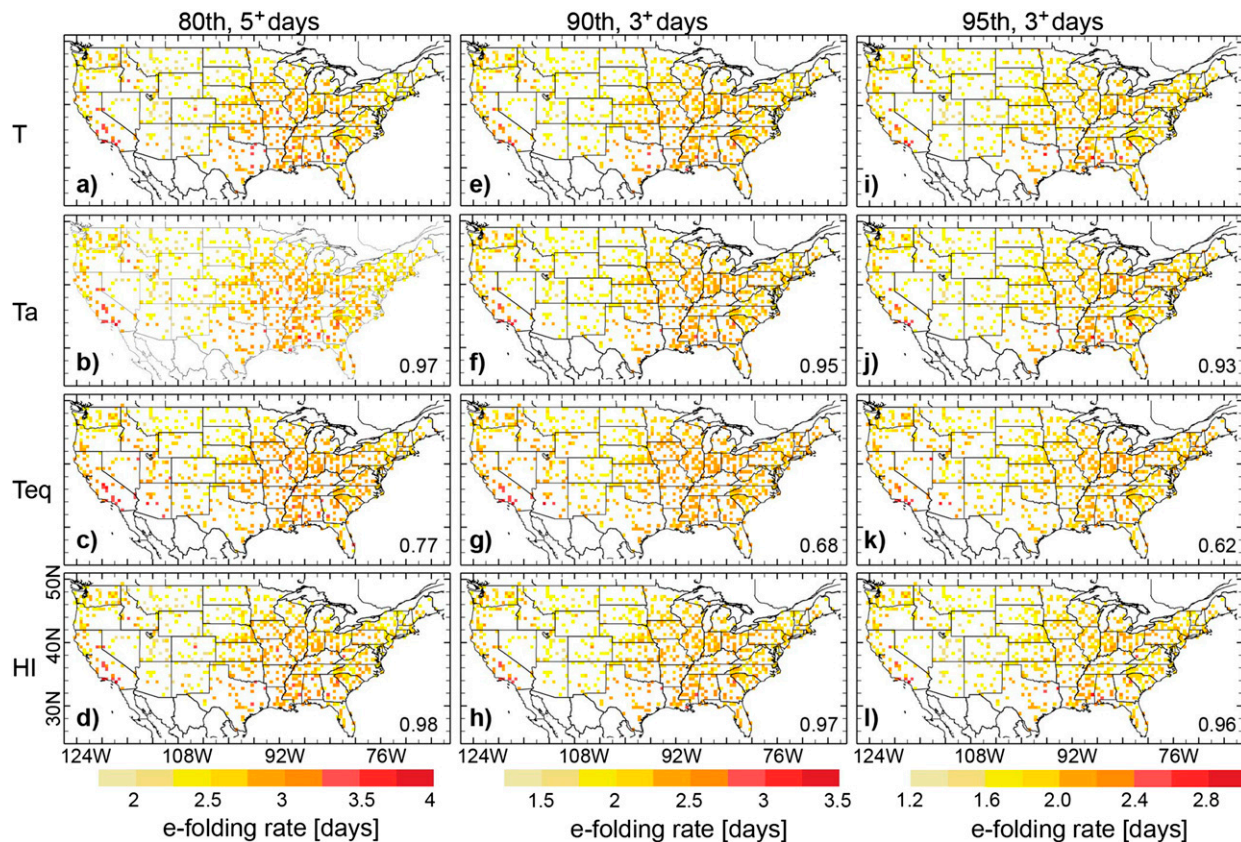


FIG. 9. As in Fig. 8, but for daily minimum temperature variables.

heat wave frequency but the same relationships are seen, with the lowest values for T_{eq} and for the most intense heat wave events.

Figure 9 is a similar analysis, but for the daily minimum temperature variables. Again, the spatial patterns are generally quite similar to those for heat wave frequency. This includes shorter e -folding times for minimum temperatures than for maximum temperatures and higher pattern correlation coefficients for the former. Spatial variations across the seven U.S. regions were again generated (not shown), which very closely mirror the results for heat wave frequency shown in Fig. 7. This includes differences in behavior among the heat wave variables by region. Taken together, the persistence results indicate that a higher frequency of heat wave days generally results from longer-lived events rather than more frequent but shorter-lived heat waves.

One consistent regional result across variables and for both maximum and minimum daily temperature variables is the minimum in heat wave frequency and persistence in the NC region of the United States. While a forthcoming paper will focus on heat wave relationships to the regional and large-scale circulation, here some insight is gained by considering the variability of the

transient eddy heat and moisture transports during the warm season, as shown in Fig. 10. The transient eddy fluxes in Fig. 10 are computed using daily departures of the meridional wind, temperature, and specific humidity values at 850 hPa from their respective monthly averages for a given year, using data from Reanalysis-2. The standard deviation of the daily eddy fluxes is first computed for each warm season month individually and then averaged over all months over the period 1981–2010. The minimum in heat wave frequency and persistence across temperature variables in the northern plains is seen to be generally collocated with a maximum in the eddy transport variance there. This suggests that, on average, the greater variability in day-to-day atmospheric circulation in this region inhibits the persistence of longer-lived heat wave events.

4. Differing behavior of daily maximum and minimum temperature variables

As a final set of analyses, the differing behavior of daily maximum and minimum temperature variables was examined in more detail. As shown in Figs. 5–9, U.S. heat waves are both less frequent and less persistent

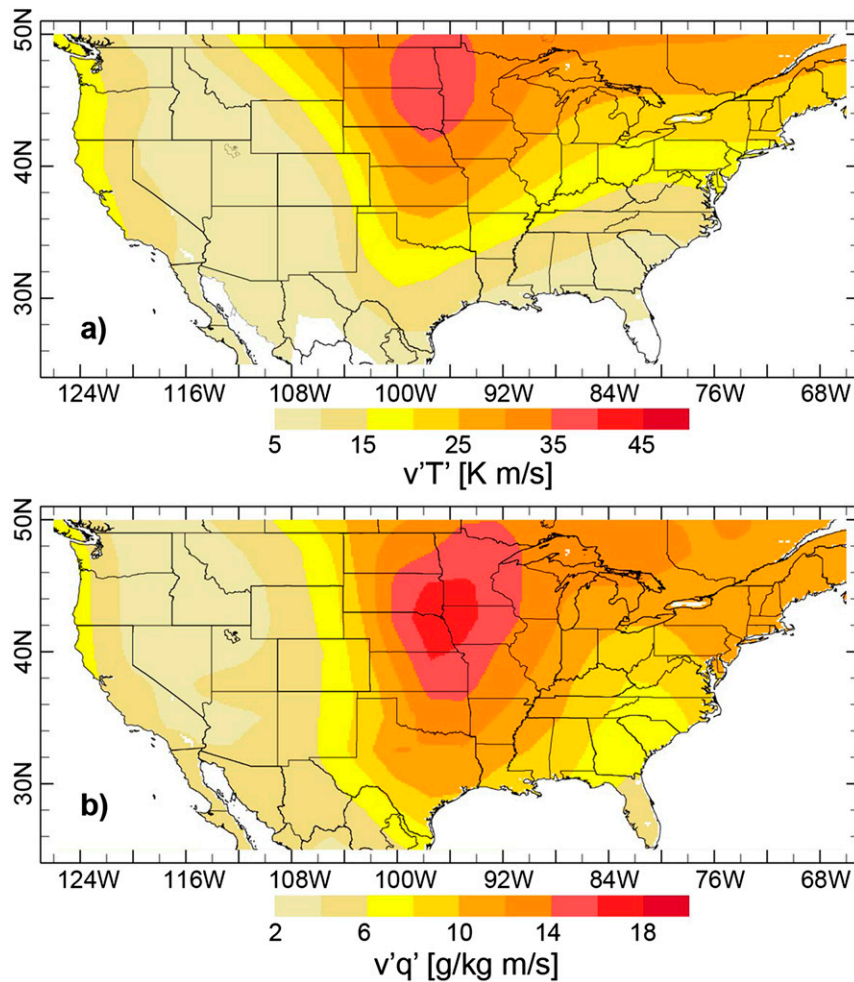


FIG. 10. Standard deviation (1981–2010) of the 850-hPa transient eddy (a) heat flux (K m s^{-1}) and (b) moisture flux ($\text{g kg}^{-1} \text{m s}^{-1}$) computed monthly and then averaged over all warm season months.

when identified using minimum versus maximum temperatures. This was true for temperature alone and for the temperature indices that included atmospheric moisture. These differences were examined further by considering the behavior of the temperature variables individually and in comparison with each other.

Figure 11 is based on the frequency of occurrence of heat wave days in a given month averaged across all stations in the United States, representing a total of 175 observations (5 months \times 35 yr). Figure 11 shows the percent of heat wave days (based on events exceeding the 90th percentile for 3 or more days) in a given month for maximum versus minimum values of a given temperature index. The dashed lines in Fig. 11 represent a 1:1 relationship and the solid lines are ordinary least squares linear regression fits to the monthly data. The regression lines for each variable are seen to have slopes

that are slightly less than one. At first glance, this may appear to be in contradiction to earlier results showing that the frequency of heat waves is greater for maximum rather than minimum temperatures. As will be shown, however, this result is due to the presence of temporal trends in heat wave frequency for all minimum temperature variables that is larger than those for maximum temperature. The weakest (strongest) relationship between maximum and minimum values is for temperature (T_{eq}), having a correlation of $r = 0.57$ ($r = 0.86$). For T_a and HI, the results are somewhere in between. For all variables, the relationships are highly statistically significant ($p < 0.01$).

Figure 12 is generated in a similar fashion as for Fig. 11, but now examines the relationships between maximum or minimum temperatures with respective values of the variables that include humidity. For

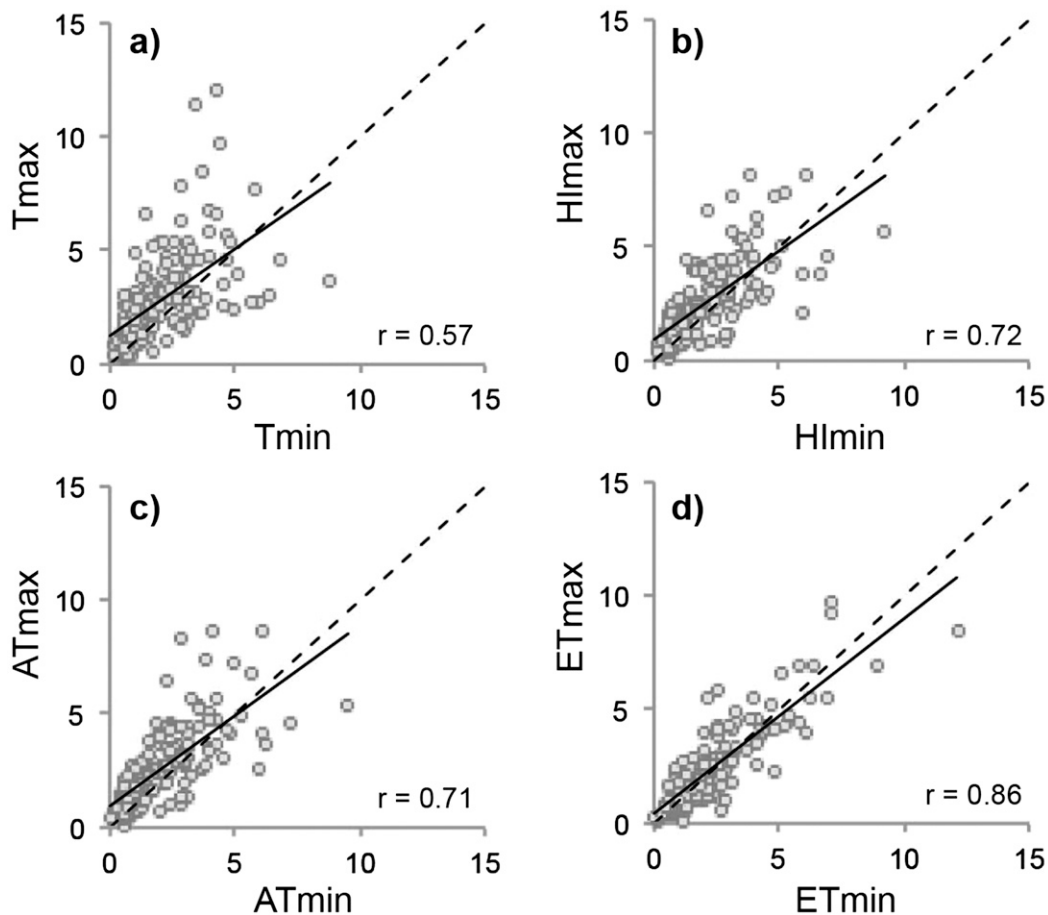


FIG. 11. Dots represent the percentage of heat wave days in a given calendar month (May–September) computed using daily maximum values of a temperature variable (vertical axes) vs that for daily minimum values (horizontal axis): (a) T , (b) HI, (c) T_a , and (d) T_{eq} . Solid black lines are a least squares linear fit to the data with associated correlation coefficient provided in the bottom right of each panel. Dashed diagonal line represents a ratio of 1:1.

maximum temperature variables the slopes of the regression lines are now all well less than unity, indicating that the frequency of occurrence of heat waves is greater for temperature alone than for the temperature and humidity indices. Roughly speaking, for the United States as a whole it is thus more likely for a heat wave to develop based solely on temperature than for both temperature and humidity to contribute to an event. This result is most pronounced for comparisons with T_{eq} (Fig. 12c), the variable having the strongest sensitivity to atmospheric moisture. Maximum values of T_{eq} also show the lowest correlation with temperature.

The same analysis for the minimum temperature variables (Figs. 12d–f) shows markedly different behavior. Here, the slopes of the regression lines for each temperature variable are very close to unity and also show a much stronger fit to the data (correlations from 0.88 to 0.99), including T_{eq} . The likely reason for this result is that, unlike maximum daily temperatures,

minimum temperatures show a stronger and more spatially consistent relationship with atmospheric moisture content (cf. Fig. 3). This is consistent with higher humidity reducing the rate of radiational cooling from the surface at night, which is well known. While the occurrence and persistence of heat waves are both less when based on daily minimum values, when they do develop they show more consistent behavior. Important regional differences in behavior of course do occur, as shown in Fig. 7.

Finally, the temporal variability in heat wave occurrence across the United States (1979–2013) is summarized in Fig. 13, which shows annual warm season values of the percent of occurrence of heat waves identified for all four variables when maximum and minimum temperatures that exceeded the 90th percentile for at least 3 days. Maximum temperatures exhibit greater differences among variables than do minimum values, consistent with our earlier results. The range in heat wave

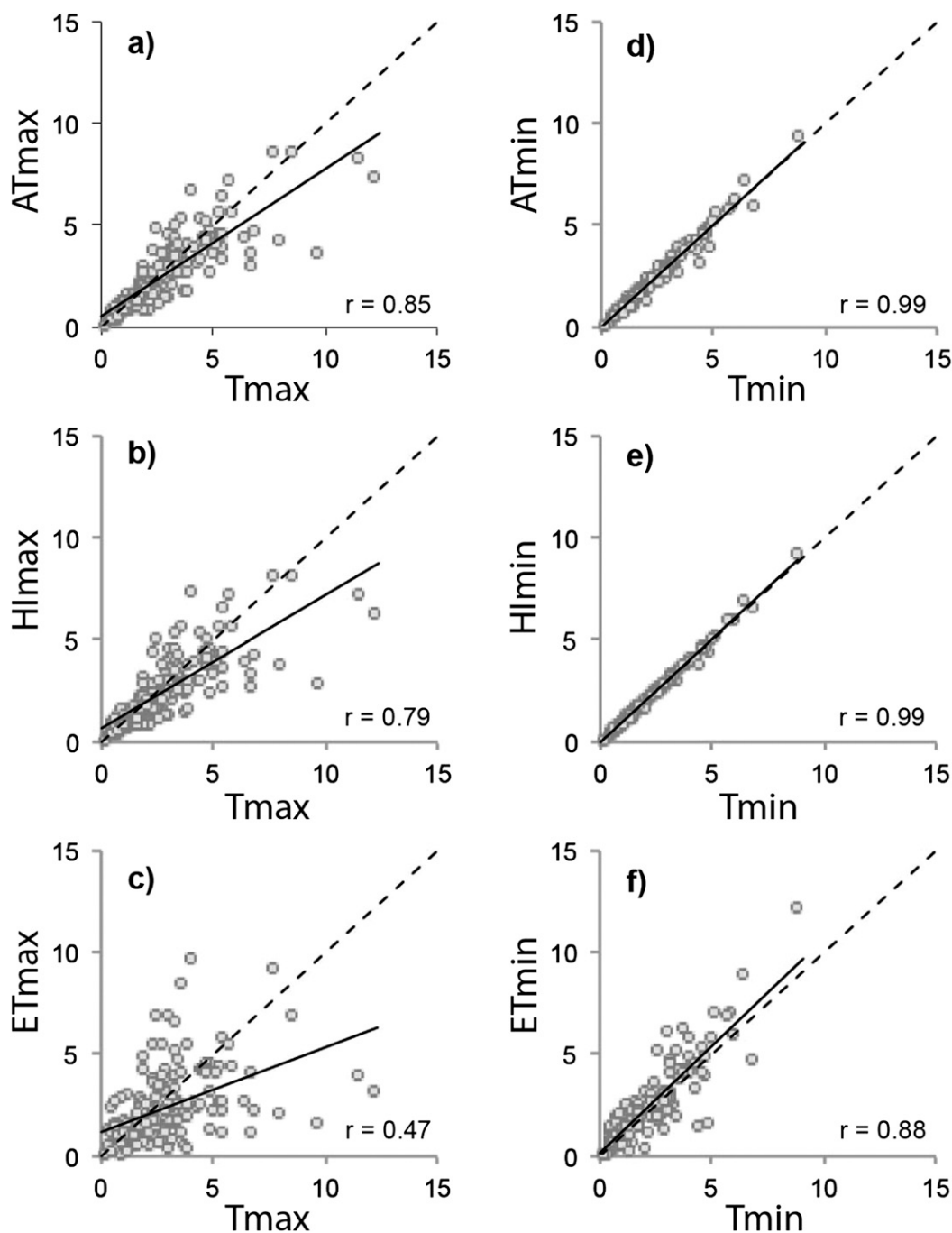


FIG. 12. As in Fig. 11, but now examining relationships between temperature variables, showing daily (a)–(c) maximum and (d)–(f) minimum values, for T vs (a),(d) T_a , (b),(e) HI, and (c),(f) T_{eq} .

frequency over the study period varies by a factor of more than 5 for both maximum and minimum temperature variables. Temporal trends in heat wave frequency for the seven U.S. regions (1979–2013) were also examined along with their statistical significance based on the two-tailed Student's t test. These trends are for events that exceeded the 90th percentile for 3 or more

days with the results summarized in Table 1. The results indicate that statistically significant trends in heat wave frequency based on daily maximum temperatures are less common than those based on daily minimum values. The NC and MW regions did not exhibit significant trends for either daily maximum or minimum values. These results are generally consistent with a study by

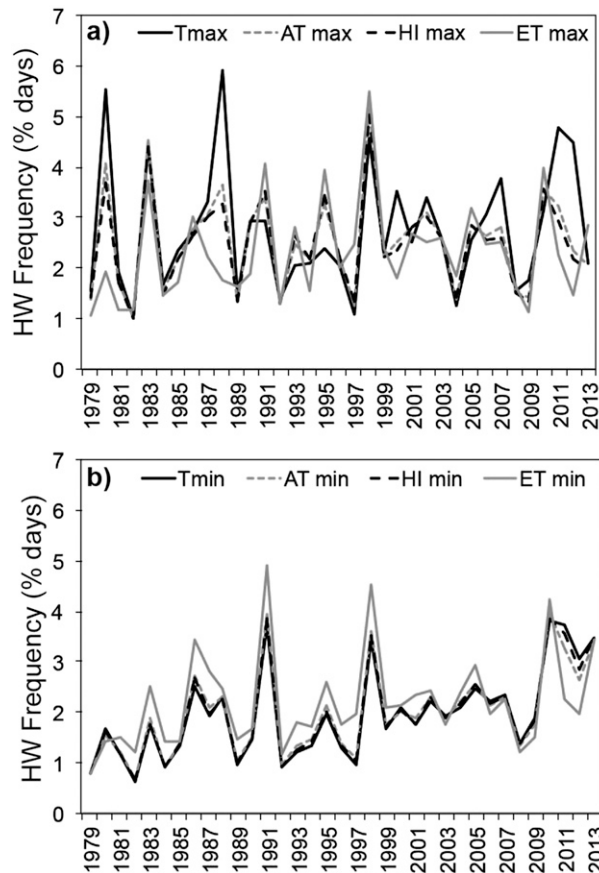


FIG. 13. The frequency of heat waves expressed as a percentage of heat wave days by year (1979–2013), based on daily (a) maximum and (b) minimum values for all four variables.

Peterson et al. (2008), who identified statistically significant upward trends in both daily maximum and minimum temperatures exceeding the 90th percentile when averaged across North American stations. However, that study did not require a minimum duration of 3 or more consecutive days above the threshold and there were substantial regional variations in trends. They also found that daily minimum temperatures exceeding the 90th percentile are increasing faster than daily maximum values. Much earlier, Karl et al. (1984, 1993) had found that mean daily minimum temperature was generally increasing at a faster rate than maximum temperature across the United States, resulting in a decreasing diurnal temperature range even in rural stations. Our results are also generally consistent with studies showing upward trends in surface specific humidity (Brown and DeGaetano 2013), with Gaffen and Ross (1999) finding a greater increase in nighttime than daytime values. Studies have also shown statistically significant upward trends in T_a and T_{eq} (Gaffen and Ross 1999; Fall et al. 2010) during overlapping time

TABLE 1. Statistical significance of linear trends in heat wave frequency of occurrence, by region, with 90%, 95%, and 99% confidence levels. No confidence level means not significant. Regions are outlined in Fig. 6l.

	Region						
	NW	SW	NC	SC	MW	NE	SE
T_{max}	—	90%	—	—	—	—	—
$T_a(max)$	—	—	—	—	—	—	—
HI_{max}	—	90%	—	—	—	—	—
$T_{eq(max)}$	90%	—	—	—	—	95%	—
T_{min}	95%	99%	—	95%	—	99%	99%
$T_a(min)$	95%	99%	—	95%	—	99%	95%
HI_{min}	95%	99%	—	95%	—	99%	99%
$T_{eq(min)}$	—	—	—	—	—	95%	90%

periods. Using the North American Land Data Assimilation System, version 2 (NLDAS-2; Xia et al. 2012) dataset, Smith et al. (2013) identify upward trends in daily maximum values of temperature and T_a over a similar analysis period as used here, although they did not use the same threshold and duration criteria as in the current study. Overall, our trend results are generally consistent with earlier findings, with the important caveat mentioned in section 2b that no bias correction was made to the USHCN daily data to adjust for changes in time of observation. Such changes have likely introduced a temporally increasing cold bias to our USHCN results, reducing the magnitude of our positive temporal trends relative to a bias-corrected version of the data or other datasets (e.g., Vose et al. 2012).

5. Discussion and conclusions

A heat wave is a fundamentally important climate extreme having myriad environmental and social impacts and yet it lacks a universally accepted definition. The analysis of heat waves is frequently undertaken either with a particular impact in mind (e.g., human health) or using a single temperature variable or heat index. The main goal of the current study was to compare the statistical characteristics of U.S. warm season heat waves when defined using four different temperature variables (and their daily maximum versus minimum values) and differing definitional intensity and duration criteria. While largely based on daily temperature data for stations in the USHCN, the study also tested and demonstrated the reliability of using the NARR data to compute three widely used temperature indices that include atmospheric moisture. Heat wave intensity thresholds were based on daily percentiles to eliminate the influence of regional variations in climatological temperatures on the analysis and to manage

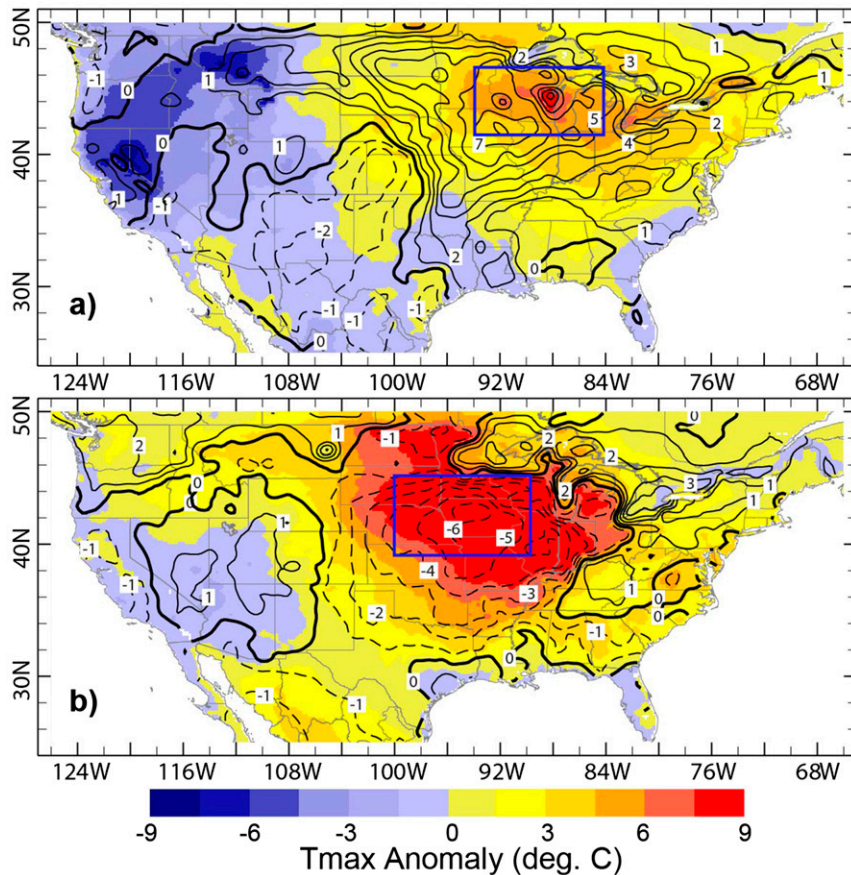


FIG. 14. Average daily maximum temperature anomaly ($^{\circ}\text{C}$; shaded) and q (g kg^{-1} ; contours) during two heat wave events based on the NARR data and a 1981–2010 base period, for (a) 11–15 Jul 1995 and (b) 15–25 Jul 2012. [The blue boxes in (a),(b) represent regions over which the variables shown in Fig. 15 have been averaged.]

large differences in absolute temperature values, particularly those based on T_{eq} , which is very sensitive to atmospheric moisture content. Emphasis was placed on the geographical distribution and regional persistence characteristics of heat waves as well as differences in behavior between events identified using daily maximum, versus minimum, temperatures. Before explicitly examining heat waves, the temporal variability and covariability of heat wave–related variables was examined, serving as a reference for the interpretation of subsequent results.

The key findings of the study include the following:

- For the country as a whole and when evaluated regionally, heat waves are more frequent and show greater persistence when defined using daily maximum versus daily minimum temperatures. This was true for all four of the temperature variables examined.
- There are notable regional variations in heat wave occurrence, being generally more frequent in the southeastern and southwestern United States for daily maximum values of all four variables. For daily minimum temperatures, heat waves are more frequent in southeastern, south-central, and midwestern areas. They are least frequent in the northern plains for both maximum and minimum temperatures.
- Substantial differences in the frequency of heat wave occurrence among the four temperature variables were identified for events defined using daily maximum versus minimum temperatures. For the country as a whole, extremes in the minimum values of temperature variables show greater spatial coherency than do maximum values. This result is consistent with a more spatially homogeneous pattern in the covariability of daily minimum temperature and specific humidity than for daily maximum temperatures.
- Statistically significant upward trends in the frequency of heat wave occurrence are identified for most U.S. regions for events based on daily minimum values, for all four variables over the period 1979–2013. Fewer statistically significant regional trends were identified

for the frequency of heat wave occurrence when events were identified using daily maximum temperatures.

Overall, the results reveal important differences in heat wave behavior depending on how they are defined. Differences in the frequency of occurrence and persistence of heat waves when defined using daily maximum versus minimum temperature are particularly noteworthy and point to an asymmetry in forcing. For example, while an anomalous atmospheric circulation pattern likely accompanies heat waves defined using either maximum or minimum temperature, anomalously dry soils favor enhanced daytime over nighttime temperatures, including in comparatively humid regions such as the southeastern United States (e.g., Durre et al. 2000). Our results also show that enhanced minimum temperatures are frequently accompanied by enhanced humidity, a condition that may accompany, but is not required for, enhanced daily maximum temperatures. In addition to being insightful from phenomenological and physical perspectives, the results also serve as a cautionary note when using heat wave information for impact analysis. Heat wave statistics derived from different temperature indicators may well lead to different conclusions.

While this study has focused on the aggregate behavior of heat waves, it is also important to realize that substantial variations in heat wave behavior can occur in any geographic location. To emphasize this point, Fig. 14 shows the average daily maximum temperature and specific humidity anomalies averaged over the peak period of two substantial July heat wave events that occurred in the Midwest (1995 and 2012) based on the NARR data. The 1995 event, frequently referred to as the “Chicago heat wave,” was a short-lived but intense heat wave that was also accompanied by anomalously high surface specific humidity. The 2012 heat wave was of much longer duration but comparably “dry” in terms of humidity. Further differences in behavior are seen in Fig. 15, which shows daily time series of daily maximum and minimum values of T_a and daily mean specific humidity q over the course of both events (expressed in percentiles, obtained by ranking daily values in the NARR data). All three variables exceeded the 95th percentile during the peak of the 1995 event. The high apparent temperature during both the day and night was a major contributor to increased human mortality in Chicago in 1995 (e.g., Kunkel et al. 1996). While the 2012 event was much longer-lived, the specific humidity remained below median values, and the daily minimum T_a was well below daily maximum values, throughout the event. This likely had important implications for heat stress on both humans and livestock. It is also important to note that the 2012 event was accompanied by

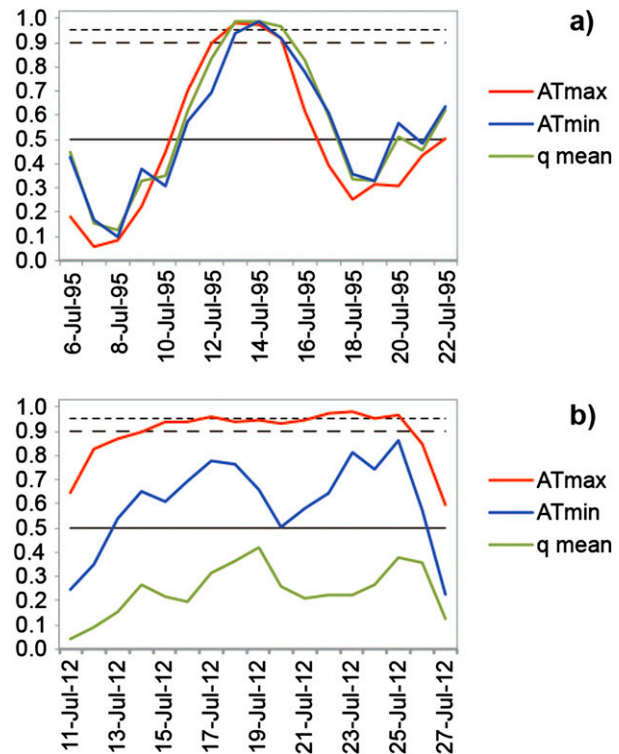


FIG. 15. Daily values of maximum and minimum T_a and mean q expressed as percentiles as averaged over the boxed regions shown in Fig. 14 and based on NARR data, for (a) 6–22 Jul 1995 and (b) 11–27 Jul 2012. Solid black line in both panels represents the median values with the long- and short-dashed lines indicating the 90th and 95th percentiles, respectively.

drought conditions while in 1995 the land surface condition was comparatively “wet.” The relationship between antecedent and concurrent land surface conditions with summer heat wave behavior is currently under study.

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REFERENCES

- Anderson, G. B., and M. L. Bell, 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**, 210–218, doi:10.1289/ehp.1002313.
- Barnett, A. G., S. Tong, and A. C. A. Clements, 2010: What measure of temperature is the best predictor of mortality? *Environ. Res.*, **110**, 604–611, doi:10.1016/j.envres.2010.05.006.
- Brown, P. J., and A. T. DeGaetano, 2013: Trends in U.S. surface humidity, 1931–2010. *J. Appl. Meteor.*, **52**, 147–163, doi:10.1175/JAMC-D-12-035.1.

- Durre, I., J. M. Wallace, and D. P. Lettenmaier, 2000: Dependence of extreme daily maximum temperatures on antecedent soil moisture in the contiguous United States during summer. *J. Climate*, **13**, 2641–2651, doi:[10.1175/1520-0442\(2000\)013<2641:DOEDMT>2.0.CO;2](https://doi.org/10.1175/1520-0442(2000)013<2641:DOEDMT>2.0.CO;2).
- Fall, S., N. S. Diffenbaugh, D. Niyogi, R. A. Pielke Sr., and G. Rochon, 2010: Temperature and equivalent temperature over the United States (1979–2005). *Int. J. Climatol.*, **30**, 2045–2054, doi:[10.1002/joc.2094](https://doi.org/10.1002/joc.2094).
- Gaffen, D. J., and R. J. Ross, 1998: Increased summertime heat stress in the US. *Nature*, **396**, 529–530, doi:[10.1038/25030](https://doi.org/10.1038/25030).
- , and —, 1999: Climatology and trends of U.S. surface humidity and temperature. *J. Climate*, **12**, 811–828, doi:[10.1175/1520-0442\(1999\)012<0811:CATOUS>2.0.CO;2](https://doi.org/10.1175/1520-0442(1999)012<0811:CATOUS>2.0.CO;2).
- Kalkstein, L. S., and K. M. Valimont, 1986: An evaluation of summer discomfort in the United States using a relative climatological index. *Bull. Amer. Meteor. Soc.*, **67**, 842–848, doi:[10.1175/1520-0477\(1986\)067<0842:AEOSDI>2.0.CO;2](https://doi.org/10.1175/1520-0477(1986)067<0842:AEOSDI>2.0.CO;2).
- , and R. E. Davis, 1989: Weather and human mortality: An evaluation of demographic and interregional responses in the United States. *Ann. Assoc. Amer. Geogr.*, **79**, 44–64, doi:[10.1111/j.1467-8306.1989.tb00249.x](https://doi.org/10.1111/j.1467-8306.1989.tb00249.x).
- Kanamitsu, M., W. Ebisuzaki, J. Woollen, S. K. Yang, J. J. Hnilo, M. Fiorino, and G. L. Potter, 2002: NCEP–DOE AMIP-II Reanalysis (R-2). *Bull. Amer. Meteor. Soc.*, **83**, 1631–1643, doi:[10.1175/BAMS-83-11-1631](https://doi.org/10.1175/BAMS-83-11-1631).
- Karl, T. R., G. Kukla, and J. Gavin, 1984: Decreasing diurnal temperature range in the United States and Canada from 1941 through 1980. *J. Climate Appl. Meteor.*, **23**, 1489–1504, doi:[10.1175/1520-0450\(1984\)023<1489:DDTRIT>2.0.CO;2](https://doi.org/10.1175/1520-0450(1984)023<1489:DDTRIT>2.0.CO;2).
- , and Coauthors, 1993: A new perspective on recent global warming: Asymmetric trends of daily maximum and minimum temperature. *Bull. Amer. Meteor. Soc.*, **74**, 1007–1023, doi:[10.1175/1520-0477\(1993\)074<1007:ANPORG>2.0.CO;2](https://doi.org/10.1175/1520-0477(1993)074<1007:ANPORG>2.0.CO;2).
- Kunkel, K. E., S. A. Changnon, B. C. Reinke, and R. W. Arritt, 1996: The July 1995 heat wave in the Midwest: A climatic perspective and critical weather factors. *Bull. Amer. Meteor. Soc.*, **77**, 1507–1518, doi:[10.1175/1520-0477\(1996\)077<1507:TJHWIT>2.0.CO;2](https://doi.org/10.1175/1520-0477(1996)077<1507:TJHWIT>2.0.CO;2).
- , R. A. Pielke Jr., and S. A. Changnon, 1999: Temporal fluctuations in weather and climate extremes that cause economic and human health impacts: A review. *Bull. Amer. Meteor. Soc.*, **80**, 1077–1098, doi:[10.1175/1520-0477\(1999\)080<1077:TFIWAC>2.0.CO;2](https://doi.org/10.1175/1520-0477(1999)080<1077:TFIWAC>2.0.CO;2).
- Lyon, B., 2009: Southern Africa summer drought and heat waves: Observations and coupled model behavior. *J. Climate*, **22**, 6033–6046, doi:[10.1175/2009JCLI3101.1](https://doi.org/10.1175/2009JCLI3101.1).
- McGregor, G., 2015: Heatwaves and health: Guidance on warning-system development. World Health Organization, WMO-No. 1142, 114 pp. [Available online at <http://www.who.int/globalchange/publications/heatwaves-health-guidance/en/>.]
- Melillo, J. M., T. C. Richmond, and G. W. Yohe, Eds., 2014: *Climate Change Impacts in the United States: The Third National Climate Assessment*. U.S. Global Change Research Program, 841 pp, doi:[10.7930/J0Z31WJ2](https://doi.org/10.7930/J0Z31WJ2).
- Menne, M. J., C. N. Williams, and R. S. Vose, 2009: The U.S. Historical Climatology Network monthly temperature data, version 2. *Bull. Amer. Meteor. Soc.*, **90**, 993–1007, doi:[10.1175/2008BAMS2613.1](https://doi.org/10.1175/2008BAMS2613.1).
- , C. N. Williams Jr., and R. S. Vose, 2015: United States Historical Climatology Network Daily Temperature, Precipitation, and Snow Data. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, accessed 2 February 2015. [Available online at <http://cdiac.ornl.gov/epubs/ndp/ushcn/ushcn.html>.]
- Mesinger, F., and Coauthors, 2006: North American Regional Reanalysis. *Bull. Amer. Meteor. Soc.*, **87**, 343–360, doi:[10.1175/BAMS-87-3-343](https://doi.org/10.1175/BAMS-87-3-343).
- NCDC, 2011: U.S. heat stress index. Daily maximum and minimum apparent temperature for 187 stations, National Climatic Data Center, accessed 5 February 2015. [Available online at <https://www.ncdc.noaa.gov/societal-impacts/heat-stress/data/>.]
- Peterson, T. C., X. Zhang, M. Brunet-India, and J. L. Vázquez-Aguirre, 2008: Changes in North American extremes derived from daily weather data. *J. Geophys. Res.*, **113**, D07113, doi:[10.1029/2007JD009453](https://doi.org/10.1029/2007JD009453).
- Robinson, P. J., 2000: Temporal trends in United States dew point temperatures. *Int. J. Climatol.*, **20**, 985–1002, doi:[10.1002/1097-0088\(200007\)20:9<985::AID-JOC513>3.0.CO;2-W](https://doi.org/10.1002/1097-0088(200007)20:9<985::AID-JOC513>3.0.CO;2-W).
- , 2001: On the definition of a heat wave. *J. Climate Appl. Meteor.*, **40**, 762–775, doi:[10.1175/1520-0450\(2001\)040<0762:OTDOAH>2.0.CO;2](https://doi.org/10.1175/1520-0450(2001)040<0762:OTDOAH>2.0.CO;2).
- Rothfus, L. P., 1990: National Weather Service (NWS) Technical Attachment (SR 90-23), 2 pp. [Available online at https://www.weather.gov/media/bgm/ta_htindx.pdf.]
- Schlenker, W., and M. J. Roberts, 2009: Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proc. Natl. Acad. Sci. USA*, **106**, 15 594–15 598, doi:[10.1073/pnas.0906865106](https://doi.org/10.1073/pnas.0906865106).
- Semenza, J. C., C. H. Rubin, K. H. Falter, J. D. Selanikio, W. D. Flanders, H. L. Howe, and J. L. Wilhelm, 1996: Heat-related deaths during the July 1995 heat wave in Chicago. *N. Engl. J. Med.*, **335**, 84–90, doi:[10.1056/NEJM199607113350203](https://doi.org/10.1056/NEJM199607113350203).
- Sheridan, S. C., and L. S. Kalkstein, 2004: Progress in heat watch-warning system technology. *Bull. Amer. Meteor. Soc.*, **85**, 1931–1941, doi:[10.1175/BAMS-85-12-1931](https://doi.org/10.1175/BAMS-85-12-1931).
- Smith, T. T., B. F. Zaitchik, and J. M. Gohlke, 2013: Heat waves in the United States: Definitions, patterns and trends. *Climatic Change*, **118**, 811–825, doi:[10.1007/s10584-012-0659-2](https://doi.org/10.1007/s10584-012-0659-2).
- Souch, C., and C. S. B. Grimmond, 2004: Applied climatology: ‘Heat waves’. *Prog. Phys. Geogr.*, **28**, 599–606, doi:[10.1191/0309133304pp428pr](https://doi.org/10.1191/0309133304pp428pr).
- Steadman, R. G., 1979: The assessment of sultriness. Part I: A temperature–humidity index based on human physiology and clothing science. *J. Appl. Meteor.*, **18**, 861–873, doi:[10.1175/1520-0450\(1979\)018<0861:TAOSPI>2.0.CO;2](https://doi.org/10.1175/1520-0450(1979)018<0861:TAOSPI>2.0.CO;2).
- , 1984: A universal scale of apparent temperature. *J. Appl. Meteor.*, **23**, 1674–1687, doi:[10.1175/1520-0450\(1984\)023<1674:AUSOAT>2.0.CO;2](https://doi.org/10.1175/1520-0450(1984)023<1674:AUSOAT>2.0.CO;2).
- Vose, R. S., C. N. Williams Jr., T. C. Peterson, T. R. Karl, and D. R. Easterling, 2003: An evaluation of the time of observation bias adjustment in the U.S. Historical Climatology Network. *Geophys. Res. Lett.*, **30**, 2046, doi:[10.1029/2003GL018111](https://doi.org/10.1029/2003GL018111).
- , S. Applequist, M. J. Menne, C. N. Williams, and P. Thorne, 2012: An intercomparison of temperature trends in the U.S. Historical Climatology Network and recent atmospheric reanalyses. *Geophys. Res. Lett.*, **39**, L10703, doi:[10.1029/2012GL051387](https://doi.org/10.1029/2012GL051387).
- White, M. A., N. S. Diffenbaugh, G. V. Jones, J. S. Pal, and F. Giorgi, 2006: Extreme heat reduces and shifts United States premium wine production in the 21st century. *Proc. Natl. Acad. Sci. USA*, **103**, 11 217–11 222, doi:[10.1073/pnas.0603230103](https://doi.org/10.1073/pnas.0603230103).
- Xia, Y., and Coauthors, 2012: Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. *J. Geophys. Res.*, **117**, D03109, doi:[10.1029/2011JD016048](https://doi.org/10.1029/2011JD016048).