

Investigating teleconnection drivers of bivariate heat waves in Florida using extreme value analysis

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Abstract Maximum and minimum daily temperatures from the second half of the twentieth 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. The temperature dataset is combined with indices of the El Niño-Southern Oscillation (ENSO) and the Atlantic multi-decadal oscillation (AMO) to explore the influence of these oscillations on heat wave characteristics in Florida. In order to investigate the influence of a time varying signal (ENSO and AMO) on heat waves the signals are introduced into non-stationary models as covariates in the location and log-transformed scale parameters. The improvements to the model obtained by introducing covariates are examined using the deviance statistic whereby the difference in negative log-likelihood values between two models is tested for significance using a Chi squared distribution. Significant improvements in the non-stationary models with ENSO and AMO covariates indicate spatially varying impacts in the frequency, magnitude, and duration of heat waves. In particular, the warm phase of the AMO brings heat waves earlier in the summertime while also increasing their magnitude, frequency, and duration.

Keywords Heat wave · ENSO · AMO · Bivariate extreme value analysis · Florida

1 Introduction

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 (Coumou and Rahmstorf 2012; Grumm 2011; IPCC 2012; World Meteorological Organization 2012). In general, approaches to quantifying risk of extreme events, such as heat waves, assume stationarity in their statistical properties. However, climatological studies indicate that the statistical properties of climate records change through time due to time varying signals such as sea surface temperature (SST) oscillations and climate change (Chang et al. 2006; Chavez et al. 2003; Graham 1994; IPCC 2012; Keellings and Waylen 2012; Levitus et al. 2000; Nitta and Yamada 1989). Therefore, time-varying signals should be incorporated into the modeling of heat wave events in order to improve overall model fit and to investigate possible drivers of events. A trend analysis of heat waves could be used to explore their temporal evolution under climate change but such an approach is beneficial only after the effects of climate variability have been accounted for Kundzewicz and Robson (2004). In this study we focus on the dependence of heat waves on atmospheric oscillations rather than on trends in the observational record.

Characterizing and predicting the changing frequency, magnitude, duration, and timing of heat waves may be accomplished by combining statistical and physical approaches through inclusion of known atmospheric driving patterns within extreme value analyses (EVA). EVA is well-established in the literature and has been applied extensively to studies of extreme hydrological and meteorological events (Rice 1945; Leadbetter et al. 1983; Rodriguez-Iturbe and Bras 1985; Waylen 1988; Waylen and LeBoutillier 1989; Katz et al. 2002; Goto-Maeda et al. 2008; Waylen et al. 2012;

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Keellings and Waylen 2014). Several studies have combined EVA with atmospheric drivers to examine impacts on temperature extremes in a non-stationary fashion (Brown et al. 2008; Cebrián and Abaurrea 2006; Gershunov and Douville 2008; Unkašević and Tošić 2008; Sillmann et al. 2011). These studies were limited to an examination of temperature magnitude without inclusion of event frequency or duration. Furrer et al. (2010) combined EVA with a stochastic algorithm based heat wave simulator in order to incorporate trends in heat wave frequency, magnitude, and duration. Another recent study included an examination of frequency, duration, and magnitude of heat wave events above a high threshold in Europe with relation to three large-scale circulation patterns (Photiadou et al. 2014). We add to these aforementioned works through: the use of a higher spatial resolution gridded dataset, a bivariate heat wave definition (joint crossing of high maximum and minimum temperature thresholds), and an examination of event timing within the year in Florida.

Some of the more dominant low-frequency drivers of climate variability in the Northern Hemisphere have been shown to impact Florida's weather patterns. Enfield et al. (2001) found that the long-term variations of the Atlantic multi-decadal oscillation (AMO) have a strongly positive correlation with Florida rainfall, a pattern further confirmed by Kelly and Gore (2008) in a study of AMO's impact on river discharges. Enfield et al. (2001) also showed that the AMO has a spatially varying impact on Florida rainfall bringing heavier precipitation to south Florida during warm phases. The AMO is known to have a significant influence on mean air temperatures in both the eastern United States and Western Europe (Kerr 2000; Sutton and Hodson 2005; Goto-Maeda et al. 2008; Arguez et al. 2009). The high or warm phase (above average) of multi-decadal Atlantic SSTs has been associated with mean temperature anomaly increases of up to 1.5 °C (~3 °F) in the North Atlantic region with peaks in these anomalies occurring during the summer months of June, July, August, and September (Arguez et al. 2009). The influence of the AMO also decreases during both cold and warm phases of the more dominant pattern of El Niño-Southern Oscillation (ENSO) (Enfield et al. 2001). The warm phase of ENSO tends to bring increased amounts of precipitation to Florida, while the cold phase brings drier conditions (Douglas and Englehart 1981; Kahya and Dracup 1993). Goodrick and Hanley (2009) found that 56 % of the areas burnt by wildfires in Florida happened during the cold phase of ENSO (La Nina), while only 10 % of the areas burned during the warm phase (El Niño).

In our previous study (Keellings and Waylen 2014) we employed EVA in a static manner to examine changes in bivariate heat wave properties between two time periods using stationary bivariate extreme value distributions. In this paper we build upon our previous work through exploration of the influence of ENSO and the AMO as possible drivers

of the magnitude, frequency, timing, and duration of Florida heat waves (combined high maxima and minima temperature events) during the second half of the twentieth century. We investigate the relative influence of these time-varying signals on the occurrence of bivariate heat waves by introducing these atmospheric variables as covariates in non-stationary extreme value analysis based models. The methodology applied in this study is designed to test the basic hypothesis that one or both of the aforementioned large scale atmospheric circulation patterns influence heat wave properties in Florida with a varied intensity and spatial context.

2 Data

2.1 Gridded surface dataset

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 et al. 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 that can be mapped across the entire state.

2.2 Teleconnection indices

All of the teleconnection indices are obtained from National Oceanic and Atmospheric Administration and cover the same period (1949–2000). The AMO index is based on North Atlantic SST anomalies calculated from detrended long run averages of mean SST observations (Enfield et al. 2001). The ENSO signal at the monthly/seasonal scale is transmitted through the atmosphere and thus the Bivariate EnSo Timeseries (BEST) index—obtained by combining the standardized Southern Oscillation Index with Niño 3.4 SST standardized anomalies (Smith and Sardeshmukh 2000) will be used to couple the interaction between SST anomalies and atmospheric waves.

2.3 Heat wave definition

We define heat waves based on the definition used in Keellings and Waylen (2014). 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 cell from the entire temperature record (1949–2000) at each grid cell. Minimum duration criterion of at least 2 days of consecutive above threshold days is set. Only joint crossings of high daily maximum temperature thresholds and high daily minimum temperature thresholds are examined. Events are considered to be independent if separated by at least 4 days of below threshold temperatures; otherwise data of consecutive events are amalgamated (Keellings and Waylen 2014). Independence criterion was set in this manner to account for the possible epidemiological significance of having fewer than four relief days between events as is confirmed in medical literature for three major population centers in Florida by the weak association between heat-related mortality on any given day and temperatures in excess of 3 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 (Ferro and Segers 2003).

3 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 et al. 1983; Rodriguez-Iturbe and Bras 1985; Waylen 1988; Waylen and LeBoutillier 1989; Goto-Maeda et al. 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 point process 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 approach, as all values above the threshold are included resulting in more reliable results.

The point process approach has been extended further by utilizing a bivariate extreme value distribution definition of events, adding a geometric distribution to explore heat wave duration, and by incorporating a time-dependent Poisson function to examine heat wave timing within the year (Keellings and Waylen 2014). In this paper we

use univariate extreme value theory to fit a point process model and subsequent distributions to an a priori series of maximum daily temperatures that has been filtered to include only above high (90th percentile) threshold maximum temperatures that were accompanied by above high (90th percentile) minimum threshold temperatures. Another approach would be to use bivariate extreme value theory for modeling maximum and minimum temperature extremes jointly (see Coles et al. 1994; Keellings and Waylen 2014) but in this paper we propose a simpler, and perhaps more numerically stable (Furrer et al. 2010), approach making use of the more widespread univariate extreme value theory. All computations in this paper have been done in the free software environment for statistical computing and graphics, R, using the extremes and ismev packages (see <http://www.r-project.org/>).

The occurrence of a heat wave can be thought of as an independent event above a high threshold that is drawn from an extreme data series that conforms to an Extreme Value Distribution (Coles 2001). Events from such an extreme series are said to be part of a Poisson process as they are occurring randomly and at a variable rate (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:

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

The magnitude of event or cluster maxima, within a POT framework, follow a Generalized Pareto Distribution (GPD). The cumulative distribution function of a GPD is given by Coles (2001):

$$P(x) = 1 - \left[1 + \xi \frac{x - u}{\sigma} \right]^{-1/\xi} \quad (2)$$

The parameters of the GEV and that of the corresponding POT approach are directly related through (Davison and Smith 1990):

$$\begin{aligned} \xi &= \xi_{\text{GPD}} = \xi_{\text{GEV}} \\ \sigma_{\text{GPD}} &= \sigma + \xi(u - \mu) \\ \Lambda &= [1 + \xi(u - \mu)/\sigma]^{-1/\xi} \end{aligned} \quad (3)$$

These GEV parameter transformations can then be used to describe a Poisson process with rate parameter (Λ) derived from the estimated scale parameter σ , shape parameter ξ and location parameter μ , 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:

$$P(m(t) = n) = e^{-\lambda(t)} \cdot \lambda(t)^n / n! \quad (4)$$

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 (Keellings and Waylen 2014):

$$\lambda(t) = G(t : \mu, \sigma) \cdot \Lambda \quad (5)$$

where $G(t : \mu, \sigma)$ is a Gaussian distribution fitted to the timing of events with μ being mean date of exceedances, σ their standard deviation, and Λ the annual rate.

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 and Leadbetter 1967). A discrete geometric distribution was adopted (Keellings and Waylen 2014; Wilks 2005):

$$P(D) = (1 - \theta)^{D-1} \theta \quad (6)$$

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

The point process approach to extremes has a further advantage over the block maxima and POT approaches to extremes in that it allows for the simple introduction of covariate effects (Coles 2001). Here we examine the influence of atmospheric covariates (AMO, ENSO, NAO) on the occurrence of heat waves by introducing these signals into non-stationary models as covariates in Generalized Linear Models (GLMs) of both the location and log-transformed scale parameters of the distributions such that:

$$\begin{aligned} \mu(x) &= \beta_{0(i)} + \beta_{1(i)}x \\ \ln\{\sigma(x)\} &= \beta_{0(i)} + \beta_{1(i)}x \\ \xi(x) &= \beta_{0(i)} \end{aligned} \quad (7)$$

where $\beta_{0(i)}$ are the stationary model parameter estimates and $\beta_{1(i)}x$ are linear transformations of the time-varying atmospheric covariates AMO, ENSO and NAO. The shape parameter, ξ , was modeled as an intercept only term as this parameter is numerically difficult to estimate with any accuracy (Katz et al. 2002).

The influence of atmospheric covariates on heat wave duration were examined using a GLM, where the reciprocal of the mean of the geometric distribution of a hot spell with duration of D days is governed by the stationary parameter

estimates, $\beta_{0(i)}$, and linear transformations of the atmospheric covariates, $\beta_{1(i)}x$ (see Furrer et al. 2010). GLMs were fitted using the `glm` function within R.

$$\ln\{\theta(x)\} = \beta_{0(i)} + \beta_{1(i)}x \quad (8)$$

To assess the influence of each signal on the occurrence of heat waves the improvement over the stationary model was examined using the deviance statistic or log-likelihood ratio test, as this is most appropriate for comparing nested models fitted with fixed MLEs (Coles 2001), whereby the difference in negative log-likelihood values between two models is tested for significance using a Chi squared distribution.

4 Results

4.1 Significance of covariates

In the following section, a description of significant point process and geometric model improvements with each teleconnection as a covariate term are presented. Significance is shown at 0.05 level and covariates are applied simultaneously to both the location and log-transformed scale parameters or, in the case of durations, to the mean of the geometric distribution.

4.1.1 Point process parameter estimates

The inset map in Fig. 1a shows significance of improvements to both the GEV location and log-transformed scale parameters with ENSO incorporated as a covariate term. ENSO significantly improved the point process model estimates in 30 % of Florida's land area with most located across areas in northeast and south Florida. ENSO, therefore, has a significant influence on the joint occurrence (frequency and magnitude) of high daily maximum and high daily minimum temperature events or heat waves in these areas within Florida.

Significant improvements to the point process models occur with the inclusion of the AMO as a covariate on both the GEV location and log-transformed scale parameters (inset in Fig. 2a). The AMO has a significant influence on heat wave frequency and magnitude across much of Florida (approximately 80 % of Florida's land area), particularly in the north.

4.1.2 Geometric parameter estimates

The inset map in Fig. 3a shows that improvements to the geometric model for duration of events, with ENSO as a covariate, are spatially scattered across Florida. Approximately 50 % of Florida's land area exhibits a significant

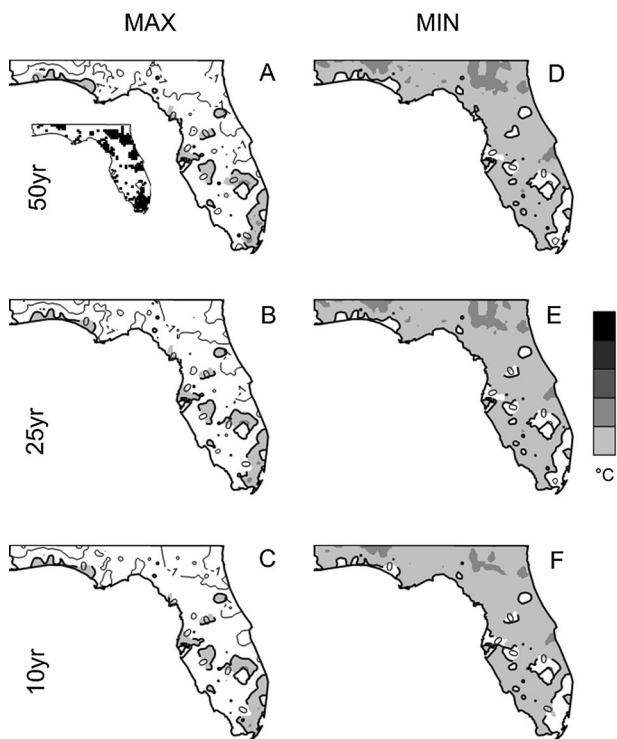


Fig. 1 ENSO impacts on 50, 25, and 10 year return period temperatures. Shown as difference of maximum (a–c) and minimum (d–f) value of ENSO model in relation to stationary model. *Inset map* in (a) shows significance ($\alpha = 0.05$) of improvement with ENSO as covariate in GLM of both location and scale parameters

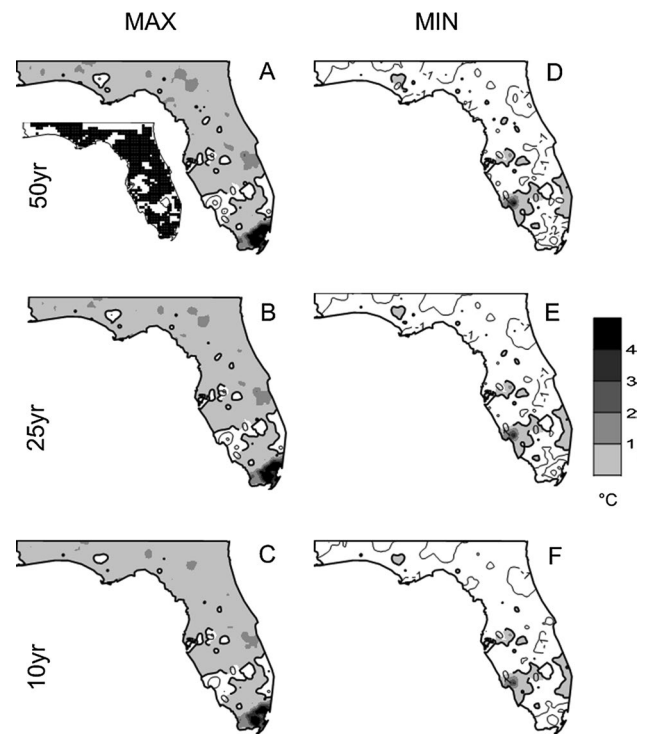


Fig. 2 AMO impacts on 50, 25, and 10 year return period temperatures. Shown as difference of maximum (a–c) and minimum (d–f) value of AMO model in relation to stationary model. *Inset map* in (a) shows significance ($\alpha = 0.05$) of improvement with AMO as covariate in GLM of both location and scale parameters

improvement with the largest areas of significance occurring in the north and south.

Significant improvements to the geometric model with AMO as a covariate occur throughout much of Florida (Fig. 3b). Approximately 75 % of Florida’s land surface exhibits a significant improvement with the inclusion of AMO. Both ENSO and AMO are found to have a significant impact on the duration of events with that of the AMO being more pervasive across Florida.

4.2 Impacts of covariates

In the following section, we present a description of the impact that ENSO and AMO have on estimated return periods, frequency, duration, and timing of heat waves. To examine the impact of each teleconnection we extracted the maximum and minimum value of each teleconnection index observed during the months of May through September. Each heat wave measure (return period, frequency, duration, timing) was then estimated using the maximum and minimum index value as covariates in GLMs of the point process and geometric parameters.

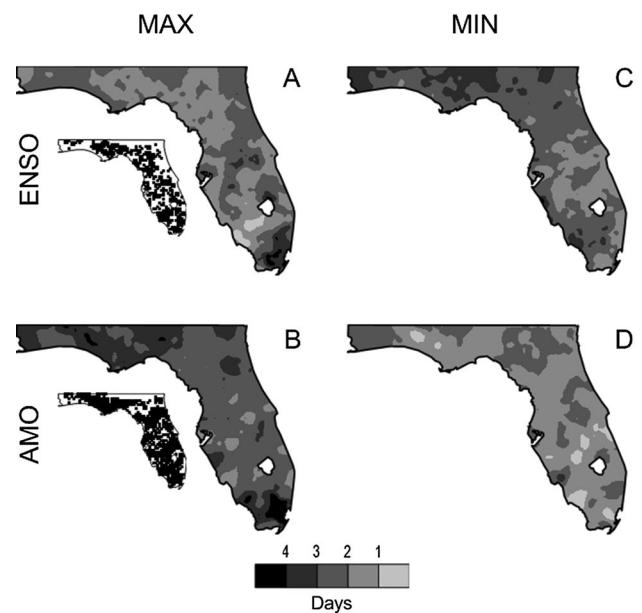


Fig. 3 Impact of ENSO (a, c) and AMO (b, d) on duration of heat waves. Shown as difference between maximum/minimum value of covariate geometric model and stationary geometric model. *Inset maps* show significance ($\alpha = 0.05$)

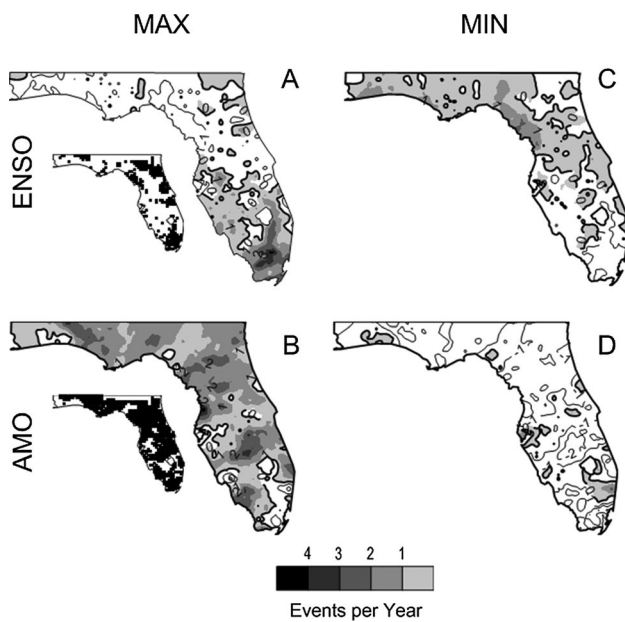


Fig. 4 Impact of ENSO (a, c) and AMO (b, d) on frequency of heat waves. Shown as difference between maximum/minimum value of covariate location and scale model and stationary model. *Inset maps* show significance ($\alpha = 0.05$)

4.2.1 ENSO

The influence of highly positive (maximum value) or warm phase ENSO on heat wave magnitude, in absolute difference in degrees Celsius from the stationary model, is shown in Fig. 1 for the 50, 25, and 10 year return period estimates (i.e. 2, 4, and 10 % chance of occurrence in any year). Areas of model significance (shown in the inset map) in the northern half of Florida coincide with decreases in heat wave magnitudes by over 1 °C. In contrast, areas of model significance in south Florida coincide with increases in heat wave magnitudes in excess of 1 °C. Figure 1 also shows the influence of highly negative (minimum value) or cool phase ENSO on heat wave magnitude. Cool phase ENSO brings the opposite effect on return periods to that of the warm phase. Areas of significance in north Florida exhibit increases in heat wave magnitudes in excess of 1 °C while those in south Florida decrease by over 1 °C.

Figures 3 and 4 show the influence of ENSO on heat wave duration and frequency. Warm phase ENSO shows little impact on the frequency of heat waves in north Florida but brings increases in the average number of events by in excess of four per year in south Florida. Cool phase ENSO also has relatively little impact on frequency in north Florida bringing increases of up to two events per year in only an isolated area. In south Florida the cool phase again brings the opposite effect to that of the warm phase by decreasing heat wave frequency by over 1. Duration of

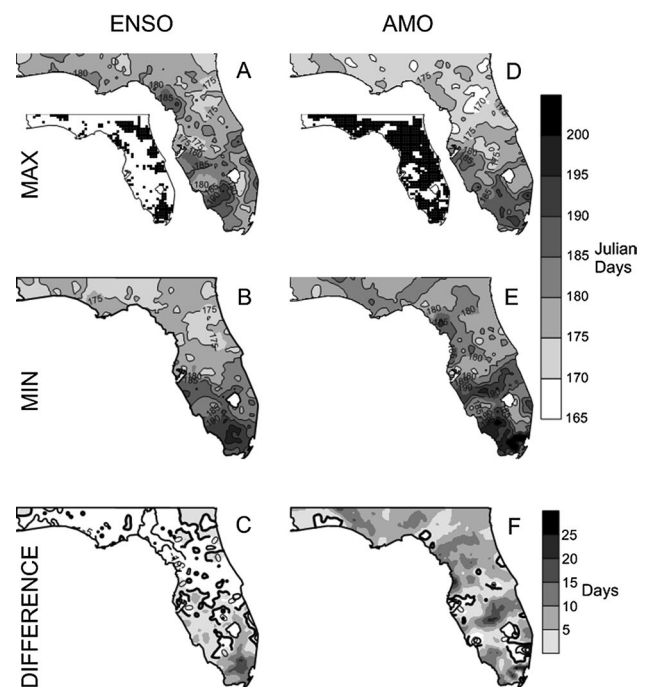


Fig. 5 Impact of ENSO (a–c) and AMO (d–f) on day of year on which the chance of having at least one heat wave equals or exceeds 50 %. Shown as Julian day for maximum (warm phase) and minimum (cool phase) value of covariate location and scale model and the difference calculated from the minimum minus the maximum. *Inset maps* show significance ($\alpha = 0.05$)

events generally increase across Florida with either maximum or minimum values of ENSO as covariates. Warm phase ENSO brings relatively modest increases to the duration of events in north Florida and larger increases in south Florida of up to 4 days increased duration. Cool phase ENSO increases duration in north Florida by up to 3 days but brings relatively modest increases in south Florida.

The influence of ENSO on timing of heat waves is shown in Fig. 5. We mapped the day of the year on which the chance of having at least one heat wave equals or exceeds 50 %. In south Florida the warm phase of ENSO is associated with events occurring up to 25 days earlier in the year than during cool phase ENSO. There is relatively little change in event timing between warm and cool phases of ENSO in areas of model significance in north Florida.

4.2.2 AMO

The influence of highly positive (maximum value) or warm phase AMO on heat wave magnitude, in absolute difference in degrees Celsius from the stationary model, is shown in Fig. 2. The majority of Florida exhibits an increase in heat wave magnitudes during warm phase AMO. In the southern tip of Florida warm phase AMO is associated with large increases in heat wave magnitude (>4 °C). In contrast,

highly negative (minimum value) or cool phase AMO coincides with decreases (< -1 °C) in heat wave magnitude across much of the Florida.

The warm phase of AMO is associated with general increases in heat wave frequency across much of Florida by up to four more events per year (Fig. 4b). Although, the southern tip of Florida exhibits decreases in frequency by in excess of one event per year. Cool phase AMO coincides with widespread decreases in heat wave frequency by over two events per year (Fig. 4d). The duration of heat waves increases under both highly warm and cool phases of AMO (Fig. 3b, d). However, the warm phase is associated with relatively large increases in excess of 4 days in duration. Warm phase AMO brings a 50 % risk of having at least one heat wave up to 25 days earlier in the year (Fig. 5). Under the influence of the warm phase, events occur earlier across most of Florida with the largest shifts taking place in the south.

5 Discussion and conclusions

We demonstrated a statistical model combining the point process with a time-dependent function, a geometric distribution, and GLMs of parameter estimates to examine the impact of ENSO and the AMO on the frequency, magnitude, timing, and duration of heat waves in Florida. We implemented our methodology over a high-resolution historical gridded dataset, allowing for an extensive spatial and temporal representation of the influence of these teleconnections on heat waves. Using this methodology and dataset we established the impact of the teleconnections on each heat wave property, which may be beneficial for quantifying future heat wave properties as part of forecasts or longer-term projections from climate models.

We find only small and isolated areas of significance with ENSO as a covariate of heat wave magnitude, frequency, and timing. Furthermore, within these areas of model significance we found only relatively weak impacts on heat wave properties. ENSO has a significant impact on heat wave duration across half of Florida but again exhibits only a weak influence. Despite the relatively modest impact of ENSO on all investigated heat wave properties, the models indicate that warm phase ENSO and cool phase ENSO result in geographically opposing heat wave impacts. Warm phase ENSO brings more intense events to south Florida in terms of increased magnitude, frequency, duration, and earlier timing while diminishing events in the north. Cool phase ENSO amplifies events in north Florida while diminishing events in the south. The small areas of significance with ENSO as a covariate and the relatively weak impact on heat wave properties are supported by others who found that ENSO is limited to wintertime impacts on precipitation

and temperature in Florida (Douglas and Englehart 1981; Kahya and Dracup 1993; Gershunov and Barnett 1998; Goodrick and Hanley 2009).

In agreement with others, we find that the AMO is a significant driver of extreme summertime temperatures (Sutton and Hodson 2005; Arguez et al. 2009). These previous studies have concluded that the AMO is associated with warmer mean summertime temperatures across the eastern United States. We add to those prior findings by concluding that the AMO is also a driver of extreme temperature events in Florida. The AMO was found to be positively associated with heat wave properties across much of Florida. The warm phase of AMO brings heat waves earlier in the summertime (up to 25 days earlier) while also increasing their magnitude (> 4 °C), frequency (up to four more events per year), and duration (up to 4 days longer). The strongest impacts occur on the magnitude and duration of events in south Florida. Interestingly, warm phase AMO is associated with slight decreases in the frequency of events in south Florida. This is likely a result of a merging effect from the increase in magnitude and duration of heat waves bringing events with fewer intervals and so apparently reducing their frequency.

A limitation of the current approach is that taken separately, ENSO or AMO can only explain part of the variability in Florida heat waves. The inclusion of additional atmospheric covariates such as the North Atlantic Oscillation and Pacific-North American could improve the fit of the extreme value theory based models. Another avenue of research would be to explore these additional covariates both individually and in combination as covariates in the extreme value models. In the present paper our aim was to first explore individual covariates in order to gain a better understanding of their stand-alone impact on Florida heat waves. Exploring combinations of covariates will be the topic of a future paper in which we will look at the conditional affects of atmospheric covariates on Florida heat waves. However, there may be a trade-off in such an approach as given the lack of extreme data (further limited by our joint crossing approach), models that include multiple covariates are likely to exhibit only insignificant improvements over single covariate models. In the case of ENSO and AMO, we find little evidence to suggest that ENSO has much of an impact on summertime extreme temperatures (heat waves) in Florida and empirical evidence suggests that ENSO is limited to wintertime impacts. Therefore, we believe that the inclusion of ENSO and AMO in a single model of heat waves in Florida will bring little further explanation of variability, especially given little evidence of their combination as a summertime heat wave generating process.

The novel methodology adopted in this study is intended to allow for a more complete representation of bivariate

heat waves by defining joint thresholds and including more information regarding their properties (magnitude, frequency, duration, timing) than have hitherto been applied in modeling efforts. We also demonstrated the inclusion of teleconnection indices in this approach to facilitate an investigation of how different phases of ENSO and the AMO affect each heat wave property. We have assessed the influence of teleconnections to gain a greater understanding of the consequences of ENSO and the AMO, two of the main drivers of Florida's climate, on periods of extreme heat in Florida. This knowledge could be implemented in climate models to improve estimates of future responses of heat wave properties in Florida.

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