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# The Impact of Recent Heat Waves on Human Health in California

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**Abstract** This study examines the health impacts of recent heat waves statewide and for six subregions of California: the north and south coasts, Central Valley, Mojave, southern deserts, and northern forests. Using Canonical Correlation Analysis applied to daily maximum temperatures and morbidity data in the form of unscheduled hospitalizations from 1999 to 2009, we identified 19 heat waves spanning 3-15 days in duration that had a significant impact on health. On average, hospital admissions were found to increase by 7% on the peak heat wave day, with a significant impact seen for several disease categories including cardiovascular disease, respiratory disease, dehydration, acute renal failure, heat illness and mental health. Statewide, there were 11,000 excess hospitalizations due to extreme heat over the period, yet the majority of impactful events were not accompanied by a heat advisory or warning from the National Weather Service. Regionally, the strongest health impacts are seen in the Central Valley and the north and south coasts. The north coast contributes disproportionately to the statewide health impact during heat waves with a 10.5% increase in daily morbidity at heat wave peak, compared to 8.1% for the Central Valley and 5.6% for the south coast. The temperature threshold at which an impact is seen varies by subregion and timing within the season. These results suggest heat warning criteria should consider local percentile thresholds to account for acclimation to local climatology as well as the seasonal timing of a forecasted heat wave.

## 1. Introduction

The devastating effects of extreme heat events have been seen in recent years. The 2003 European heat wave and the 2010 Russian heat wave each resulted in tens-of-thousands of deaths (Agence Frence-Presse 2010, Robine et al. 2007) and the 2006 California heat wave killed more than 600 (Trent et al. 2006; Ostro et al. 2009) and resulted in over 16,000 excess hospital emergency department visits (Knowlton et al. 2009). Adding to the tragedy of these losses is the fact that most heat-related deaths are preventable with adequate warning tools and effective emergency planning. Since climate change has the potential to increase the frequency of these types of events (Meehl and Tebaldi 2004; IPCC 2007, 2012), improved heat warning systems are urgently needed. This would require a better knowledge of the full impact of extreme heat on morbidity and mortality.

California has unique challenges for heat wave preparedness owing to its diversity of population and climate zones. Some residents live in desert conditions just inland of coastal populations who are used to relatively mild temperatures. Additionally, many residents lack air conditioning, especially along the coast, making them particularly vulnerable during extreme heat events (Sailor and Pavlova 2003; Reid et al. 2009). This vulnerability was apparent during the 2006 California heat wave that affected most of the state. Health impact studies of that heat wave showed that while temperatures were hotter inland, the health impacts were stronger along the coast (Knowlton et al. 2009; Gershunov et al. 2011). The 2006 heat wave was unusually humid and nighttime temperatures were unprecedented, therefore the nighttime recovery, typical for California, was stifled. Recent work shows a clear trend in humid heat waves in the

Western US with a disproportionate increase in nighttime temperatures (Gershunov et al. 2009; Bumbaco et al. 2013). In fact, California coastal communities are becoming increasingly susceptible to mid-summer, humid heat waves to which they are not accustomed (Gershunov and Guirguis 2012, hereinafter GG2012). Thus, coastal populations may be at a higher risk for heat-related illness in the short- and long-term future, since they are neither physiologically nor technologically acclimatized to this type of heat.

California heat alert criteria relies on the Heat Index, which is based on empirical relationships between temperature/humidity thresholds and mortality in a few major US cities. However, the National Heat Index threshold of 105 used by the National Weather Service (NWS) to issue a heat warning does not work well in California. Desert communities regularly exceed this threshold, but residents are well adapted to extreme heat. Coastal communities rarely exceed this threshold but are much more vulnerable to heat illness because they are accustomed to much milder conditions. For effective weather warnings, events posing a danger to health should be identified locally with higher or lower thresholds directed at populations living in hotter or cooler climates, respectively (Robinson 2001). Additionally, mortality only accounts for a small portion of acute health effects so for effective preparedness, nonfatal illness should also be considered. Local NWS offices typically modify the alert criteria to better suit California conditions, but these decisions are put in place with only limited information about local heat-health relationships. Such information would be highly beneficial for making informed decisions about when to issue a warning, which could prevent heat-related illnesses and save lives.

There have been many studies investigating the impacts of extreme heat on human health (e.g. Basu and Samet 2002; Martiello and Giacchi 2010). However, most of this work has focused on health impacts related to daily ambient apparent temperatures observed throughout the summer (e.g. Basu et al. 2009; Basu et al. 2012) with much less attention given to health outcomes from one heat wave to another. Health impact studies of heat waves (multiple days of hot weather) have primarily focused on a few notorious heat waves such as Chicago 1995 (e.g. Kaiser et al. 2007), Europe 2003 (e.g. Le Terte et al. 2006), or California 2006 (e.g. Knowlton et al. 2009). Long-term heat wave studies require some definition of a heat wave, and there is no universal definition. Usually heat waves are defined by magnitude as days exceeding a set temperature or percentile threshold and may also include a duration requirement (e.g. Hajat et al. 2006; Mastrangelo et al. 2007; Son et al. 2012; Vaneckova and Bambrick 2013) or by synoptic weather type (e.g. Sheridan et al. 2012; Sheridan and Kalkstein 2010; Vaneckova et al. 2008) and the heat-health impact is subsequently quantified. Our methodology takes a new approach by using health and meteorology data simultaneously to identify dangerous historical heat waves occurring in California between 1999 and 2009. The advantage is we make no *a priori* assumption about the kinds of conditions affecting human health. This leaves open the possibility of detecting a health impact during events that might not typically be considered extreme. Coastal communities who are not well acclimated to heat, for example, may be adversely impacted during a heat wave at lower temperatures than inland communities.

In addition to statewide impacts, this study also investigates regional impacts using six regions defined empirically based on heat wave expression over the State's complex geography. These are the north and south coasts, Central Valley, Mojave, southern deserts, and northern forests. Heat risk warnings issued by the NWS during specific heat waves are considered in the context of actual health risks as measured by excess hospitalizations. Beyond improved understanding of the meteorological impacts on heat illness, we aim for the results presented below to be practical and useful for optimizing the effectiveness of regional heat warnings.

## 2. Data

### *a. Climate and Weather Data*

The daily maximum temperatures (Tmax) are from Maurer et al. (2002), comprised of daily station data interpolated onto a regular 12x12 km grid with temperature lapsed to grid cell center elevations. The source station data are from the National Climatic Data Center (NCDC) first-order Automated Surface Observing System (ASOS) and cooperative observer (coop) summary of the day (NCDC 2003). Grid to station differences would depend on location with larger differences seen in areas of complex elevation or strong spatial temperature gradients over relatively short distances. For example, the 1999-2009 summertime temperature record from the downtown San Francisco coop station is approximately 0.13 °C warmer than that of its nearest grid cell. This is because the grid cell represents temperatures over a larger area including parts immediately on the coast. For this study, grid cells that were co-located with the zip-code level health data (described below) were averaged over six pre-defined California subregions to give regional daily maximum temperatures from 1999-2009. These subregions were defined empirically using Principal Components Analysis applied to temperature data as described in GG2012. As a result of the regionalization, localities grouped within a given region exhibit a similar temporal variability in heat wave activity. These six regions are shown in Figure 2b.

Daily specific humidity (SH) data are from the North American Regional Reanalysis (NARR, Messinger et al. 2006). The SH data were processed just as for Tmax to give daily, regional averages of specific humidity.

*b. Health Outcome Data*

Data were compiled from the Office of Statewide Health Planning and Development (OSHPD) Patient Discharge (PD) Data for the warm season (May-Sept) spanning 1999-2009. These data were limited to only include hospitalizations at acute care facilities that were designated as unscheduled, so they would represent a subset of emergency department visits in which conditions were serious enough to require hospitalizations. The data were aggregated to zip code level to protect patient privacy and include zip code, date of hospital admission, day of week, and counts for each health outcome category and stratification by age and race/ethnicity. The outcome categories (Table 2) included all cardiovascular diseases and cardiovascular subcategories (ischemic heart disease, acute myocardial infarction, cardiac dysrythmias, and essential hypertension), all respiratory diseases, acute renal failure, mental health, dehydration, and heat illness. We also considered "all causes" as an outcome category, which was taken as the sum of all the outcome categories listed in Table 2.

For the purposes of this study, the PD data were aggregated regionally in the same regions as for Tmax. The regional PD data were then filtered to remove periodic signals and long-term trends. Because of annual variation in viral activity and other causes, morbidity is higher in spring and fall than in mid-summer. This annual and semiannual harmonic seasonal cycle was removed using least squares regression analysis. Hospitalizations are notably lower on weekends and holidays. The weekly cycle was removed by subtracting the long-term day-of-the-week average from each daily admissions count, and the holiday effect was removed by subtracting the average holiday admission count from each Memorial Day, Labor Day, or July 4$^{th}$ holiday. Very low admissions also occurred on July 5$^{th}$ when the July 4$^{th}$ holiday occurred on a Sunday, since most Americans would have received a work holiday on that Monday. During those years, July 5$^{th}$ was treated as a holiday. Finally, any long-term trend in the data was removed using locally weighted scatterplot smoothing (LOWESS, Cleveland 1979), which fits a quadratic curve to the nearest 30% of data points. Figure 1 provides an illustration of the filtering process for the Coastal North region.

*c. Historical Heat Alert/Advisory Information*

Historical information about heat advisories or alerts issued by the National Weather Service (NWS) was obtained from NOAA's Hierarchical Data Storage System (HDSS) available at http://hurricane.ncdc.noaa.gov/pls/plhas/HAS.FileAppSelect?datasetname=9957ANX for the non-precipitation warnings, watches and advisories category, as well as other internal NWS communication.

*d. Historical Electrical Alert Information*

Information on historical power alerts issued by the California Independent System Operator (ISO) was obtained from the ISO Alert, Warning, and Emergency Records from 1998 available at http://www.caiso.com/Documents/Alert_WarningandEmergenciesRecord.pdf. Local utilities generally follow the ISO recommendations and issue their own alerts to promote conservation. However, occasionally a local utility may issue an alert unaccompanied by the ISO. For this research we only had access to those alerts issued by the California ISO.

## 3. Methods

### *a. Canonical Correlation Analysis*

This study uses Canonical Correlation Analyses (CCA) to identify space-time patterns of heat wave expressions optimally related to morbidity. CCA is a multivariate statistical approach used to linearly summarize information contained in the cross-correlation matrix between two sets of variables, in this case daily maximum temperatures and morbidity as represented by hospitalizations. CCA transforms the original data pairs (x and y) into new variables called canonical variates defined as

$$v_m = a_m^T x' = \sum_{i=1}^{I} a_{m,i} x_i' \qquad (1)$$

$$w_m = b_m^T y' = \sum_{j=1}^{J} b_{m,j} y_j' \qquad (2)$$

where x (Tmax) and y (PD) are the centered data vectors (standardized for this study), I is the number of elements in x, J is the number of elements in y and m is the number of pairs of canonical variates that can be obtained from the two datasets and is equal to the lesser of I and J. Each canonical variable v and w is a linear combination of elements of the respective data vectors, or in other words a weighted average with weights given by a and b in the above equations (Wilks, 2006). Pairs of canonical variates are ordered sequentially by the degree of correlation between v and w, such that the first pair (CC1) exhibits the maximum canonical correlation. CCA was originally developed by Hotelling (1935, 1936) to identify and quantify associations between two sets of variables and was initially used in the social sciences. In climate prediction, CCA has been used to match patterns in two fields of variables, typically with the intention to forecast one with the other, i.e. the predicted with the predictor (Barnett and Preisendorfer 1987; Gershunov and Cayan 2003; Alfaro et al. 2006). Here, we use CCA as a purely diagnostic tool to identify periods in the recent historical record when daily maximum temperatures and morbidity were strongly correlated. We have previously used CCA to identify heat and humidity effects on county-level emergency department (ED) visits over California in a limited ED data set spanning only one year (2006) and resolving the impacts of only one heat wave (Gershunov et al. 2011). Here, the daily input Tmax (x') and PD (y') data arrays span 11 years, are regionally averaged, as well as filtered and standardized to filter out local noise and remove population density bias, while focusing on meteorologically relevant regions. For the purposes of discussion, we refer to the first canonical variable $v_1$ as $CC1_{Tmax}$ and the first canonical variable $w_1$ as $CC1_{Health}$ (Figure 2a). These variables represent the simultaneous pattern of strongest linear co-evolution of temperature and hospitalizations throughout California (Figure 2b). Higher order canonical modes were poorly related to temperatures and health. So, while they do explain some heat-health covariability, we focus our analysis on the primary mode, which best represents the spatial-temporal pattern of heat-related health outcomes in California.

In preliminary analyses we tested our methodology using daily minimum temperatures (Tmin). However, the Tmax results were found to be more robust both in terms of the correlation between the canonical variable and the source data (i.e. the correlation between CC1 and x') and the correlation between the two canonical variables (i.e. u and w). Therefore the results using Tmax were superior in describing the heat-health relationship in California. This is likely because California experiences both dry and humid heat waves and Tmax is elevated during both varieties while Tmin may not be strongly elevated during dry events.

### *b. Identifying Heat-Health Events*

We identified those heat waves in the 11-year record having an impact on human health by looking for cases where three criteria were met: (1) canonical variables $CC1_{Tmax}$ and $CC1_{Health}$ (Figure 2a) were significantly correlated (at the 95% level, r>0.51) using a running 15-day window, (2) a strong temperature anomaly was observed as represented by canonical variable $CC1_{Tmax}$ crossing a 1 SD threshold and (3) a strong health anomaly was observed as represented by canonical variable $CC1_{Health}$ crossing a 1 SD threshold. To allow for some flexibility in timing, a heat-health event (HHE) is defined to span the full duration of the heat anomaly from when it first becomes warm ($CC1_{Tmax}$ is positive), peaks (at least once) and then drops back to normal again. The health impact can occur at any point within this heat event, so would allow for lags in response and additionally allows us to quantify the full health impact of an individual heat wave.

## 4. Results

### *a. Heat-Health Events*

Figure 2a shows the first pair of canonical variates $CC1_{Tmax}$ and $CC1_{Health}$. These time series are only moderately, yet significantly, correlated (r=0.3) over the 11-year record signifying that, as expected, disease processes associated with heat are not the main cause of morbidity. However, over shorter intervals the relationship between heat and illness can become much stronger than the long-term average (Figure 3). For example, using a 15-day running window, the correlation reaches 0.79 and 0.82 during the July 2006 and 2003 heat waves, respectively. Figure 2b gives the homogeneous correlation maps showing how well each of the input data vectors are represented by their canonical variates. $CC1_{Tmax}$ best represents Tmax on the Coastal North (r=0.94) and also does reasonably well in capturing Tmax variability on the Coastal South (r=0.62), Central Valley (r=0.55) and Southern Deserts (r=0.51) while the Mojave and Northern Forests are weighted less strongly (r=0.41 and r=0.40, respectively). A similar regional pattern is observed for the health results although with generally weaker correlations. $CC1_{Health}$ best represents hospitalizations in the Coastal North (r=0.82) followed by the Coastal South (r=0.62) and Central Valley (r=0.54) while hospitalizations in the Southern Deserts, Mojave and Northern Forests are not well represented by $CC1_{Health}$ ($r<0.23$). The heavy weighting of the Coastal North in both $CC1_{Tmax}$ and $CC1_{Health}$ highlights the sensitivity/vulnerability of this region's population to extreme heat. This is a region where summers are typically cool due to the proximity of cool coastal Pacific waters, which is further enhanced by marine layer clouds. Coastal heat waves therefore do not need to be as hot as those over the hotter and air-conditioned inland to come as a stark contrast to typical conditions and catch residents unprepared. This result is consistent with recent studies that considered the health impacts of the 2006 heat wave, and also found an increased sensitivity to heat in this region (Knowlton et al. 2009, Gershunov et al. 2011).

Using the criteria described in Section 3 to identify heat-health events (HHEs): namely strong positive anomalies observed in both $CC1_{Tmax}$ and $CC1_{Health}$ as well as a significant correlation between them over a 2-week period, we identified 19 heat waves with a significant impact on human health. These HHEs are outlined in red in Figure 3 and additional details including peak date, duration and if a power alert or NWS heat advisory/warning was issued are provided in Table 1. These results show that at least one HHE occurred each year except 1999 and 2005 and five years (2000, 2001, 2003, 2006 and 2009) had more than one event. Records show a NWS heat warning was issued for only six of the 19 events. The strongest health signal is seen for 12-16 June 2000, when $CC1_{Tmax}$ and $CC1_{Health}$ both exceeded 3.9 standard deviations above normal (Figure 3). This event occurred during the California energy crisis (e.g. Sweeny 2002) when market deregulation and high energy prices caused power shortages. In fact, on the peak date of June 14 rolling blackouts affected 97,000 customers in northern California (Bergman, 2001) while temperatures in San Francisco reached 105 °F. High energy prices were passed on to consumers during this time, which could have influenced personal decisions about air conditioning (AC) use, even where AC was available. Of the five HHEs that occurred during the 2000-2001 crisis, four were accompanied by a power alert. Other summers that stand out as remarkable are the summer of 2003, which had six HHEs of varying strengths and duration, and the summer of 2006 for the duration and intensity of the mid-summer heat wave.

Figure 4a (4b) shows the peak daily maximum and minimum temperatures (standardized anomalies) for each HHE. Also in 4a are the number of days exceeding the warm season (May-Sep) $95^{th}$ percentile for each HHE and region, and an indicator of whether the monthly $95^{th}$ percentile was reached (*). From Figure 4a, the Central Valley and Southern Deserts were hottest during all events, with daytime temperatures usually exceeding 37°C (~98°F). From Figure 4b, the Coastal North tends to reach hotter temperatures (especially daytime) relative to its climatology as compared to other regions. This means that, while the temperatures may be lower, these coastal residents are experiencing heat conditions that are very extreme relative to what they are used to and may experience health impacts at lower temperatures than inland populations more acclimatized to heat. This figure also highlights the notorious 2006 heat wave affecting most of California, which was unprecedented in magnitude and spatial extent since at least the late forties (Gershunov et al. 2009) and nighttime temperatures are shown to be even more extreme than those experienced during the day. Figure 4b also shows that during nighttime-accentuated events, when Tmin is extremely elevated, multiple regions are impacted (e.g. July 2002, 2003, 2006) indicative of a particularly expansive heat wave with the potential for large-scale, statewide impacts.

It is interesting that in terms of summertime temperatures, these events often do not fall in the top 5% of daytime or nighttime highs, except in the Coastal North.

However if we look at monthly percentiles, the majority of events do fall in the top 5% (above the 95$^{th}$ percentile) for all regions except the Coastal South. This means that, for example, while a May event might not meet the summertime threshold for extreme temperatures, it would be extremely hot for that time of year. This suggests populations may be more heat sensitive during cooler parts of the season. An increased vulnerability early in the season has also been found in other studies (e.g. Basu and Samet 2002, Ebi et al. 1998). This is generally attributed to the loss of acclimatization that occurs during the winter, as well as mortality displacement whereby the most vulnerable populations succumb to the first dangerous event of the season (Basu and Malig 2011).

### *b. Statewide Health Impact*

The statewide heat-health impacts are shown in Figure 5 and Tables 1 and 2. Figure 5a shows the distribution of daily hospitalization anomalies during non-HHE days, during the span of a HHE and during the peak HHE day for all causes. There is a dramatic increase in hospitalizations during HHEs, especially at the peak day. This difference is statistically significant at the 95% level using a two-sample t-test to compare sample means. For all causes, there was an average daily increase of 102 hospitalizations during the HHE span, which increased to 173 excess hospitalizations on the peak day. In California during the 1999-2009 record there were, on average, 2519 hospitalizations per day. Therefore, 173 excess hospitalizations at the peak represent nearly a 7% increase above what would occur on an average day.

A similar comparison was done for each of the disease categories accounting for unequal variances as necessary for some categories. A statistically significant increase in hospitalizations was seen for all outcomes except essential hypertension, a cardiovascular subcategory. This non-significant result for essential hypertension could be physiological as blood pressure goes down with increased heat exposure (Basu et al. 2012), or due to the small sample size (Table 2). Hospitalizations due to all cardiovascular diseases increased by an average of 36 (49) per day for the HHE span (peak), or 3.5% (4.7%) above the typical cardiovascular disease admission rate (Table 2). Admissions for respiratory diseases, mental health, acute renal failure, dehydration, and heat illness increased by 20 (42), 2 (6), 5 (10), 8(16), and 4 (10), respectively, on average per day for HHE span (peak). Expressed as a percentage of daily mean hospitalizations during the record for these disease categories, this translates to an increase of 7.7%, 9.8%, 17.7%, 22.5%, and 505% at the peak of the heat wave.

Figure 5b gives the cumulative statewide health impact for each of the 19 events. To quantify the cumulative impact, hospitalization anomalies (y') were summed over the span of each event and this value was compared to all non-HHE days in the historical record spanning the same duration. For example, the impact of the 2006 July 13-26 event was determined by comparing that 14-day sum of hospitalization anomalies to those obtained by resampling the record for all consecutive, non-HHE days spanning 14 days. Similarly, the 2000 June 12-16 event was compared to non-HHE days spanning 5 days. The health impact is said to be significant (using the 90$^{th}$ percent level for a one-sided test) if it falls above the 95$^{th}$ percentile of the resampled distribution. From Figure 5b, a significant statewide health impact is observed for 15 of the 19 HHEs identified. Taken together, these 15 events are associated with more than 11,000 excess hospitalizations statewide. The number of excess hospitalizations associated with each of these 15 events (Table 1) ranges from 367 for the short, 3-day 2006 HHE to 1657 for one 17-day, heat wave in September 2004. During the notorious 14-day July 2006 heat wave affecting most of the state, there were 1254 excess hospitalizations in California, a result that is similar to Knowlton et al. (2009) which found 1182 excess hospitalizations and 16,166 excess emergency department visits. The magnitude of the impact from one event to another is strongly associated with its duration. By looking at the health impact in terms of quantiles of the resampled data, which accounts for duration, we see that the health impact of these 15 events are all in the top 3%, with several in the top 1%, as compared to non-HHE days spanning the same duration (Table 1), i.e. they are highly significant.

### *c. Regional Health Impact*

Table 3 shows the regional impacts for HHE span and peak for each of the six California subregions using a two-sample t-test comparing non-HHE days with HHE span and HHE peak (same methodology as for disease categories in Table 2). A significant health impact is observed for four of the six regions. Daily admissions for the Coastal South, Coastal North, Central Valley, and Southern Deserts increased by 50 (71), 23 (47), 24 (43), and 4 (9), respectively, for HHE span (peak). Expressed as a percentage of average daily hospitalizations for these regions, this translates to an increase of 5.6%, 8.1%, 10.5%, and 6.3% at the peak of the heat wave. While the largest impact in terms of total admissions is greatest for the Coastal South owing to its larger population, the Coastal North contributes disproportionately to the health impact during heat waves. This region represents 18% of all California hospitalizations during 1999-2009, but this increases to 27% during heat waves. There are a few possible explanations for this. First, a poor acclimation to extreme heat both physiologically and through air conditioning use (air conditioning coverage is low in the Coastal North; for example, San Francisco has only 21% air conditioning saturation, Sailor and Pavlova 2003). Second, residents typically have easier access to hospitals and better insurance coverage than other parts of the state making it more likely they would seek medical treatment. Third, heat waves in the Coastal North are hotter relative to the mean climate (c.f. Figure 4b) simply due to the regional temperature distribution.

Figure 6 gives the cumulative health impact of the 19 HHEs for each California subregion using the same resampling method described above. Eighteen HHEs are associated with a significant health impact in at least one subregion of California (7-17 Aug 2009 is the only exception). There is very little impact seen in the deserts with only two (one) events associated with a significant health impact in the Southern Deserts (Mojave). This result is likely due to the fact that CC1 does not well represent desert heat waves, especially for the Mojave (c.f. Figure 2). CC1 also does poorly in representing heat waves in the Northern Forests, and here we see only a modest impact (four significant events). Our methodology is designed to explain the strongest co-relationships between heat and heath in California. However, not all heat waves are represented. There are likely some additional, more regionally focused heat waves that may have a regional health impact but these would need to be studied on a smaller spatial scale.

For the remaining regions, there is a strong health signal. Morbidity in the Central Valley was significantly impacted during 9 events and the Coastal North and

South each experienced 11 impactful heat waves. The Coastal South, the most populous region, shows the strongest overall impact in terms of patient numbers, with excess hospitalizations in the range 300 to more than 800 depending on event. In general, excess hospitalizations in the Coastal South are 1.5-3 times those in the Coastal North or Central Valley where the most intense heat waves cause typically 300-400 excess hospitalizations. In terms of quantiles of historical observations (color scale, Figure 6), which equalizes the regions in terms of population, the health impact is similar across the three regions with a mean percentile rank of 86-89% for the 19 events, although the coastal regions see a larger number of impacts in the top 5% (i.e. more are significant at the 90% level).

Figure 7a shows the peak temperatures for those HHEs identified as having a significant regional health impact (significant HHEs, hereinafter SHHEs) in the context of the full Tmax distribution by region and timing within the season, and Figure 7b gives the results in terms of degrees above normal. A health impact is seen in the Central Valley for Tmax in the range of 33-42°C (92-108°F) depending on month. For the Coastal North and South, where mean summertime temperatures are much lower, a health impact is seen for temperatures reaching 27-36°C (81-97°F). Most impacts occur at temperatures above the 90$^{th}$ percentile in the Central Valley and Coastal North with many falling above the 95$^{th}$ or even the 99$^{th}$ percentiles. An exception is one event (5-9 Sept 2000) affecting the Central Valley when temperatures peaked at 33° C (92° F), which is approximately the 70$^{th}$ percentile for that region in September. The Coastal South is more vulnerable, with health impacts seen for four SHHEs having peak temperatures at or below the 85$^{th}$ percentile. Relative to monthly normal conditions, Tmax is elevated by an average of 6.1°C in the Central Valley, 9.1°C in the Coastal North, and 4.5 °C in the Coastal South. From Figure 7a there are several observations above the $99^{th}$ percentile including 11-year highs in the Coastal South that were not associated with a significant health impact. We analyzed those 13 days, which spanned five separate events. Four of the five events were not identified as a HHE by the CCA methodology, so were not examined in terms of health impacts. The reason they did not meet the HHE criteria is because on the large scale there was no strong correlation between temperatures and health in California. However, it is possible there were more localized health impacts. The fifth event (13-26 July 2006) was identified as a HHE but no significant health impact was found for the Coastal South. This was a particularly impactful heat wave statewide (c.f. Table 1), and in the south coast there were 3 days above the $99^{th}$ percentile and an 11-year high that occurred on July 22. While the health impact was not statistically significant by our criteria, in the Coastal South there were 515 excess hospitalizations during that 14-day period, which is above the $93^{rd}$ percentile as compared to all other 14-day periods in the record.

### *d. Effect of Humidity*

Current heat warning systems attempt to account for the effect of humidity on heat wave morbidity and mortality. The Heat Index uses relative humidity or dew point temperature to estimate the human health impact based on empirical relationships with mortality. More sophisticated systems use empirical relationships between morbidity and forecasted synoptic air masses (e.g. Ebi et al. 2004). While quantifying the heat-humidity-health relationship is beyond the scope of this study, we attempt to describe the relative impact of dry versus humid heat waves using regional anomalies in specific humidity. An event is categorized as dry or humid depending on if the daily, regional specific humidity was below or above normal, respectively. The anomalies are calculated using the 1999-2009 May-September climatology.

Figure 8 shows the proportion of hospitalizations by month and heat wave type for those HHEs found to have a significant regional impact on health. For the Central Valley and Coastal North, humid heat waves account for 65% of the impactful heat waves in each region (6 of 9 in the Central Valley and 7 of 11 in the Coastal North). In terms of health impact, humid heat waves account for 66% of the hospitalizations in each of these regions with no appreciable difference seen within our sample of impactful events in terms of health outcome during dry versus humid heat waves. However, since health data was used directly in the identification of these events, the fact that the majority of impactful heat waves are humid suggests that humid heat waves are the more dangerous variety in the Central Valley and Coastal North. For the Coastal South, dry and humid events are approximately equal both in occurrence rate and health impact. In terms of seasonal timing, mid-summer events have the strongest impact on health in the Central Valley, but early-season heat waves have the strongest impact in the coastal regions. In general, early and mid-season heat waves tend to be getting stronger and more frequent in California due to climate change and specifically trending towards the humid variety (GG2012). Since the coastal populations show more vulnerability early in the season due to loss of acclimation over the winter and mortality displacement as discussed above; and are more prone to heat illness during humid events (at least in the northern part of coast), this means heat waves are changing towards the most dangerous variety in terms of human health.

## 5. Discussion and Conclusions

This study investigated the health impacts of recent heat waves from 1999 to 2009. Using Canonical Correlation Analysis applied to daily maximum temperatures and hospitalization data we identified 19 heat events spanning 3-15 days in duration that had a significant impact on human health. Taken collectively, these events resulted in more than 11,000 excess hospitalizations statewide. However, a heat advisory or warning from the National Weather Service was only issued during six of them. In terms of individual heat waves, the 17-day September 2004 heat wave showed the greatest impact, with 1657 excess hospitalizations. The 14-day July 2006 heat wave and the 15-day July 2003 heat wave were also very harmful to health with 1254 and 1063 excess hospitalizations, respectively. These events were not only long in duration, but were particularly extreme with temperatures exceeding the 95$^{th}$ percentile for several days. The 2003 and 2006 events were additionally humid with very high nighttime temperatures that hindered physiological recovery at night. Previous research has shown heat waves in the Southwest are becoming more durable and spatially expansive, especially the humid variety (Gershunov et al. 2009). Therefore local and statewide planning is needed to adequately prepare for these types of events, which can be devastating in terms of health impacts and can greatly strain resources designated for emergency response.

Regionally, the strongest health impacts were seen in the Central Valley and the north and south coasts. While the largest impact in terms of patient numbers is greatest for the Coastal South owing to its larger population, the Coastal North is disproportionately affected by extreme heat. During heat waves, the Coastal South sees a 5.6% increase in hospitalizations on peak heat wave days while the Coastal North experiences an increase of 10.5%.

In the Central Valley, temperatures in the range of 33-42°C (6.1°C above normal, on average) were associated with a health impact while in both coastal regions we detected an impact for temperatures in the range of 27-36°C (9.1°C and 4.5°C above normal, on average, for the Coastal North and Coastal South, respectively). Generally these temperatures are above the 90$^{th}$ percentile in the Central Valley and Coastal North, while the Coastal South is more vulnerable with impacts occurring when temperatures are at or below the 85$^{th}$ percentile. While the Coastal North appears most vulnerable in terms of increased hospitalizations (10.5% increase on peak heat waves), the Coastal South appears to be more vulnerable to lower temperatures. This could be due to differences in demographics or access to care. Additionally, there are other factors possibly contributing to the observed health effects other than high temperatures such as air pollution, Santa Ana winds, or smoke from wildfires that often accompany dry, late-season heat waves in the Coastal South.

The relative impact of dry versus humid heat waves was investigated using regional anomalies in specific humidity. The results showed that humid heat waves have a stronger impact on human health in the Central Valley and Coastal North, accounting for 66% of heat-related excess hospitalizations in both regions. In the Coastal South there was an approximately equal impact seen during humid and dry heat waves. In terms of seasonal timing, mid-summer events have the strongest impact on health in the

Central Valley, but early-season heat waves have the strongest impact in the coastal regions. Early in the season, coastal California experiences many cloudy and cool days due to the prominent marine layer, often referred to as "May Grey" or "June Gloom". Therefore heat waves during this part of the season would come as a stark contrast to typical conditions.

These results suggest local percentile thresholds that consider seasonal timing would be more appropriate for use in issuing heat warnings than the current system, which uses a single threshold throughout the summer and regional baselines that are based on only very limited health impact information. New criteria developed by NWS San Diego uses a temperature curve based on departures from normal for different climate zones, therefore incorporating seasonality and local acclimatization. This approach will address some of the geographic and population differences in vulnerability. California could also benefit from a multi-tiered system that accounts for the vulnerabilities of different populations such as outdoor agricultural workers, the elderly and those with preexisting conditions who have been shown to be especially vulnerable to heat (e.g. Trent et al. 2006). Lower threshold warnings could be issued for these vulnerable populations. This type of analysis is beyond the scope of this study, but future work will take a more localized focus and consider local differences in outcome based on demographic and other risk factors or exasperating conditions such as air quality, occurrence of Santa Ana winds or marine layer conditions. Given that heat waves are expected to become more frequent and more severe, it is crucial to understand the impact on human health now so public health officials can respond effectively and plan adequately for the future. This is especially true for California, which has a population of nearly 40 million with the majority living along the coast where heat acclimation is poor, air conditioners in homes are sparse (especially in Northern California), and research shows heat waves will continue to become more intense and more humid.

**Acknowledgments**

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**Table 1:** Heat Health Events and associated statewide health impact. Bold font indicates statistical significance at the 90% level.

| Year | Event Span | Peak Date | Duration | Excess Hosp. (Count) | Excess Hosp. (Quantile) |
|---|---|---|---|---|---|
| 2000 | [S2]May 18-24 | May 21 | 7 | 217 | 73.4 |
| | [S1]*Jun 12-16 | Jun 14 | 5 | 299 | 80.6 |
| | Sep 5-9 | Sep 7 | 5 | **700** | **99.7** |
| 2001 | [S3]May 2-11 | May 8 | 10 | 959 | 93.1 |
| | [S2]May 29 - Jun 1 | May 31 | 4 | **460** | **99.0** |
| 2002 | [S2]*Jul 7-13 | Jul 9 | 7 | **848** | **97.8** |
| 2003 | May 19-22 | May 20 | 4 | **845** | **99.5** |
| | [S1]May 27-29 | May 28 | 3 | **454** | **99.1** |
| | Jun 24-30 | Jun 27 | 7 | **717** | **98.3** |
| | *Jul 8-22 | Jul 14 | 15 | **1063** | **97.5** |
| | Sep 10-15 | Sep 13 | 6 | **629** | **98.5** |
| | Sep 17-23 | Sep 22 | 7 | **839** | **99.0** |
| 2004 | Sep 1-17 | Sep 7 | 17 | **1657** | **99.8** |
| 2006 | Jul 7-9 | Jul 8 | 3 | **367** | **99.1** |
| | [S2]*Jul 13-26 | Jul 23 | 14 | **1254** | **97.8** |
| 2007 | May 6-9 | May 7 | 4 | **327** | **99.0** |
| 2008 | *May 13-18 | May 16 | 6 | **903** | **99.2** |
| 2009 | *May 15-18 | May 17 | 4 | 160 | 88.5 |
| | Aug 7-17 | Aug 10 | 11 | 228 | 78.4 |

* NWS Heat advisory or warning issued
S1, S2, S3: Stage 1, 2, or 3 electrical alert issued by the California ISO

**Table 2:** Average daily increase in hospital admissions with confidence intervals for HHE span and peak from a two-sample t-test. An asterisk indicates a non-significant health impact (at the 95% level). Also shown are the daily average number of hospitalizations in California over the 1999-2009 record, and the excess admissions seen on peak heat wave days expressed as percent above normal.

| Outcome Category | ICD Code | Daily Average Hospital-izations 1999-2009 | Average Excess Daily Morbidity (Count) | | Average Excess Daily Morbidity (Percent above normal) |
|---|---|---|---|---|---|
| | | | HHE span | HHE peak | HHE peak |
| **All Causes** | | 2519 | 102.2 (101.6-102.6) | 172.8 (171.5-174.2) | 6.9 |
| **Cardiovascular Diseases** | | | | | |
| All Cardiovascular diseases | 390:459 | 1042 | 36.1 (35.8-36.3) | 48.7 (48.1-49.3) | 4.7 |
| Ischemic heart disease | 410:414 | 312 | 14.8 (14.7-15.0) | 19.1 (18.7-19.6) | 6.1 |
| Acute myocardial infarction | 410 | 137 | 3.9 (3.8-3.9) | 6.8 (6.6-7.0) | 5.0 |
| Cardiac dysrythmias | 427 | 127 | 2.9 (2.8-3) | 6.4 (6.3-6.6) | 5.0 |
| Essential hypertension | 401 | 15 | *0.2 (0.17-0.22) | *0.4 (0.4-0.4) | 2.6 |
| Ischemic stroke | 433:436 | 151 | 5.9 (5.8-5.9) | 7.4 (7.3-7.6) | 4.9 |
| **Other Diseases** | | | | | |
| Respiratory diseases | 460:519 | 541 | 19.7 (19.5-19.9) | 41.6 (41.1-42.1) | 7.7 |
| Acute renal failure | 584 | 57 | 4.5 (4.4-4.5) | 10.1 (9.9-10.3) | 17.7 |
| Mental Health | 290:319 | 64 | 2.1 (2.1-2.2) | 6.3 (6.2-6.4) | 9.8 |
| Dehydration | 276.5 | 71 | 7.9 (7.8-7.9) | 15.9 (15.7-16.0) | 22.5 |
| Heat illness | 992 | 2 | 4.3 (4.2-4.3) | 10.1 (9.8-10.4) | 505 |

**Table 3:** First three columns are as in Table 2 but for the six California subregions using the all causes outcome category.

| | Daily Average Hospital-izations 1999-2009 | Average Excess Daily Morbidity (Count) | | Average Excess Daily Morbidity (Percent above normal) |
|---|---|---|---|---|
| | | HHE span | HHE peak | HHE peak |
| Central Valley | 533 | 23.5 (23.3-23.7) | 43.4 (42.9-43.9) | 8.1 |
| Southern Deserts | 148 | 3.7 (3.6-3.8) | 9.4 (9.1-9.6) | 6.3 |
| Coastal North | 448 | 22.9 (22.7-23.1) | 46.9 (46.4-47.3) | 10.5 |
| Coastal South | 1276 | 49.7 (49.4-50.1) | 70.9 (70.0-71.8) | 5.6 |
| Mojave | 62 | *1.1 (1.0-1.2) | *1.7 (1.5-1.8) | 2.7 |
| Northern Forests | 49 | *1.4 (1.3-1.4) | *0.5 (0.3-0.6) | 1.0 |

## Figure Caption List

Figure 1. (a) PD data, (b) data and weekly+seasonal cycle for 2006, (c) filtered PD data after removing trend, seasonal and weekly cycles and holiday effects shown for 2006.

Figure 2. (a) Canonical variables $CC1_{Tmax}$ and $CC1_{Health}$ and (b) homogeneous correlation maps showing the correlation between the input data vectors and their associated canonical variables (e.g. correlation between x' and $CC1_{Tmax}$ and between y' and $CC1_{Health)}$. The input data were regionalized using empirically defined California subregions: Central Valley (CV), Southern Deserts (SD), Coastal North (CN), Coastal South (CS), Northern Forests (NF) and Mojave (MJ).

Figure 3. Green and black time series represent the canonical variables shown for each year of the analysis period. The 15-day running correlation between $CC1_{temp}$ and $CC1_{hosp}$ is shown in blue if statistically significant. Heat-Health Events are shown in red.

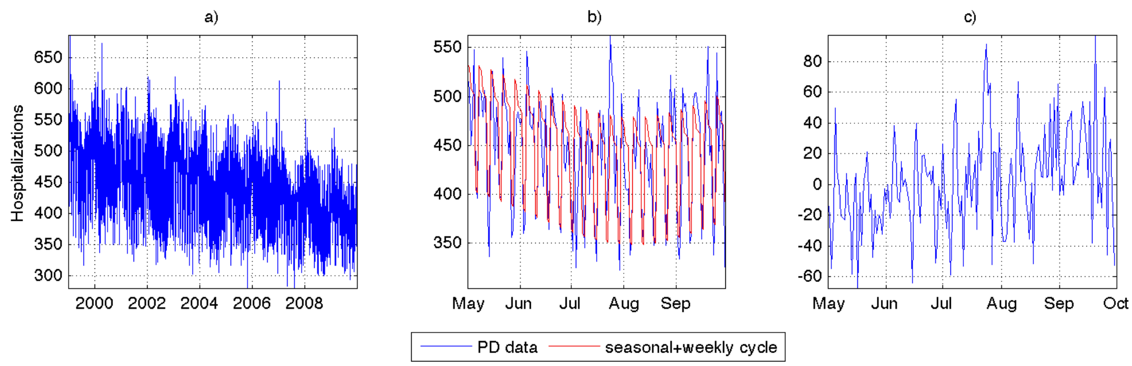
Figure 4. (a) Regionally averaged peak temperature for Tmax and Tmin during each HHE, with the number of days exceeding the summertime $95^{th}$ percentile shown in blue text and an asterisk (*) indicating if the monthly $95^{th}$ percentile was reached (b) standardized Tmax and Tmin anomaly on peak day. Note here peak day is calculated regionally for each variable (Tmin and Tmax do not necessarily peak on the same day) and may vary slightly from the peak day given in Table 1.

Figure 5. (a) Boxplot showing statewide hospitalization anomalies for non-HHE days (n=1544), HHE span (n=139) and HHE peak (n=19) and (b) morbidity associated with each event using the resampling method (see text). In (b), the boxplots show the distribution of historical non-HHE days spanning the same duration as the HHE and green markers give the cumulative health impact for each HHE (filled markers indicate statistical significance at the 90% level).

Figure 6. As in Figure 5b but for the six California subregions and with a color scale showing the impact in terms of the percentile of the resampled distribution.

Figure 7. (a) Distribution of Tmax by region and season and showing Tmax on the peak day of those HHEs identified as having a significant health impact, and (b) showing results as °C above normal.

Figure 8. Proportion of hospitalizations by month and heat wave type. Individual events are separated by white horizontal lines.

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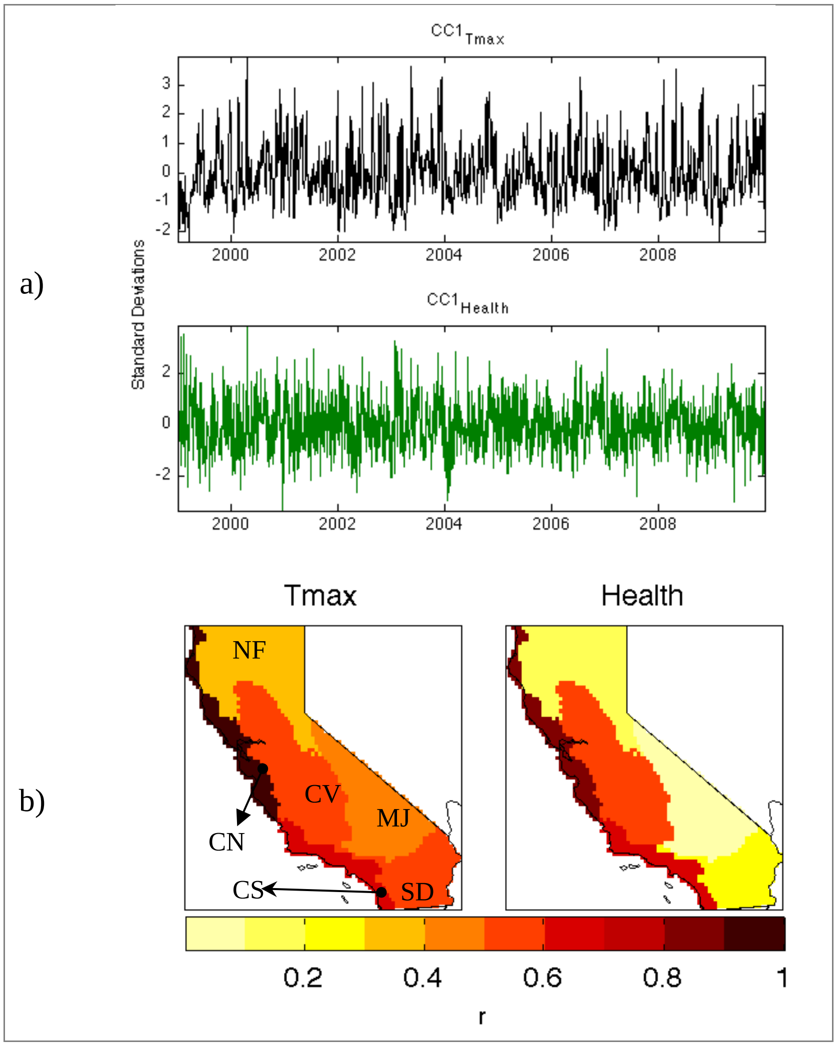


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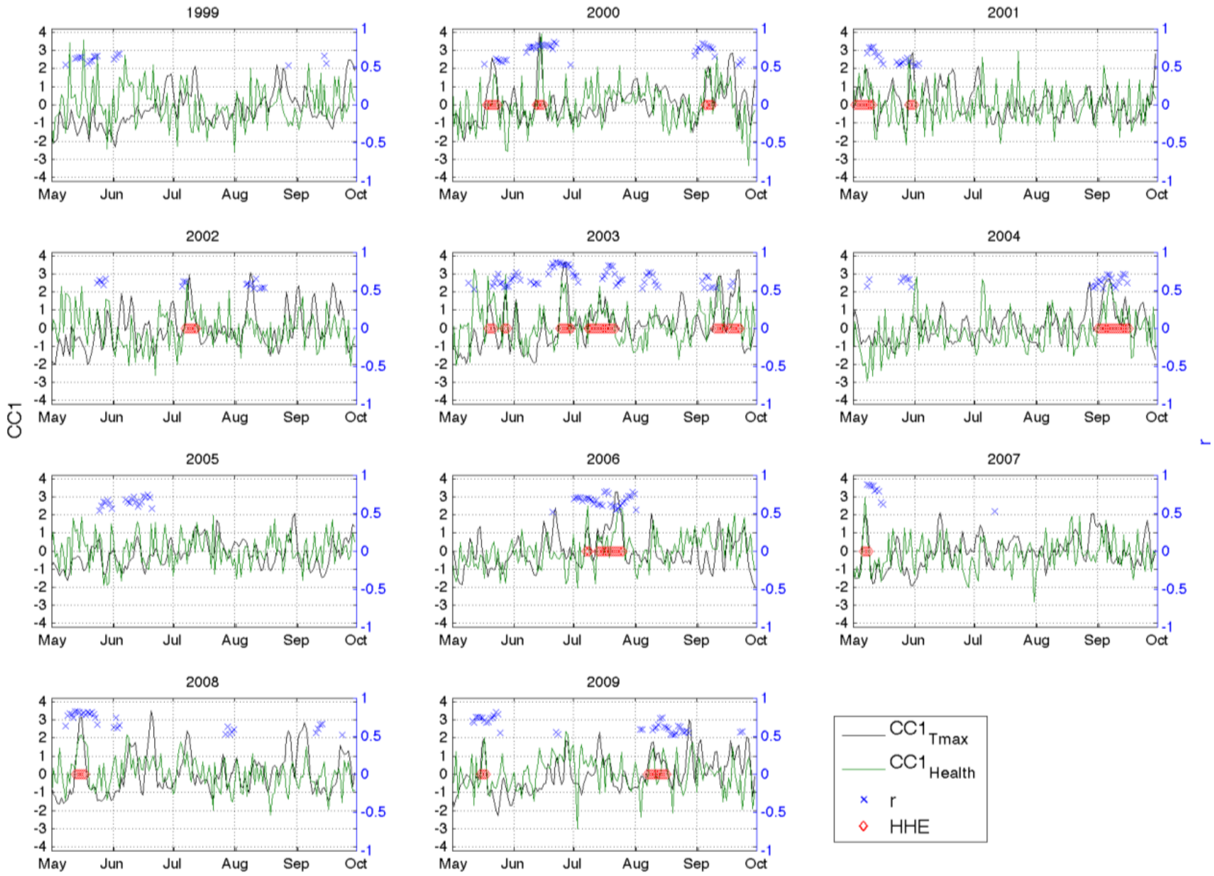


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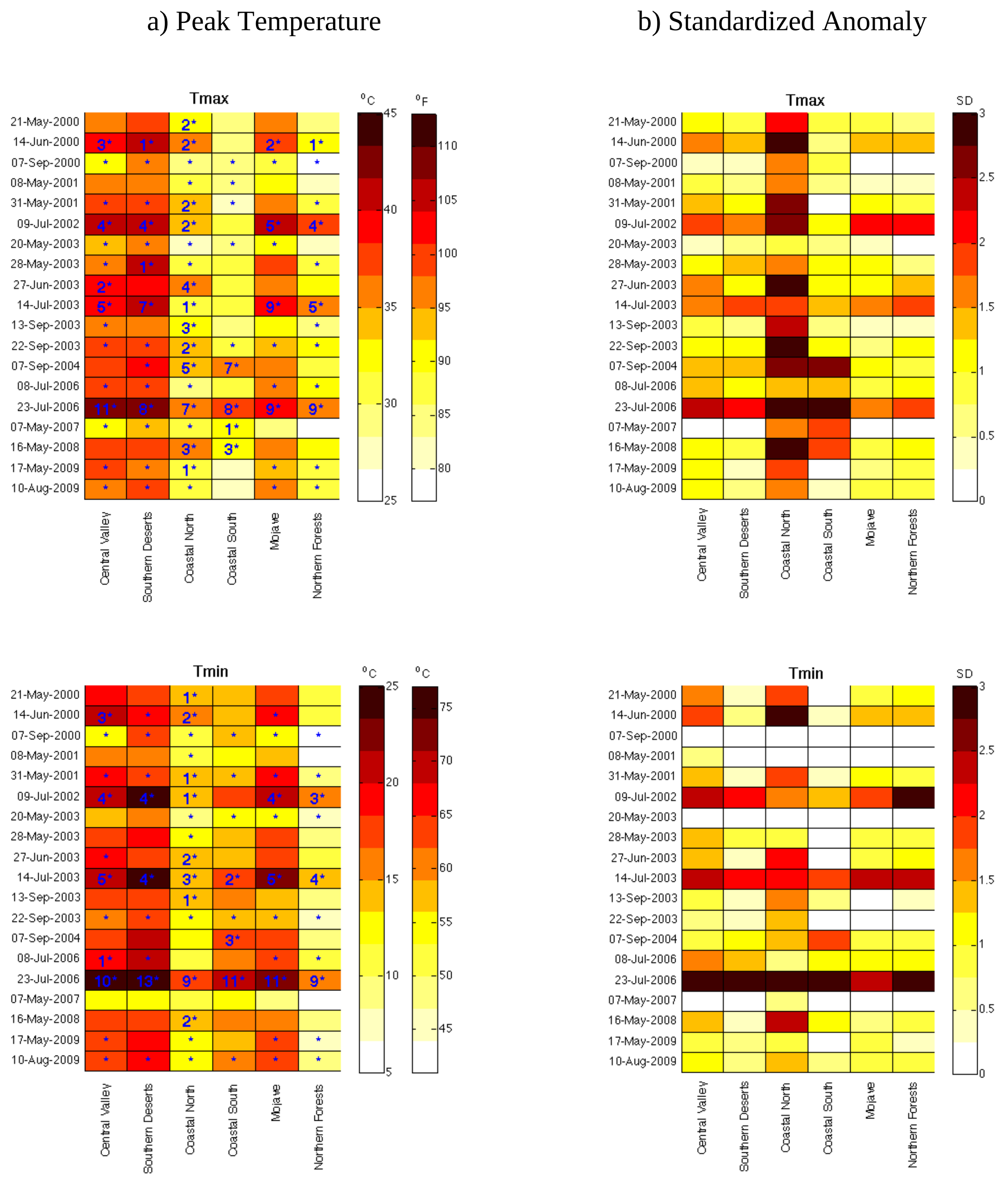


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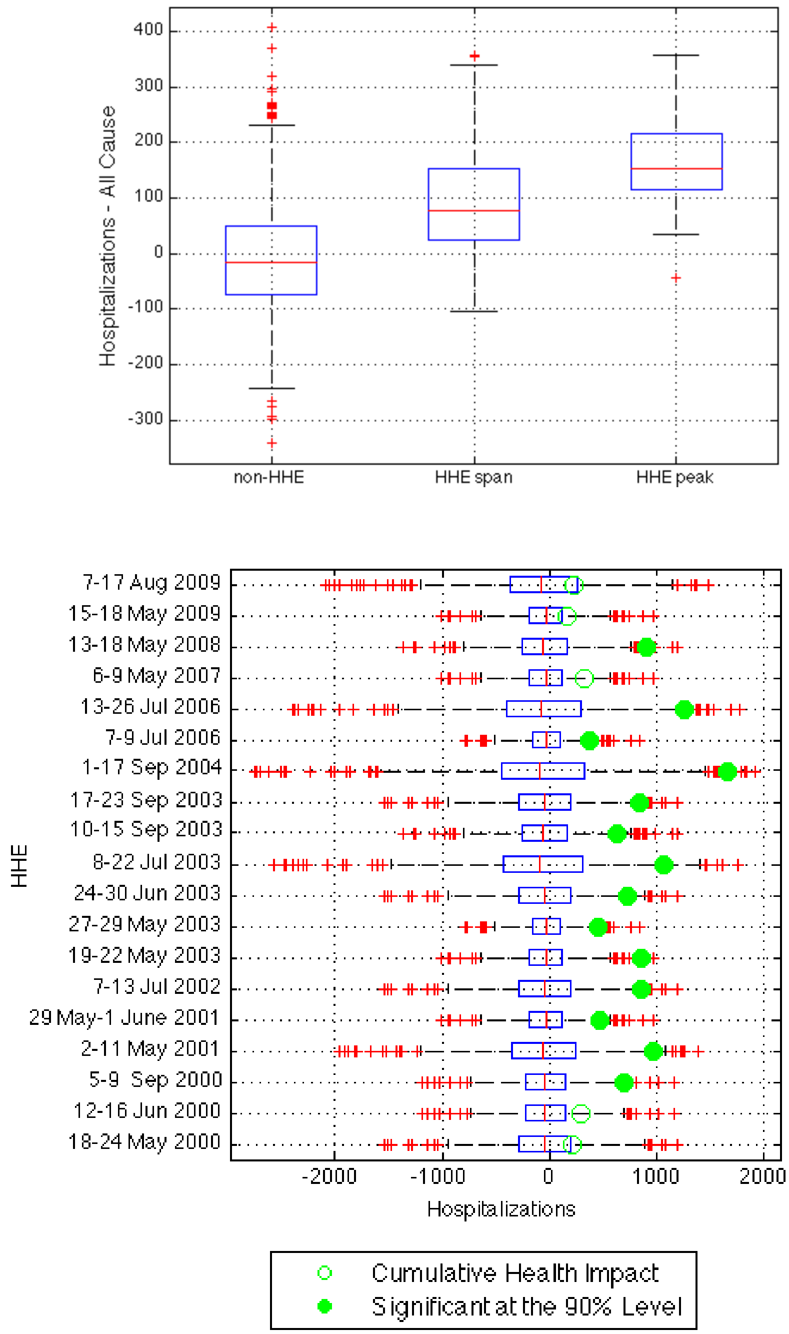
a)

b)

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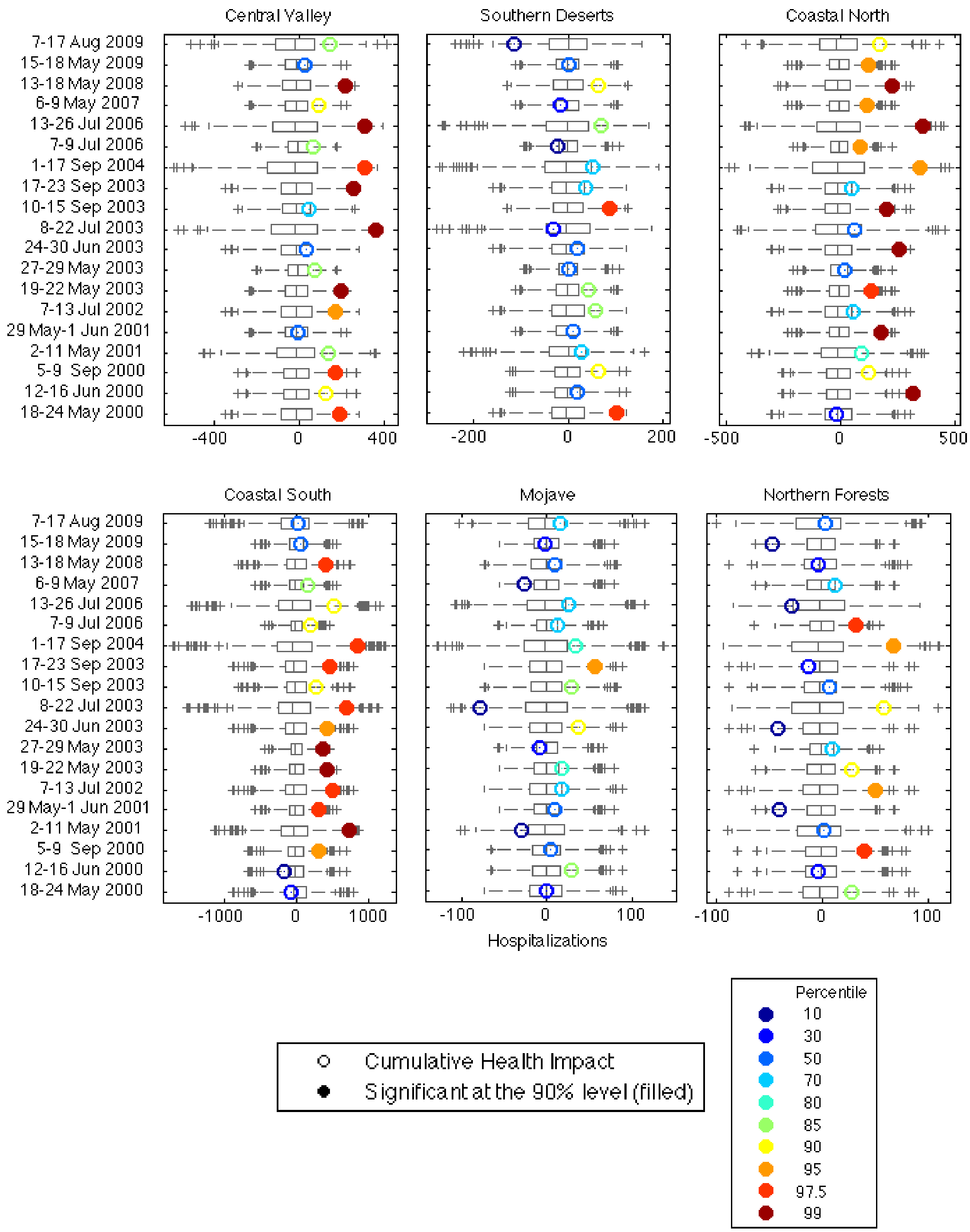


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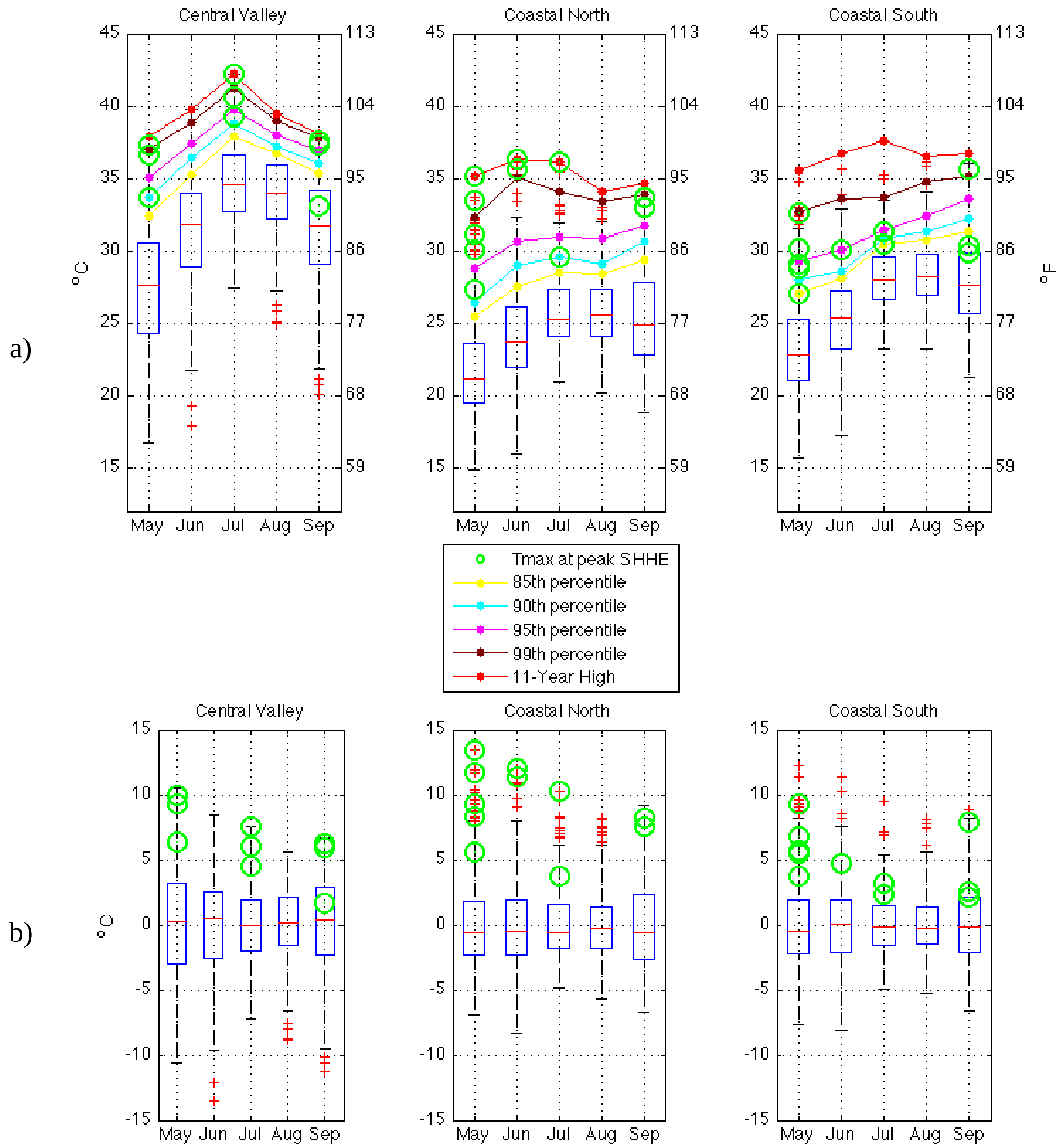


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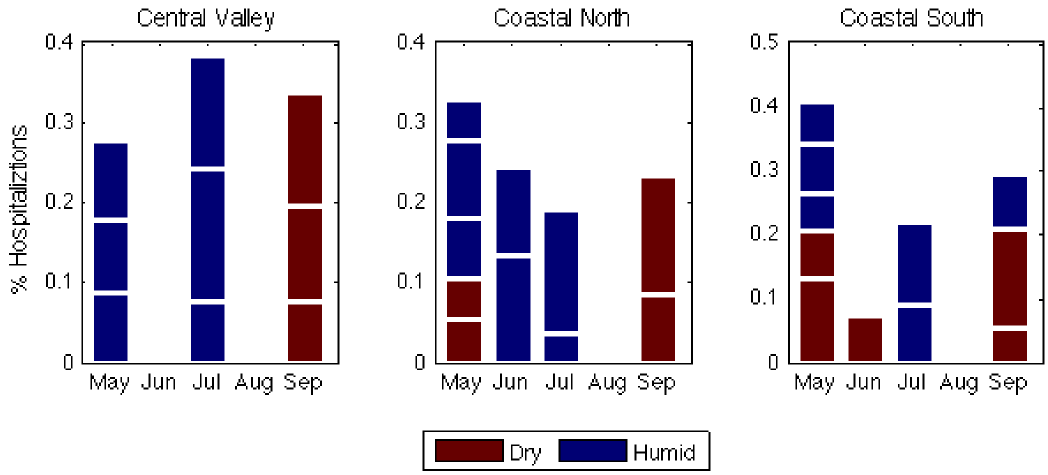


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