Increased risk of heat waves in Florida: Characterizing changes in bivariate heat wave risk using extreme value analysis

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Abstract

Maximum and minimum daily temperatures from the second half of the 20th century are examined using a high resolution dataset of 833 grid cells across the state of Florida. A bivariate Extreme Value Analysis Point Process approach is used to model characteristics including the frequency, magnitude, duration, and timing of periods or heat waves during which both daily maximum and minimum temperatures exceed their respective 90th percentile thresholds. Variability in heat wave characteristics is examined across the state to give an indication of those areas where heat waves with certain characteristics may be more likely to occur. Changes in heat wave characteristics through time are examined by halving the temperature record and determining changes to heat wave characteristics between the two periods. This exploration of changes in heat wave risk through time gives a possible suggestion of trends in future heat wave risk. Findings indicate that there is considerable spatial variability in heat wave characteristics although heat waves have become increasingly frequent and intense throughout much of the state.

Introduction

Heat waves are meteorological events that can have pronounced impacts on mortality (CDC, 2006; Comrie, 2007; Ebi, 2008). The occurrence of heat waves and their detrimental health impacts are evident in recent episodes, such as those in 2003 (Europe), 2010 (Russia), and 2012 (U.S.). High temperatures exacerbate pre-existing medical conditions and cause overall death rates to increase, especially when the temperature rises above the local population’s threshold or critical value (Comrie, 2007; Ebi, 2008; Hajat, Kovats, Atkinson, & Haines, 2002; Kunst, Looman, & Mackenbach, 1993; World Health Organization Europe, 1998). Events occurring very early or late within the expected hot season may have greater epidemiological significance and therefore the timing of events is also an important consideration (Sheridan & Kalkstein, 2004). Health impacts are not only the result of the maximum daily temperatures, but also high minima which prevent night-time relief (Hajat et al, 2006). Heat waves are reportedly occurring more frequently across much of the globe, and under a warming climate they are expected to increase in frequency, intensity, and duration (Counou & Rahmstorf, 2012; Grumm, 2011; IPCC, 2012; WMO, 2012). Epidemiological studies have found that aged and high-density populations are at increased health risk during a heat wave (Vandentorren et al., 2006; Hajat and Kosatsky, 2010).

Florida, the fourth most populous state with a relatively large proportion of its population over the age of 65 (U.S. Census Bureau, 2011) is therefore an important location for the study of heat waves. A study of temperature effects on mortality in cities in the Eastern U.S. found that the rate of increase in heat-related mortality in Miami and Jacksonville was greater than several more northern locations (Curriero et al., 2002). Heat waves can be viewed as extreme meteorological events involving a crossing of a high threshold and can be characterized using extreme value theory. A statistical investigation of these events based in extreme value theory allows for a characterization of their magnitude, frequency, timing, and duration (Coles, 2001; Furrer, Katz, Walter, & Furrer, 2010; Keellings & Waylen 2012; Waylen, Keellings, & Qiu, 2012).

This paper seeks to examine changes in probability or risk of heat wave (combined high maxima and minima) characteristics (magnitude, frequency, timing, and duration) during the second half of the 20th century across Florida. We take an approach based on bivariate extreme value theory in which we examine simultaneous crossings of both high daily maximum and minimum temperatures. This novel approach allows for an exploration of spatial patterns of changes in climatological heat wave risk that moves beyond univariate extremes to provide a more complete characterization of heat waves while also giving an indication of future trends.

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Heat wave definition

Heat waves can be defined as a sequence of days/night with maximum/minimum temperature above a certain high percentile threshold, which have various been described as being between the 90th and 99th percentiles of the entire daily temperature distribution (Anderson & Bell, 2009; Hajat et al. 2006). In this study, the 90th percentile of the entire distribution of daily maximum and minimum temperature is adopted as a common threshold to identify an extremely hot day. These threshold levels are calculated separately for each grid point from the entire temperature record (1949–2000) at each grid point. However the methods developed are equally suitable for use with other thresholds, defined in either the frequency (percentiles) or magnitude (temperature) domains, for specific applications. Heat waves can also be defined by their duration in terms of how many consecutive days of above threshold temperatures occur (Tan et al., 2017). In this study, a duration criterion of at least 2 days of consecutive above threshold days is set.

High maximum daily temperatures may be accompanied by relatively low nightly minimum temperatures that provide relief from daytime heat. The separate occurrence of both extreme high daily maximum temperatures and high daily minimum temperatures, as well as their combination, are examined in order to account for heat waves that allow little such nighttime relief.

Events are considered to be independent if separated by at least four days of below threshold temperatures, otherwise data of consecutive events are grouped. This independence criterion was set to account for the possible epidemiological significance of having fewer than four relief days between events and its choice is confirmed in medical literature by the weak association between heat-related mortality on any given day and temperatures in excess of three days prior (Curriero et al. 2002). The use of an empirical independence criterion is also necessary to satisfy the underlying statistical assumption of independence between events.

Fig. 1 illustrates the heat wave definition used in this study. It shows examples of separate events where above threshold maximum and minimum temperatures are not occurring simultaneously and are therefore not considered to be a heat wave. Two simultaneous crossings of daily maximum and daily minimum thresholds are also shown and represent two separate heat wave events with illustration of maximum exceedances in each margin, duration, events per year, and timing. The second example heat wave event contains one day of below daily maximum and two days of below daily minimum threshold temperatures and thus illustrates the use of four day independence between events which in this case is not exceeded and the series is considered to be one heat wave rather than two heat waves.

Atmospheric moisture has been shown to have an exacerbating effect on mortality, however this variable is collected at far fewer points over space and generally for shorter spans of time than temperatures. For climatological (as opposed to meteorological) purposes, large sample sizes from a long, high resolution historic dataset are favored over the shorter records some of which may contain humidity data. Given Florida’s subtropical climate, dominantly peninsular characteristics and generally southerly flow during the summer months (Winsberg, 2003), relative humidity tends to be high throughout the season during which heat waves are likely to occur. It can also be argued that by adopting a bivariate heat wave definition, including minimum temperatures, we are indirectly capturing humidity. High nighttime minima are likely accompanied by high humidity that traps heat (outgoing longwave radiation).

Theory and methods

Extreme value analysis using a point process approach is chosen to characterize and model the frequency, timing, magnitude, and duration of heat waves. This approach unifies existing approaches to the modeling of extremes, namely the peak over threshold (POT) and block maxima approaches which have been applied extensively in hydrological and climatological studies of events above high or low thresholds (Rice, 1945; Leadbetter, Lindgren, & Rootzen, 1983; Rodriguez-Iturbe & Bras, 1985; Waylen, 1988; Waylen & LeBoutillier, 1989; Goto-Maeda, Shin, & O’Brien, 2008; Waylen et al., 2012). The point process is formulated in terms of the limiting Generalized Extreme Value (GEV) distribution parameters (μ, σ, ξ) and as a result, extremal properties are characterized by only these three parameters (Coles, 2001). Modeling of the frequency and magnitude of events are effectively combined in a single model instead of being fitted separately as in the POT approach. The approach also optimizes the use of available data, unlike the traditional block (annual) maxima, approxim, as all values above the threshold are included resulting in more reliable results.

If the occurrence of a “heat wave” day is considered as a point in time, then the expected waiting time until the next event is a point process occurring randomly in time, with a variable rate — i.e. a non-homogenous Poisson process with independent occurrence of each point (Coles, 2001). Maximizing the likelihood of this Poisson process leads to estimates of the parameters μ (location or central tendency), σ (scale or variance), ξ (shape or skew) of the limiting GEV distribution of the corresponding block maximum (Coles, 2001). The cumulative distribution function of the GEV is given by:

$$P(x) = \exp \left( - \left( 1 + \frac{x - \mu}{\sigma} \right)^{-1/\xi} \right)$$

Considering N independent events exceeding a threshold u, then

$$N \sim \text{Poisson}(\lambda)$$

where
\[ P(N = n) = \frac{\Lambda^n e^{-\Lambda}}{n!} \quad \text{and} \quad \Lambda = \left[ 1 + \xi (u - \mu)/\sigma \right]^{-1/\xi} \]  

(2)

which describes a Poisson process with rate parameter (\( \Lambda \)) derived from the GEV estimated scale parameter \( \sigma \), shape parameter \( \xi \) and location parameter \( \mu \), and \( u \) equal to the threshold. The Poisson distribution assumes that events are equally likely within a time period, in this case a year. However, this assumption is unrealistic as heat wave events are strongly seasonal in their nature. The Poisson distribution should therefore be modified to include a time-dependent or non-homogeneous function:

\[ P(m(t) = n) = e^{-\lambda(t)} \cdot \lambda(t)^n/n! \]

(3)

where \( \lambda(t) \) is the mean number of events expected up to the day of the year, \( t \), and \( n \) is the number of events up to that time in a year. Modeling of distributions of the timings of events throughout the year can be accomplished through estimation of \( \lambda(t) \) by a Gaussian distribution:

\[ \lambda(t) = G(t : \mu, \sigma) \cdot \Lambda \]

(4)

where \( G(t : \mu, \sigma) \) is a Gaussian distribution fitted to the timing of events with \( \mu \) being mean date of exceedance, \( \sigma \) standard deviation, and \( \Lambda \), the annual rate.

As we are considering joint crossings of both maximum and minimum temperatures a Bivariate Generalized Pareto Distribution (GPD) is used to describe magnitudes of crossings in both the minimum and maximum margins. The cumulative distribution function of GPD is given by Coles (2001):

\[ P(x) = 1 - \left[ 1 + \frac{x - \mu}{\sigma} \right]^{-1/\xi} \]

(5)

The bivariate GPD is fitted to both margins and then both sets of marginal parameters are transformed using Coles (2001):

\[ \hat{x} = -\left( \log \left( 1 - \gamma_x \left[ 1 + \frac{x - \mu}{\sigma_x} \right]^{-1/\xi_x} \right) \right)^{-1} \]

(6)

\[ \hat{y} = -\left( \log \left( 1 - \gamma_y \left[ 1 + \frac{y - \mu}{\sigma_y} \right]^{-1/\xi_y} \right) \right)^{-1} \]

(7)

where subscripts \( x \) and \( y \) denote first (e.g. maximum temperatures) and second margin (e.g. minimum temperatures) parameters and \( \xi \) is equal to the rate of threshold exceedance in each margin. The final distribution function is then given by (Coles, 2001):

\[ F(\hat{x}, \hat{y}) = \exp \{ -V(\hat{x}, \hat{y}) \} \]

(8)

where \( V \) is equal to the asymmetric logistic dependence model:

\[ V(x, y) = \frac{1 - \theta_1}{x} + \frac{1 - \theta_2}{y} + \left[ \left( \frac{x}{\theta_1} \right)^{-1/\alpha} + \left( \frac{y}{\theta_2} \right)^{-1/\alpha} \right]^\alpha \]

(9)

where \( \theta_1 \) and \( \theta_2 \) are the asymmetry parameters and \( \alpha \) equals the dependence parameter. Independence between margins is attained when either \( \alpha = 1 \), \( \theta_1 = 0 \) or \( \theta_2 = 0 \).

The duration of events represents the length of time between successive upward and downward crossings of the temperature threshold. It is reasonable to assume that the duration of events will follow an exponential-like distribution (Cramer & Leadbetter, 1967). A discrete geometric distribution was adopted (Wilks, 2005):

\[ P(D) = \theta e^{-\theta D} \quad \text{or} \quad P(D) = (1 - \theta)^{D-1} \theta \]

(10)

where \( D \) is the duration (1, 2, 3, ...) of the event in days and \( \theta \) equals the reciprocal of the mean duration.

To analyze changes in characteristics of heat waves over 1949–2000 the temperature record is divided into two equal time periods. Changes to heat wave properties are analyzed between the two periods in a similar approach to that of Waylen et al. (2012). This date was also chosen based on evidence of increasing global temperatures from that point (see for example Xoplaki et al., 2005) and a general shift in many aspects of global climate (Chang, Yamagata, & Schopf, 2006; Chavez, Ryan, Lluch-Cota, & Niquen, 2003; Graham, 1994; Levitus, Antonov, Boyer, & Stephens, 2000; Nitta & Yamada, 1989). Division of the record in this manner allows for estimation of parameters in each period and an examination of changes in probabilities between the two periods.

**Data**

Statistical modeling of heat wave characteristics is based on historic gridded maximum and minimum daily temperature data provided by the Surface Water Modeling group at the University of Washington (Maurer, Wood, Adam, Lettenmaier, & Nijssen, 2002). The dataset is model-derived from observed data and has a spatial resolution of 0.125° yielding 833 cells covering the entire state for the period 1949–2000. These temperature data are from Co-op stations and are gridded using a synergraphic mapping system (SYMAP) algorithm and then interpolated using an asymmetric...
spline (Maurer et al., 2002). The interpolated surface provides a complete dataset, representing an advantage over historic station records which are spatially and temporally scattered and often incomplete. The dataset provides a solid basis for the probabilistic characterization of heat wave events at a high resolution which can be mapped across the entire state.

Results

Heat wave frequency

A point process approach was applied to the series at each grid cell and examples of the distribution fits are shown in Fig. 2. These

Fig. 3. Percent difference in frequency (Poisson rate parameter, \( \lambda \)) of events exceeding the 90th percentile threshold of (A) daily maximum temperature, (B) daily minimum temperature, and (C) simultaneous exceedance of daily maximum and minimum thresholds for the period 1975–2000 minus 1949–1974 divided by mean frequency for the entire record.

Changes in fitted bivariate GPD scale and shape parameters for the period 1975–2000 vs. 1949–1974. Shown for both the maximum and minimum temperature margins. A) Change in scale for maximum margin B) Change in scale for minimum margin C) Change in shape for maximum margin D) Change in shape for minimum margin.

Fig. 4. Changes in fitted bivariate GPD scale and shape parameters for the period 1975–2000 vs. 1949–1974. Shown for both the maximum and minimum temperature margins. A) Change in scale for maximum margin B) Change in scale for minimum margin C) Change in shape for maximum margin D) Change in shape for minimum margin.
diagnostic plots were used to assess model fit. They show model fit for magnitude of event, frequency of event, and duration of event. The distributions used in the modeling effort appear to give appropriate representations for the majority of events. Division of the data sets into two equal 25 year periods (pre- and post-1975) allows for an examination of changes in heat wave characteristics. Observed changes in the frequency of events are shown in Fig. 3. The occurrence of maximum daily temperature events above high thresholds has increased, particularly in southern Florida. High minimum events have also increased in number throughout much of the state with the greatest increases occurring in south Florida. Simultaneous exceedances of both high maximum and high minimum thresholds have increased throughout much of the state (80% of Florida’s total land area exhibits increased occurrence) with the largest increases occurring in highly populated central and south Florida. These findings indicate that throughout much of the state high minimum (nighttime) temperatures have increased as well as high maximum (daytime) temperatures. As a result, we can expect more events where there are simultaneous crossings of high thresholds in both daytime and nighttime temperatures. An increased prevalence of this type of event may equate to greater impacts on health due to a lack of nighttime relief from hot daytime temperatures.

**Heat wave magnitude**

Changes to the parameters of the bivariate GPD are shown in Fig. 4. Positive changes in maximum and minimum scale parameters suggest that some measure of central tendency (mean or median) of above-threshold event magnitude is increasing across much of the state, particularly in southern Florida where scale is increasing in excess of 0.4 °C. The scale parameter in the maximum margin has increased across 80% of Florida’s total land area and across 85% of the state in the case of the minimum margin. Negative changes observed in maximum and minimum shape parameters suggest that skewness (thickness of the upper tail of the distribution) of above-threshold event magnitude is increasing across much of the state, particularly with regard to the daily minimum temperature. The shape parameter has decreased in 53% of Florida’s total land area. The effect of positive changes to scale and negative changes to shape parameters of the bivariate GPD are shown for a grid cell in Fig. 5. These prevailing directions of parameter changes in the bivariate GPD suggest that higher magnitude combined maximum and minimum heat events have become increasingly likely across much of Florida, particularly as result of the increased risk of high daily minima. The “worst” combination of parameter changes in terms of elevated risk of higher magnitude (“hotter”) events would be an increase in scale and decrease in shape in both maximum and minimum margins. The “best” case in terms of decreased risk of “hotter” events would be parameter changes in the opposite direction. Fig. 6 shows where the “worst” and “best” case changes are observed. Much of north and central Florida indicates “worst” case warming as does south Florida (27% of Florida’s total land area) with comparatively few locations indicating “best” case cooling (2% of Florida’s total land area).

Fig. 5. Fitted bivariate GPD function contours for the period 1949–1974 and 1975–2000 at example cell. Contours represent cumulative probability of achieving a particular simultaneous combination of daily maximum and daily minimum temperature in each 25 year period. One minus these probabilities indicates chance of occurrence of an event reaching that magnitude of combined maximum and minimum temperature.

Fig. 6. Locations at which bivariate GPD parameters changed post 1975 to values indicating hotter events (+) and cooler events (−) with regard to magnitude of events above both high daily maximum and high daily minimum thresholds.
Heat wave duration

Observed changes in the fitted geometric distributions of the duration of bivariate events are shown in Fig. 7. Much of the state (80% of Florida’s land area) exhibits increasing duration with south Florida showing the largest relative changes. An example of the number and timing of events within the year is shown in Fig. 8. Changes to the fitted non-homogeneous Poisson function post-1975 indicate that events are occurring earlier in the summer. It also indicates that the probability of having at least one event has increased greatly.

Heat wave timing

A simple Gaussian distribution is used to model the time-dependent parameter of the Poisson function, however visual inspection of Fig. 8 suggests that this may not be optimal. Mixture models were investigated as a possible better representation of intra-seasonal variability (Fraley & Raftery, 2002; Fraley, Raftery, Murphy, & Scrucca, 2012). Within the summer months in Florida we observed throughout much of the state that the daily temperature series is somewhat bi-modal in nature. The simple link between temperature and albedo provides a likely physical explanation. Precipitation and cloud cover increase later in the summer as afternoon convective thunderstorms dominate across the state (Winsberg, 2003). However, the use of mixed-Gaussian models added little improvement to the modeling effort. Application of Hartigan’s Dip test (Hartigan, 1985; Hartigan & Hartigan, 1985) to event timing within the year revealed that the majority of the state conforms to a unimodal distribution. In 89% of the cells the null hypothesis of a unimodal distribution could not be rejected at the 0.05 significance level.

Heat wave risk

The spatial nature of changes in risk of heat wave events pre and post 1975 is shown in Fig. 9. Here we bring together the heat wave characteristics of bivariate magnitude, frequency, and duration in order to examine changes in event risk. As an example, we define an event using set maximum and minimum temperature thresholds (now defined in the magnitude rather than frequency domain) of 35 °C (95 °F) and 25 °C (77 °F) as well as a duration of above threshold temperatures of at least 4 days and annual frequency of at least one, i.e. an event occurs. Any combination of temperature thresholds, duration, and frequency could be defined and the risk simply calculated from the model parameters. In Fig. 9 it is clear that the majority of the state (75% of Florida’s land area) exhibits an increase of up to 5% with much of south Florida and the Sarasota

Fig. 7. Percent difference in duration (reciprocal of geometric distribution parameter, 1/\( q \)) of events exceeding simultaneously exceeding the 90th percentile threshold of daily maximum temperature and daily minimum temperature for the period 1975–2000 minus 1949–1974 divided by mean duration for both periods.

Fig. 8. Modeled timing of events (0, 1, 2, 3, 4) within the year shown as Poisson probability of number of events having occurred by day of the year for A) 1949–1974 and B) 1975–2000.

Fig. 9. Example of the impact that observed changes in parameter values pre and post 1975 has had on the risk (as percentage) of heat wave events simultaneously equaling or exceeding a daily maximum temperature of 35 °C (95 °F) and a daily minimum temperature of 25 °C (77 °F) for a period of at least 4 days. Shown as absolute difference in risk percentage.
area in southwest Florida increasing risk in excess of 10%. As multiple heat wave characteristics are defined here using associated distribution parameters the exact nature and spatial distribution of change in risk between time periods will vary based on the level of the selected characteristics (magnitude, frequency, duration).

Discussion and conclusions

The focus of this study is to introduce a novel approach to the statistical characterization of heat waves. We employ a bivariate definition of heat waves to account for high daily maximum temperatures as well as high nightly minima. We show how this basic modeling effort can be expanded beyond simple frequency and magnitude events to a more complete characterization accounting for duration and timing of events. There is both theoretical and empirical support for the use of the distributions chosen to characterize all aspects of heat waves investigated. Examination of changes in the fitted model parameters is a useful way of describing temporal and spatial variability in the properties of heat waves. Throughout much of the state, these changes indicate that heat waves have become increasingly more frequent in their occurrence, more intense in their magnitude, and longer in their duration. An examination of changes within the summaries are indicative that heat waves are occurring earlier and that more events can be expected throughout the summer. Many of these observed changes are more pronounced in southern Florida and in areas of rapid urban growth such as the “I-4 corridor” in the center of the state.

While the choice of distributions applied in this study are largely appropriate for more frequently observed events it is also apparent from model fits (e.g. Fig. 2(A)) that the most extreme or rarely observed events are not adequately represented. This suggests that another set of distributions may better represent the rarest events or that some controlling influence may exert itself over the most extreme events (Counoum & Rahmstorf, 2012; Sornette, 2009). Lack of extreme data makes exploring other mixed distributions problematic and treatment of external influences which may include large scale atmospheric circulation patterns is left for a future paper.

An examination of possible causes of the observed parameter changes between the two time periods is not the focus of this study. However, an additional benefit of the statistical approach employed in this paper is that each of the models used to characterize the heat wave properties are readily adaptable to include covariate terms. Such covariates as large scale atmospheric drivers including the North Atlantic Oscillation (NAO), El Niño-Southern Oscillation (ENSO), or the Atlantic Multi-decadal Oscillation (AMO) could be included. Temporal trends may also be included as covariates to account for probable non-stationarity or climate change. Improvements to the models as a result of covariate inclusion can then be assessed to determine if the covariate is a driver of any aspect of heat waves in the state. The use of covariates in the heat wave modeling effort will be the focus of a future paper.

Although the study is also not concerned directly with modeling or quantifying heat-related mortality in the populations subject to increased heat wave risk, it does illustrate the nature and spatial extent of the increased occurrence and intensity of heat waves which pose a threat to human health. Much of Florida’s population is made up of segments, such as those over the age of 65 or those of low socioeconomic status, that may be considered to be at an increased risk of heat-related mortality. The changes in climatological heat wave risk illustrated in this paper are intended to give an indication of future trends in the properties of flexibly defined heat waves employing a more complete bivariate perspective. In general, our results show areas where heat waves have become more intense and frequent and also show flexibility in how heat waves can be defined within the same modeling methodology. As we illustrated, the probability distributions and model parameters for other heat wave definitions can easily be derived without reanalysis. These models of the physical aspects of heat waves can then be integrated with population datasets and health outcome data to inform public health decision making.

References


