A Trend Analysis of the 1930–2010 Extreme Heat Events in the Continental United States^{*,†}

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ABSTRACT

Extreme heat events (EHEs) are linked to mortality rates, making them an important research subject in both the climate and public health fields. This study evaluated linear trends in EHEs using the U.S. Historical Climatology Network (USHCN), version 2.0, dataset and quantified the longer-term EHE trends across the continental United States (CONUS). The USHCN-daily, version 1, dataset was integrated with the homogenized USHCN-monthly, version 2.0, dataset to create daily data for trend analysis. Time series and estimated trends in multiple characteristics of EHEs (number, total days, mean duration, etc.) were calculated as were the continental means and spatial maps. The differences between EHEs based on daily maximum temperatures, minimum temperatures, and both minimum and maximum temperatures were explored. To focus on warming and cooling periods, the trends were also estimated separately over the first half and second half of the study period (1930–2010). The results indicated that the trends for different EHE characteristics were coherent (e.g., temporally correlated, similar spatial pattern of trends). Maps indicated negative trends in the interior of the CONUS and positive trends in coastal and southern areas. Continental-scale increases between 1970 and 2010 were mostly offset by the decreases between 1930 and 1970. Several daily maximum (minimum) EHEs near the 1930s (2000s) led to 1930–2010 trends of daily maximum (minimum) EHEs decreasing (increasing). Last, the results suggest that linear trends depend on which daily temperature extreme is required to exceed the threshold.

1. Introduction

Knowledge of past extreme heat event (EHE) trends assists in the prediction of future EHEs trends. Recent studies have quantified past continental United States (CONUS) annual daily mean near-surface air temperatures (Hansen et al. 2010) and annual daily minimum and maximum temperatures (Menne et al. 2009; Shen et al. 2011). While these studies benefit both the climate and applications communities, trend analyses consistent with the epidemiological literature might inform heat-health decision makers more. The current study fills gaps between the epidemiological literature (linking

mortality and weather) and the climate community (exploring extreme temperatures over time), while still producing new climate knowledge.

In the epidemiological literature, features of hot weather linked to mortality rates have been identified. For example, the epidemiological literature has established the importance of duration in elevated temperatures (e.g., Kalkstein 1991; Díaz et al. 2002; Hajat et al. 2006; Anderson and Bell 2009; Ostro et al. 2009) as well as the importance of the sum of cumulative degree-days over a heat stress-relevant threshold (i.e., intensity) (Díaz et al. 2002, 2006; Fouillet et al. 2007, 2008; Gershunov et al. 2009). Timing within the heat season is also important, with EHEs early in the season having a larger impact on mortality (Kalkstein and Smoyer 1993; Rooney et al. 1998; Hajat et al. 2002; Páldy et al. 2005; Baccini et al. 2008).

Epidemiological studies have linked mortality to daily minimum temperatures (e.g., Kalkstein 1991; Grize et al. 2005; Schwartz 2005; Hajat et al. 2006; Fouillet et al. 2007, 2008; Basu et al. 2008), daily maximum temperatures (e.g., Hajat et al. 2002; Díaz et al. 2002; Tan et al. 2007;

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Baccini et al. 2008; Anderson and Bell 2009), and daily mean temperatures (Hajat et al. 2002, 2006; Basu et al. 2008; Anderson and Bell 2009; Ostro et al. 2009). While it is not clear which daily temperature is more closely related to mortality, the heat–mortality relationship likely varies with region (Kalkstein and Davis 1989). Some studies used biometeorological indices (e.g., heat index) as predictors (Grize et al. 2005; Hajat et al. 2006), but sensitivity analyses have not found substantial differences with conventional temperatures (Anderson and Bell 2009; Vaneckova et al. 2011).

EHEs with unusually elevated temperatures in both daily minimums and maximums have been associated with intense mortality impacts. Fouillet et al. (2006) showed in France during the 2003 EHE that mortality was linked to simultaneously elevated minimums and maximums. Similarly Karl and Knight (1997) in the 1995 Chicago EHE, Henschel et al. (1969) in the 1966 St. Louis EHE, and Grumm (2011) in the 2010 Russian EHE observed extreme minimums and maximums. Most studies only impose requirements on the daily minimums (e.g., Tamrazian et al. 2008) or maximums (e.g., Tomozeiu et al. 2006; Kyselý 2010; Huth et al. 2000; Meehl and Tebaldi 2004). This could give the impression that trends of EHEs focusing on different daily temperature extremes, or both daily extremes, are interchangeable. Kuglitsch et al. (2010) is the only study we are familiar with that required both extremes to be simultaneously elevated over a threshold.

Though epidemiologists have identified the importance of the duration of EHEs, trend analyses including a duration requirement (e.g., Gaffen and Ross 1998; New et al. 2006; Gershunov et al. 2009; Kuglitsch et al. 2010) are less common than studies of trends in single-day extremes (e.g., 90th and 10th percentiles). Studies of single-day exceedance counts exist on the global scale (Frich et al. 2002; Alexander et al. 2006), and regional studies have focused on the CONUS (Gaffen and Ross 1998; DeGaetano and Allen 2002; Peterson et al. 2008; Portmann et al. 2009), the north-eastern United States (Griffiths and Bradley 2007; Brown et al. 2010), Italy (Tomozeiu et al. 2006), Europe (Klein Tank and Können 2003; Moberg and Jones 2005; Della-Marta et al. 2007), South Africa (New et al. 2006), and southern and central Asia (Klein Tank et al. 2006).

Many climate studies employ extreme heat indices such as the “warm spell duration indicator” (e.g., Frich et al. 2002; Alexander et al. 2006; New et al. 2006; Brown et al. 2010), heat wave frequency index (e.g., Wu et al. 2012), and heat wave duration index (e.g., Griffiths and Bradley 2007). While using these indices assists comparisons with other studies, they also have limitations. For instance, none of these indices require anything of

the daily minimum temperatures, quantify the number of separate EHEs, or consider EHEs with shorter durations (e.g., 3 days).

A multi-aspect approach describing the different characteristics of EHEs is taken here. Quantifying the trends in only one aspect only partially explains the trends, and trends in indices sensitive to numerous aspects might not be specific enough. For instance, trends in duration, intensity, and frequency all provide different information. Nevertheless, sometimes indices that incorporate numerous aspects are desirable and therefore aspects of both specific and inclusive nature are examined here. Perkins and Alexander (2013) recently took a similar multiaspect approach in their analysis of Australian heat waves. Gershunov et al. (2009) evaluated the California region’s trends in EHE intensity, duration, and spatial extent. The Kuglitsch et al. (2010) study quantified the EHE intensity as well as duration and number of EHEs per summer in the Mediterranean region.

As detailed in section 2, the current study is designed to address the aforementioned gaps. For instance, the current study requires duration and examines trends in duration. Also inspected were the trends in EHEs with both daily extremes simultaneously meeting the EHE requirements, as well as the differences between EHE trends based on different daily temperature extremes. Last, multiple aspects of EHEs were examined in hopes they convey more information to heat–health decision makers.

An examination of EHE timing within the season was undertaken but omitted because of content limitations.

Similar to this study, DeGaetano and Allen (2002) focused on the CONUS trends starting in 1930. The EHEs had either 2 or 3 days, at various percentiles, for either (not both) the daily minimums or maximums. The current study has differences from the DeGaetano and Allen (2002) study; for instance, the EHEs are specific to summertime and were based on dynamic (with calendar date) percentiles instead of annual percentiles.

Another similar study, by Gaffen and Ross (1998), quantified modern trends in EHEs across the CONUS. The authors presented linear trends since 1949 in apparent temperature-based (Steadman 1984) EHEs. The current study has differences from Gaffen and Ross (1998) such as independence from the hydrological trends, quantifying multiple EHE characteristics, and quantifying EHEs with respect to both daily temperature extremes (instead of daily mean). As described in section 2, conventional temperatures facilitated this analysis. They simplify interpretation of the results and are easier to project into the future. Furthermore,

homogenized long-term time series of water vapor observations are rare.

In the next section the datasets and definitions are described. In section 3 the results are presented and in section 4 they are discussed. In section 5 the conclusions are discussed and suggestions for future work are provided.

2. Methods

a. Dataset

This investigation required a daily dataset that was suitable for trend analysis (i.e., homogenized). The process of homogenization removes nonclimatic biases (e.g., urbanization, microclimate changes) that cause temporal discontinuities in climate observation time series. To form this dataset a temporal downscaling method, similar to methods used by Di Luzio et al. (2008) and Hamlet and Lettenmaier (2005), was used that mapped day-to-day variability onto monthly resolution data. This method provided a daily dataset more suitable for trend analysis. This approach was chosen because a similar dataset with an effective daily adjustment scheme was not available.

This combined information is from two products of the U.S. Historical Climatology Network (USHCN). The USHCN, version 1, dataset (USHCNv1-daily; Menne et al. 2012) is a quality-controlled (Durre et al. 2008) dataset with daily variability, but it is not homogenized. The USHCN, version 2.0, monthly dataset (USHCNv2.0-monthly; Menne et al. 2009, 2011) uses the same 1218 stations as the USHCNv1-daily dataset but is both homogenized and has serially complete data at each station over that station's respective operational period. The USHCNv2.0-monthly dataset is ideal for trend analyses (Menne et al. 2010; Williams et al. 2012) because the homogenization process is robust (Menne and Williams 2005, 2009; Hausfather et al. 2013).

The USHCNv1-daily dataset was acquired online from the Carbon Dioxide Information Analysis Center (CDIAC). The data from 1930 through 2010 and from May through September were used. 9.78% (9.81%) of the station months from the Tmax (Tmin) variable were missing during that period. The focus on the summer months is crucial to informing heat-health decision makers; hot season temperature manifests itself as a hazard to human health. The starting date 1930 was chosen because our confidence in Cooperative Observer Program-based data was lower prior to 1930 than after it (J. A. Andresen 2012, personal communication). Furthermore, the performance of the homogenization process of the USHCNv2.0-monthly dataset (Menne and

Williams 2009) was low before 1930 but high after (Hausfather et al. 2013).

The daily temperature values first needed to be converted into anomalies relative to their respective monthly means. The monthly-mean temperature ($\overline{T_{m,y}}$) from the USHCNv1-daily dataset was calculated in this manner:

$$\overline{T_{m,y}} = \frac{\sum_{d=1}^{\text{Tot_day}_m} \text{Tdaily}_{d,m,y}}{\text{Tot_day}_m}.$$

The quantity Tdaily represents the USHCNv1-daily temperature, Tot_day represents the total number of days in each month, d represents the day of the month, m represents the month, and y represents each year. This was done for months with no consecutive missing/flagged days and less than four total missing/flagged days. Months with more missing/flagged days were not used because missing/flagged data points add uncertainty to monthly-mean temperature estimates; 6.07% (6.19%) of the months for the Tmax (Tmin) variable did not pass these requirements.

Missing/flagged days were filled in via linear interpolation using the values one day before and after the date. This infilling method might affect the accuracy of single-day percentile exceedance count trends (DeGaetano et al. 2002); however, this study examines multiple-day events, and thus the infilling of a single day should be small. The error this infilling introduces into estimating the monthly mean is 0.03 multiplied by the degrees the estimated sum is over (or below) the actual monthly sum. For the Tmax (Tmin) variable, 7.88% (8.52%) of the total months had one missing/flagged date, 1.76% (1.94%) of the months had two missing/flagged dates, and 0.64% (0.67%) had three missing/flagged dates. Then each day's temperature was converted into an anomaly w.r.t. its monthly-mean temperature in this manner:

$$\text{Anomaly}_{d,m,y} = \text{Tdaily}_{d,m,y} - \overline{T_{m,y}},$$

The daily anomalies were combined with the USHCNv2.0-monthly dataset. First the fully adjusted (F52) September 2011 version of the dataset was acquired from the CDIAC. To create the new temperature time series, the anomaly time series was combined with the USHCNv2.0-monthly mean temperature time series in the following manner:

$$\text{NewTemperature}_{d,m,y} = \text{Tmonthly}_{m,y} + \text{Anomaly}_{d,m,y},$$

where Tmonthly represents the USHCNv2.0-monthly temperatures. The resulting time series at each station

composed the new dataset and retained both the homogenization of the USHCNv2.0-monthly dataset and the daily variability of the USHCNv1-daily dataset. This process has its limitations and is at best an empirical method. The assumption that the monthly homogenization adjustments made in the USHCNv2.0-monthly dataset apply equally to all daily values (within that month) may be weak, but since its accuracy is likely invariable with time the effect on a trend analysis should be minimal.

b. Station selection

Three time periods—1930–70, 1970–2010, and 1930–2010—were evaluated. This allowed quantification of the entire period as well as two periods of equal length. This isolated the general CONUS warming since 1970 and the general cooling between the mid-1930s and 1970 (Menne et al. 2009; Hansen et al. 2010), which informs the description of uncertainty for end users. Splitting the total period into separate sections improved spatial density as compared with the full time span. Even when accounting for spatial variability in the sampling density in the calculations of the CONUS spatial mean (CONUS mean) trends, some uncertainty still exists from sampling at different locations. Results were confirmed by recalculating half-period trends using the 161 overlapping stations.

Since the resulting temporally downscaled dataset was not serially complete, a series of quality criteria were needed to filter out inappropriate stations. These requirements were applied separately for each study period, and all stations meeting the requirements during that study period were retained. Stations used for 1930–2010 were required to pass the requirements for both 1930–70 and 1970–2010.

The first criterion insured each station would have enough data to assume variability due to missing data was small. Specifically, each station was required to (i) have available data for at least 80% of the years in the period, (ii) have available data at least 70% of the years within each half of each period, and (iii) have available data for both the first or second and last or second-to-last years in the period. A year's data were only considered *available* if all five summer months were present for both daily temperature extremes. This left 581 stations for 1930–70, 312 stations for 1970–2010, and 171 stations for 1930–2010. The discrepancy between early and late periods was due to the amount of available data within our temporally downscaled dataset. Each station was sequentially tested for meeting the aforementioned (i), (ii), and then (iii) requirements and resulted in 844, 33, and 29 disqualifications (respectively) in 1970–2010 and 564, 34, and 39 disqualifications

in 1930–70. The amount of available data in the resulting dataset was controlled by both the completeness of the USHCNv1-daily dataset and the station density of the USHCNv2.0-monthly dataset (the USHCNv2.0-monthly dataset is serially complete but not all stations span the entire dataset). Interestingly, the USHCNv2.0-monthly dataset station density was lowest at the end of the 1930–2010 period (Menne et al. 2009).

The next criterion focused on station siting quality. A list of station rankings was acquired from surfacestation.org (http://surfacestations.org/fall_etal_2011.htm on 14 February 2012) and any station with the lowest ranking was excluded. This further reduced the number of stations for 1930–70 to 546, 1970–2010 to 303, and 1930–2010 to 165.

The next criterion was sufficient data for a climate base sample. Here the availability was determined at the monthly level and it was not dependent on the other daily extreme. The specific requirement was to have at least 125 available months and at least 25 years of available data for each month during that climatological period. This brought the number of stations for 1930–70 to 543, for 1970–2010 to 302, and for 1930–2010 to 165. The last criterion was based on originality of the monthly values from the USHCNv2.0-monthly dataset. At least 80% of the present months in the period were required to be original values (i.e., not filled in/estimated within the USHCNv2.0-monthly dataset). This reduced the number of stations for 1930–70 to 541 and for 1970–2010 to 295, and the number of stations in both periods to 161.

c. Percentiles

Each station's time series of temperature was turned into a time series of percentiles relative to both calendar date and station. These percentiles are sensitive to the geographical location and the annual cycle, thus accounting for human adaption and accordingly important to the heat–health discussion. The percentiles at each station were determined from the values at that station during a common period called the climate base period. Here the climate base period for 1930–70 was 1941–70 and the climate base period for both 1970–2010 and 1930–2010 was 1970–99. These climate base periods exclude the hot decades of the 1930s and 2000s.

The method of selecting the values within the climate base period for calculating the percentiles was a window size of 15 consecutive days centered on the date (Fig. 1). To avoid the climate-base-period-related inhomogeneity (Zhang et al. 2005), methods similar to those of Zhang et al. (2005) were used to ensure that a temperature observation was not used to calculate its own percentile value (i.e., an average of the other 29 yr within the climate base period replaced that value). The percentiles

FIG. 1. Two schematics. (top) How EHEs are diagnosed. Light (dark) colored bars indicate Tmax (Tmin) percentile exceedance on that date. The Tmin EHE dates are 8, 9, 14, 15, and 25–30 Jul; Tmax EHE dates are 8, 9, 15, 16, 24, 25, 28, and 29 Jul; two Tmnx EHEs exist and are diagnosed as two days in length (8 and 9 Jul), and two days (24–26 Jul) and 2.5 days (28–30 Jul) in length. (bottom) The calendar date-dynamic climate base sample used to calculate the percentiles at each station; 30 years of the dates marked with a dark gray (light gray, mild gray) line through them determined the percentiles on the date marked with a dark gray (light gray, mild gray) X.

were calculated empirically; first the empirical cumulative distribution function (Kaplan and Meier 1958) was calculated, which assigned a percentile (y_o) to each temperature value (x_o) from the climate base period sample. Subsequently, bilinear interpolation was used to find the value (y_i) of the aforementioned percentile function (y_o) at the target temperature value point (x_i) in the climate base period temperature function (x_o). If the target temperature value (x_i) was larger (smaller) than any value in the climate base period sample (x_o) then it (y_i) was assigned a 1.0 (0.0).

d. Extreme heat events

The exceedance threshold in EHE definitions varies throughout the literature but is typically between the

81st and 99th percentiles. This study chose the 92.5th percentile because 1) the 90th percentile was exceeded too frequently (Zhang et al. 2012), 2) the 99th percentile was exceeded too infrequently (Zhang et al. 2012), and 3) the higher the percentile the more uncertainty exists in the mathematical estimation of that percentile.

EHE duration requirements also vary throughout the literature. Here trends in EHE duration were explicitly quantified, so this study only required *any* duration, and thus two consecutive dates with percentiles over the 92.5th percentile were required to start an EHE. Requirements of EHE continuation also vary; some studies require consecutive exceedances of the threshold (e.g., Alexander et al. 2006; New et al. 2006; Griffiths and Bradley 2007) and others require an EHE-mean

temperature to stay above a threshold (e.g., Huth et al. 2000; Meehl and Tebaldi 2004). The current study terminated an EHE when the EHE-mean percentile no longer exceeded the 92.5th percentile threshold. By using the EHE-mean percentile, an extended EHE in which a single day in the middle modestly falls below the daily percentile threshold is counted as a single heat event. This improves relevance to human health, as humans may perceive periods of hot weather as one event without distinguishing slightly missing a statistical threshold. The EHE-mean percentiles ($\bar{P}$) were calculated as follows:

$$\bar{P}_i = \frac{\sum_{n=1}^i P_n}{i},$$

where n represents each day within an EHE and i represents the day number within the EHE.

EHEs requiring (i) only daily minimum compliance (Tmin type), (ii) only daily maximum compliance (Tmax type), and (iii) both minimum and maximum compliance (Tmnx type) were investigated. In this study EHE *type* refers to one of these three EHEs and is used to differentiate between EHEs with definitions based on the different daily extremes. Distinguishing Tmnx EHEs from Tmax and Tmin EHEs was essential because from 1930–2010 during a Tmin or Tmax EHE date the opposing daily extreme percentile was over the same threshold (92.5 percentile) roughly 35% of the time, over a lower threshold (80.0 percentile) around 60% of the time, and above normal (50.0 percentile) about 85% of the time.

Tmnx-type EHEs were diagnosed using the time series of Tmin and Tmax EHEs. Tmnx EHEs were triggered when either 1) two calendar dates overlapped of Tmin and Tmax EHEs or 2) the two Tmax EHE dates were one single date behind the Tmin-type dates (Fig. 1). A Tmnx EHE event continued until a date was reached that was not diagnosed as an EHE by either Tmin or Tmax type. Thus, half days were the temporal resolution of the Tmnx EHE diagnosis and whole days were used for Tmin and Tmax EHEs (Fig. 1). Since this study focused on the summertime the earliest (latest) possible EHE start (end) date was 15 May (September).

The following five specific EHE *characteristics* were calculated for every year that the station had available data: the number of EHEs, the total number of days categorized as EHEs (EHE days), the mean EHE duration, the mean EHE intensity, and the sum of all EHE intensities. The EHE mean duration, number per year, and intensity were considered specific characteristics

because they focused on particular aspects of EHEs, whereas EHE days and sum intensity were considered inclusive characteristics because they describe the combination of multiple aspects of EHEs. To examine the relationships between the different EHE characteristics Pearson's correlation coefficients were calculated over the 1930–2010 period using the CONUS-mean time series.

The intensity for each EHE was calculated in a cumulative degree-day manner, similarly to Díaz et al. (2006). However, here percentiles replaced the role of temperatures. Calculating the intensity (w.r.t. either daily temperature extreme) was determined by

$$\text{Intensity}_x = \sum_{\text{dur}_x}^{n=1} (P_n - 92.5),$$

where x represents each EHE, dur represents the duration in days for that EHE, n represents each day within that EHE, and P represents each date's percentile. Percentiles below the 92.5 value were set to 92.5. The intensity was based on the daily maximum percentiles only for the Tmax EHE type, on the daily minimum percentiles for the Tmin EHE type, and on both daily minimum and maximum percentiles for the Tmnx EHE type. The intensity was calculated for each EHE and the units are referred to as cumulative percentile exceedances (CPEs). CPEs depend on how far the percentiles exceeded the threshold and how long the event lasted. The sum intensity then depends on both mean intensity and the number of events in a summer.

e. Sensitivity to time, space, and EHE definition

The linear trends of each EHE characteristic for the three time periods were calculated for each EHE type and station. Both the magnitude and significance of trends were determined through the often-used least squares regression method. Significance refers to non-inclusion of the zero value within the 90% confidence interval. While the results were verified with non-parametric alternatives (not shown), the study was not primarily undertaken using them because the impact of missing values on nonparametric tests.

When calculating the CONUS means, two separate methods were employed for added confidence. The first was used to create time series, per region and EHE type, from 1930 to 2010. The country was divided into six geographical regions: northwest, southwest, north-central, south-central, northeast, and southeast; delineated using the 100° longitude line, the 39.72° latitude line, and either the 83° or 87° longitude line (in the north and south, respectively). Then stations that spanned 1930–2010 within the regional boundaries produced

arithmetic means for each region (*regional means*). The CONUS mean was then the areal-weighted mean of the regional means.

The second method determined the CONUS-mean linear trends for each period. Grids over the CONUS at 100-km resolution were filled by the estimated linear trends (at each station) within their boundaries using the nearest-neighbor spatial interpolation method (Gold 1991), which places randomly spaced data onto the nearest locations of a grid. Grids without stations in their boundaries had values filled in by solving Poisson's equation via relaxation over the input domain using the National Center for Atmospheric Research (NCAR) Command Language (NCL) software (Brown et al. 2012). The CONUS means were calculated with all the retained grid points by weighting grid values by the cosine of the latitude.

The spatial characteristics of the different trends were examined via maps showing the trend magnitudes at each station and their significance. Visual analysis allows one to look beyond the spatial coverage biases and differences when assessing spatial patterns and scales of spatial variability.

To explore the relationships between the trends in Tmin, Tmax, and Tmnx EHE types, Pearson's correlation coefficients were calculated across all stations between the Tmin and Tmax, the Tmin and Tmnx, and the Tmax and Tmnx trend magnitudes. To further explore the relationships between the EHE type trends, Student's *t* tests determined if the arithmetic mean trend magnitudes of the different EHE type trends were statistically different at the 0.01 significance level. The spatial coverages were identical across the comparisons and thus spatial coverage differences should be minimized.

3. Results

The arithmetic means for all EHE characteristics over all stations and years are listed in Table 1 for both the 1930–70 and 1970–2010 periods. Compared to EHEs based on both the maximum and minimum temperatures (Tmnx), EHEs based on the daily maximum (Tmax type) and those based on the daily minimum (Tmin type) had roughly twice the number of events per summer, 1.5 times the duration but 75% of the intensity. These results also indicate Tmax-type EHEs are typically slightly longer, more frequent, and more intense than Tmin-type EHEs.

Time series of the CONUS-mean EHE days for all three EHE types (Fig. 2) demonstrated both temporal and regional variability of EHEs. They showed parallels in the behavior of different EHE types (e.g., fewer EHE days during the 1960s and 1970s) and dissimilarities (e.g., a stronger recent increase in Tmin EHEs and

TABLE 1. Mean EHE characterization values per year. Listed are the sample means (with standard deviations in parentheses) of the temporal means. Each EHE characterization metric, both periods, and all three EHE types are listed. Intensity is in units of cumulative percentile exceedances (described in text).

Variable	Tmin EHE	Tmax EHE	Tmnx EHE
1930–70 period (<i>n</i> = 541)			
No. of EHE	2.1(0.3)	2.5(0.4)	1.0(0.4)
No. of EHE days	7.5(1.7)	11.0(2.3)	3.7(1.7)
Mean EHE duration	2.7(0.4)	3.5(0.6)	1.9(0.7)
Mean EHE intensity	10.0(1.6)	12.9(2.1)	15.3(5.7)
Sum EHE intensities	27.6(6.6)	41.9(9.7)	30.9(15.3)
1970–2010 period (<i>n</i> = 295)			
No. of EHE	2.3(0.3)	2.5(0.4)	1.0(0.3)
No. of EHE days	8.1(1.7)	9.8(1.8)	3.3(1.1)
Mean EHE duration	3.0(0.4)	3.2(0.5)	1.9(0.5)
Mean EHE intensity	10.6(1.4)	11.5(1.7)	15.0(4.0)
Sum EHE intensities	29.6(6.1)	36.0(6.7)	28.3(8.9)

stronger past decrease in Tmax EHEs). Correlation coefficients between time series of different EHE characteristics of the same EHE type (Table S1, found in the supplemental material) indicated they behaved coherently; the lowest coefficient being 0.85 (mean duration, number of EHEs per year) and highest being 0.99 (sum EHE intensity, EHE days).

The results of CONUS-mean linear trends are provided in Table 2. All EHE type trends were negative in the 1930–70 period and positive in the 1970–2010 period. However, for the Tmin (Tmax) type EHE, the increase during 1970–2010 was larger (smaller) in magnitude than the 1930–70 decrease. This led to negative (positive) trends in 1930–2010 for Tmax (Tmin) type EHE characteristics. For the Tmnx type of EHE, the two time periods had increasing and decreasing trends of similar magnitude, which led to small positive trend magnitudes during 1930–2010. The 1930–2010 CONUS-mean EHE duration trends and the trends in the number of EHEs were stronger in Tmin than in Tmax EHEs, but the mean EHE intensity trend was stronger in Tmax. This resulted in stronger EHE day trends in Tmin but stronger sum EHE intensity trends in Tmax. Last, there is uncertainty from using different stations during different periods; however, the results of trends recalculated only using the overlapping 161 stations (not shown) indicated it to be negligible.

Trend maps indicate both small-scale (i.e., sub-regional) as well as regional-scale spatial variability. The small-scale variability might arise physically in part from the local level where land cover–land use (LCLU) play larger roles (Gallo et al. 1996); Pielke et al. (2011) note LCLU has significantly changed since 1920.

FIG. 2. Time series of regional and CONUS mean number of EHE days per summer. The legend assigning colors to specific regions indicates the percentage of the number of stations used to create the regional mean and the spatial weight of the region in the CONUS mean.

Additionally, because the majority of stations have some amount of missing data, differences in which years are missing between stations also cause small-scale variability in linear trend estimations. Differences in the regional-scale spatial patterns were not distinguishable between different EHE characteristics (Fig. 3), and so only the EHE characteristic-wide spatial patterns are described below; the individual maps are available as supplemental material (Figs. S1–S8). Albeit small, the

largest discrepancies in spatial patterns between EHE characteristics were observed between the mean duration and number per year. Differences in regional spatial patterns between different EHE types were noticeable but not as large as the differences between time periods.

The first maps are those of the trends in the mean EHE duration during 1930–70 (Fig. 4). Here the stations with decreasing trends outnumbered those with

TABLE 2. CONUS spatial mean of the decadal trends in EHE characteristics. Values are arranged by EHE characteristic and type of EHE. In each cell (left to right) are the values for the 1930–70, 1970–2010, and 1930–2010 periods.

EHE characteristic	Tmin EHE	Tmax EHE	Tmnx EHE
No. of EHEs	−0.24, 0.43, 0.10	−0.38, 0.28, −0.05	−0.19, 0.23, 0.02
No. of EHE days	−1.02, 2.13, 0.51	−2.23, 1.56, −0.42	−0.84, 0.96, 0.06
Mean EHE duration	−0.13, 0.34, 0.12	−0.30, 0.20, −0.08	−0.23, 0.29, 0.04
Mean EHE intensity	−0.63, 1.36, 0.38	−1.57, 0.99, −0.41	−2.37, 2.50, 0.24
Sum EHE intensities	−4.33, 8.09, 1.71	−10.22, 6.46, −2.02	−8.07, 7.91, 0.14

FIG. 3. The decadal trends of EHE characteristics in Tmnx-type EHEs at each station during the 1970–2010 period. The trend significance ($\alpha = 0.10$) is indicated by symbol color. The size-changing symbols in each panel are based on standard deviations away from the 0 value and are different for each map. (a) The trends in the number of EHEs, (b) the number of EHE days, (c) the mean EHE duration, (d) the mean EHE intensity, and (e) the sum of all EHEs intensities per year.

FIG. 4. The decadal trends at each station in the mean duration of EHEs during the 1930–70 period in (top) Tmin-based, (middle) Tmnx-based, and (bottom) Tmax-based EHEs. The trend significance ($\alpha = 0.10$) is indicated by the symbol color. The size-changing symbols in each panel are based on standard deviations away from the 0 value and are different for each map.

increasing trends. The common pattern was that of decrease from Montana eastward as far as New England and southward through most of the Southeast. The area from roughly Texas westward and northwestward to

the West Coast was mixed to generally increasing. The areas of decrease were more convincing in the Tmax-type EHE trends, and the areas of mixed sign were more positive biased in the Tmin-type EHE. The Tmnx-type

FIG. 5. As in Fig. 4, but for the 1970–2010 period.

EHE trend spatial pattern appeared to be a mixture of the other two EHE types.

Maps of the trends during 1970–2010 (Fig. 5) show increasing trends outnumbered the decreasing trends.

The common spatial pattern was that of a loose horseshoe shape of increase (e.g., increase in the west, south, and east parts of the CONUS). The northern areas were mixed but favored decreasing trends. There existed

two areas of decrease: one roughly centered on Idaho and another on Minnesota. Areas of increase and decrease varied in strength depending on EHE type, with the Tmin (Tmax) type showing more increase (decrease). The area from central Texas north through Missouri and Arkansas generally changed dominant sign based on EHE type. The Tmnx EHE trend spatial patterns were a mix of the other two EHE types.

Maps of trends during 1930–2010 (Fig. 6) showed both the most prominent regional-scale variability and the most evenhanded numbers of increasing and decreasing trends. The general spatial pattern was that of decreasing trends in the continental center (extending north and east), and increasing trends in the west, northeast, southeast, and south areas. Consistent with the other time periods, the areas of increase (decrease) are prominent in the Tmin (Tmax) EHE type trends, and the Tmnx EHE type trend spatial patterns were somewhat a mix between the two.

The results of the correlation coefficients and Student's *t* tests between the EHE types are shown in Table 3. The correlation coefficients between the EHE characteristics of the Tmin and Tmax EHE types were notably smaller than those between either types and the Tmnx type. Student's *t* test results showed that the arithmetic means were usually statistically different between EHE types. While about 20% of the Tmin and Tmnx and Tmax and Tmnx means were statistically dissimilar, all means were dissimilar between Tmax and Tmin types. Although slight, correlation coefficients indicated stronger relationships between Tmin and Tmnx EHE trends than Tmax and Tmnx EHE trends.

4. Discussion

Empirically linking physical drivers to the continental-scale trend variability was beyond the scope of this study; however, discussion of the physical relationships is an important part of the uncertainty description supporting usability of weather and climate data. Internal variability, LCLU, and moisture trends are considered below.

There are several possible driving mechanisms categorized as climate system oscillations at decadal scales and longer. Oscillations of sea surface temperatures (SSTs) in the Atlantic and Pacific Ocean basins, such as the Pacific decadal oscillation (PDO), interdecadal Pacific oscillation (IPO), El Niño–Southern Oscillation, and the Atlantic multidecadal oscillation (AMO), affect the CONUS climate through teleconnections. These oscillations play major roles in CONUS-mean summertime daily minimum and maximum temperatures (Robinson et al. 2002; Alfaro et al. 2006; McCabe et al.

2004). For example, during 1930–70 the PDO index values generally decreased and during 1970–2010 they increased; this might explain the 1930–70 (1970–2010) decrease (increase) in EHE activity. McCabe et al. (2004) demonstrated that oscillations of the IPO–PDO and AMO could account for 52% of the spatial and temporal variance over the CONUS. Other works (e.g., Pan et al. 2004; Robinson et al. 2002) have also linked the decrease in the central CONUS (i.e., the “warming hole”) to Pacific and Atlantic Ocean basin oscillations.

LCLU changes provide insight into the differences in trends between daily minimum and maximum temperatures (e.g., Pielke et al. 2011), and likewise the existence of differences between trends in Tmin and Tmax EHEs might suggest relevancy of physical mechanisms that act oppositely on different daily extremes. For instance, the United States irrigation statistics indicate substantial increases during 1930–70 compared to those during 1970–2010 (USGS 2012; Segal et al. 1998). Misra et al. (2012) showed agricultural irrigation affects both daily extremes oppositely, and thus the 1930–70 period trends would work against the daily minimum decreasing trends and aide the decreasing trends in daily maximum temperatures.

Another potential influencer is that during 1970–2010 more land area was developed (urban, exurban) than during 1930–70 (Brown et al. 2005); it is possibly responsible for the large Tmin increase during 1970–2010 relative to 1930–70. Any urbanization biases the homogenization algorithm (Menne et al. 2009) failed to eliminate would increase the daily minimum temperatures preferentially (Hausfather et al. 2013). Fall et al. (2010) demonstrated that surface temperature trends can both be a function of LCLU type and be impacted by LCLU changes (e.g., agricultural to urban). For instance, Fall et al. (2010) demonstrated the temperature trends in agriculture LCLU types were shown to have decreased during the 1979–2003 period. The agriculture LCLU type spatially occupies much of the area of decrease during 1970–2010 found in this study (i.e., the central and east-central CONUS).

Atmospheric water vapor trends also should impact Tmin and Tmax EHE type trends. Gershunov et al. (2009) showed high water vapor levels to be conducive (nonconductive) to Tmin (Tmax) type EHEs. Brown and DeGaetano (2013) showed CONUS-mean dewpoint temperature and specific humidity generally decreased (increased) during 1930–70 (1970–2010). This should have encouraged Tmin (Tmax) type EHE decrease (increase) in 1930–70 and Tmin (Tmax) type EHE increase (decrease) in 1970–2010. This could describe the discrepancies in the trends of Tmin and Tmax EHEs during 1970–2010, but not during 1930–70.

FIG. 6. As in Fig. 4, but for the 1930–2010 period.

TABLE 3. Pearson's correlation coefficients and Student's *t* tests between trends of different EHE types. Three values are displayed representing the three time periods (1930–70, 1970–2010, and 1930–2010) for each metric for the three different EHE types. Regular font values indicate the means are statistically not equal at the 0.01 significance level, and boldface font values signify a failure to prove they are not.

EHE characteristic	Tmin/Tmax	Tmin/Tmnx	Tmax/Tmnx
No. of EHEs	0.36, 0.38, 0.35	0.75 , 0.70, 0.79	0.69, 0.78 , 0.69
No. of EHE days	0.42, 0.42, 0.32	0.78 , 0.76, 0.82	0.76, 0.78 , 0.69
Mean EHE duration	0.21, 0.36, 0.34	0.72, 0.72 , 0.82	0.59, 0.67, 0.69
Mean EHE intensity	0.26, 0.32, 0.35	0.72, 0.69, 0.82	0.65, 0.67, 0.71
Sum EHE intensities	0.44, 0.39, 0.34	0.77, 0.73 , 0.820	79, 0.78 , 0.70

McCabe et al. (2004) suggested 22% of the spatial and temporal variance was explainable by drought indices (often related to SST oscillations). Brown and DeGaetano (2013) observed that the central CONUS experienced atmospheric moistening since 1930 while other regions experienced drying. This moistening is similarly located (spatially) with the region of EHE decrease in the central CONUS. The noted area of disagreement between Tmax and Tmin EHEs from central Texas north through Missouri and Arkansas is an area where aerosol–circulation feedbacks may have induced more precipitation during 1998–2007 (A. L. Steiner 2013, personal communication).

5. Conclusions

Over the 1930–2010 time span the sign of the trend in EHE characteristics (e.g., number, total days, mean duration, etc.) was a function of EHE type. Such a conclusion was cemented by results of CONUS-mean linear trends that showed during 1930–2010 all characteristics increased for the Tmin-type EHEs, decreased for the Tmax-type EHEs, and increased by an order of magnitude less for the Tmnx-type EHEs. The CONUS-mean time series of EHE days also supported these conclusions. In contrast, DeGaetano and Allen (2002) indicated decreasing continental trends in both Tmax EHEs and Tmin EHEs in 1930–96 (Tmin trends were smaller). The 14 additional (recent) years in our study potentially account for the disagreement (i.e., Tmin-type EHE increase instead of decrease).

EHE characteristics decreased over the 1930–70 period (Tmax-type EHEs most prominently), and increased over the 1970–2010 period (Tmin-type EHEs most prominently). The CONUS-mean EHE characteristics' results demonstrated that during 1930–70 all EHE characteristics decreased regardless of EHE type, and during 1970–2010 all EHE characteristics increased. Time series of the number of EHE days for all EHE types supported these conclusions. Since climate oscillations often drive multidecadal trends, further examination of the roles of climate oscillations relevant to

summertime CONUS extreme temperatures would be informative.

Shen et al. (2011) demonstrated similar trends in summertime mean daily minimum and maximum temperatures—both decreased during the 1946–75 period and increased during the 1976–2000 period. DeGaetano and Allen (2002) indicated a stronger decrease in extreme percentiles of daily maximums than minimums during 1930–96 and a stronger increase in the minimums than maximums during 1970–96. Peterson et al. (2008) showed that both daily minimum and maximum extreme percentiles decreased during 1950–70 and increased during 1970–2005. DeGaetano and Allen (2002) demonstrated during 1960–96 the percentage of increasing trend stations was larger than the percentage of decreasing stations. Thus similar to the CONUS-mean temperatures (e.g., Shen et al. 2011; Hansen et al. 2010), EHEs decreased from the mid-1930s until the late 1970s and then increased until at least 2010, albeit there were signs in our results (not shown) that suggested the summer mean temperatures were not always trending the same as the EHEs.

Regional and small-scale spatial variability existed across the CONUS for all periods, EHE characteristics, and EHE types. Small-scale variability was plainly seen in the maps, as was regional-scale variability. Examples of regional variability might be the lack of warming in the north-central CONUS during 1970–2010 or the cooling in the central CONUS region during 1930–2010. Conclusions of regional variability were also reinforced by the time series results.

Several other studies also showed regional-scale spatial variability (Gaffen and Ross 1998; DeGaetano and Allen 2002; Peterson et al. 2008; Portmann et al. 2009; Wu et al. 2012). The existence of substantial regional variability in the past insinuates CONUS-mean trends are not representative of trends in each region and differences between regions will also exist in the future. Thus regional analyses may be essential to regional and local heat–health decision makers. Several studies confirmed the existence of small-scale spatial variability (e.g., Gaffen and Ross 1998; DeGaetano and Allen 2002;

Portmann et al. 2009). The presence of notable small-scale variability is a source of uncertainty in regional and subregional EHE trend analyses.

The different EHE characteristics behaved coherently. This was evidenced by the nearly indistinguishable spatial patterns of different EHE characteristic trends and strong temporal correlations with one another, and by the CONUS-mean trends showing the same signs. Other multiaspect EHE studies also showed general agreement across trends in the different characteristics of EHEs (Kuglitsch et al. 2010; Gershunov et al. 2009; Perkins and Alexander 2013). This might suggest similar coherency in future changes in EHE characteristics as opposed to the number of EHEs decreasing at the duration's expense.

The different EHE types behaved less coherently than the characteristics of an individual type. Relationships found between EHE characteristics of T_{min} and T_{max} types were modest. By definition EHE characteristics in T_{mnx} trends are coupled to T_{max} and T_{min} EHEs and the relationships were strong (e.g., 0.6–0.8) but short of very strong (>0.8). The correlation coefficients and maps confirmed such conclusions regarding spatial structure, and Student's *t* tests confirmed them w.r.t. the large-scale arithmetic mean trends. These conclusions should convey to the climatologist that the different daily temperature extremes likely respond differently to changes in the climate system. Mathematically speaking, examination of both daily extremes relationships to the forcing variables controlling the same climate system is akin to having two solution sets.

These conclusions are consistent with Portmann et al. (2009) that showed different spatial patterns and CONUS means in the 90th percentile exceedance occurrences for minimum and maximum temperatures. Also the Gaffen and Ross (1998) results support these conclusions; they showed meaningful differences in both CONUS and regional-mean trends in the daily minimum and maximum apparent temperature percentile exceedances.

It is unusual for the dissimilarities of EHEs based on different daily temperature extremes to be discussed in EHE trend analyses. It is not obvious that the trends of EHEs depend on which daily extreme(s) is (are) required to be elevated, particularly to scientists outside the climate community. Which extreme is optimal depends on both the region and purpose, and was outside the scope of this study. The conclusions of the current study imply that changes in T_{min} and T_{max} EHEs are limited in their representativeness of changes in EHEs with requirements on both daily extremes (T_{mnx}). Trends in EHEs with both daily extremes exceeding thresholds could be quantified in trend analyses more

frequently. An epidemiological assessment linking mortality to events requiring both daily extremes to be over a threshold could further knowledge about this type of EHE.

Comparing results between extreme temperature trend analyses with different periods is problematic because linear trends are highly sensitive to many factors. For example, they are sensitive to the time period, seasonal focus, and daily temperature extreme. Generally, linear trends are limited in their ability to describe the temporal behavior of any variable in the nonlinearly behaving climate system. Despite this, maps were created to match the time periods of other studies such as 1950–2006 in the Portmann et al. (2009) study (supplemental Fig. S9), 1960–96 in the DeGaetano and Allen (2002) study (Fig. S10), 1950–2004 in the Peterson et al. (2008) paper (Fig. S11), and 1950–99 in the Meehl et al. (2012) paper (Fig. S12). It should be noted that the stations used to create these maps were not chosen with the data availability of these time periods in mind but rather the stations for the 1930–2010 period; thus additional spatial noise arises in these maps because of the effect of missing years. It was felt the disparities between our results and comparable studies' results were explainable by the differences in the data presented in the figures.

Additionally, our results show the “warming hole” investigated by multiple studies (e.g., Kunkel et al. 2006; Pan et al. 2004; Robinson et al. 2002; Meehl et al. 2012). There is debate of what mechanisms are causing the warming hole. Pan et al. (2004) demonstrated changes in the low-level jet from the gulf to the plains lead to soil moisture changes that suppressed daily maximum temperatures. Regardless of mechanism, the moisture levels have increased in this region (Brown and DeGaetano 2013). Misra et al. (2012) showed increased irrigation statistics to increase (decrease) daily minimum (maximum) temperatures. However, a decrease was seen in both T_{min} and T_{max} EHEs (albeit T_{min} EHE type showed a weaker decrease). Thus, a hypothesis that works with these results is while soil moisture efficiently suppressed T_{max} it did not increase T_{min} as much as the T_{max}–T_{min} coupling mechanism (Gershunov et al. 2009) decreased T_{min}. An analysis of the T_{max}–T_{min} coupling mechanism (e.g., which daily extreme temperature is better linked with its trailing opposite daily extreme temperature) would provide relevant knowledge to the EHE field.

With regard to describing changes in EHEs as related to human health effects, the results here show that EHEs are not a simple function in a warming climate; that is, as the planet warms EHEs do not uniformly increase

everywhere. There are important regional effects related to internal variability of the atmosphere, LCLU changes, and water vapor trends. Integrated analysis of all of these sources of variability is needed to describe the uncertainty and for the incorporation of climate information into planning.

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