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Defining heat waves and extreme heat events using sub-regional meteorological data to maximize benefits of early warning systems to population health

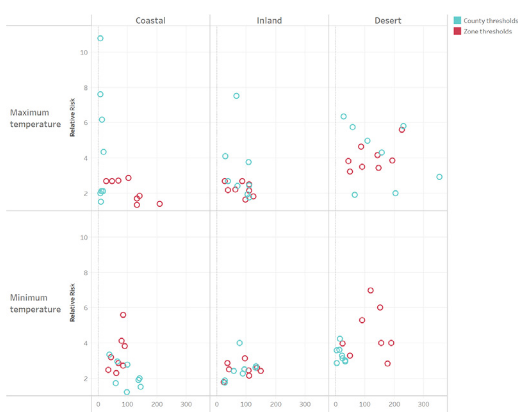
Sara McElroy [a,b,1], Lara Schwarz [a,b,1], Hunter Green [c], Isabel Corcos [d], Kristen Guirguis [e], Alexander Gershunov [e], Tarik Benmarhnia [b,e,*,**]

[a] School of Public Health, San Diego State University, San Diego, CA, USA
[b] Department of Family Medicine and Public Health, University of California, San Diego, CA, USA
[c] Fielding School of Public Health, University of California, Los Angeles, CA, USA
[d] County of San Diego Health and Human Services Agency, San Diego, CA, USA
[e] Scripps Institution of Oceanography, University of California, San Diego, CA, USA

HIGHLIGHTS

- Explores variation in health impacts for distinct heat wave measurements in climate zones of San Diego County, California.
- Demonstrates health effects vary when considering heat waves based on the entire County or by climate zone.
- Absolute risks constitute a more appropriate measure for informing early warning systems at a small scale level.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Extreme heat events have been consistently associated with an increased risk of hospitalization for various hospital diagnoses. Classifying heat events is particularly relevant for identifying the criteria to activate early warning systems. Heat event classifications may also differ due to heterogeneity in climates among different geographic regions, which may occur at a small scale. Using local meteorological data, we identified heat waves and extreme heat events that were associated with the highest burden of excess hospitalizations within the County of San Diego and quantified discrepancies using county-level meteorological criteria.
Methods: Eighteen event classifications were created using various combinations of temperature metric, percentile, and duration for both county-level and climate zone level meteorological data within San Diego County. Propensity score matching and Poisson regressions were utilized to ascertain the association between heat wave exposure and risk of hospitalization for heat-related illness and dehydration for the 1999–2013 period. We

* Corresponding author at: Department of Family Medicine and Public Health, University of California, San Diego, La Jolla, CA 92093, USA.
** Corresponding author at: Scripps Institution of Oceanography, University of California, San Diego, La Jolla, CA 92093, USA.
E-mail address: tbehmarhnia@ucsd.edu (T. Benmarhnia).
[1] Equal contribution status.

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estimated both relative and absolute risks for each heat event classification in order to identify optimal definitions of heat waves and extreme heat events for the whole city and in each climate zone to target health impacts.
Results: Heat-related illness differs vastly by level (county or zone-specific), definition, and risk measure. We found the county-level definitions to be systematically biased when compared to climate zone definitions with the largest discrepancy of 56 attributable hospitalizations. The relative and attributable risks were often minimally correlated, which exemplified that relative risks alone are not adequate to optimize heat waves definitions.
Conclusions: Definitions based on county-level defined thresholds do not provide an accurate picture of the observed health effects and will fail to maximize the potential effectiveness of heat warning systems. Absolute rather than relative risks are a more appropriate measure to define the set of criteria to activate early warnings systems and thus maximize public health benefits.

1. Introduction

The health burden of high ambient temperature has been increasingly recognized and documented in the literature. A rise in ambient temperature has been shown to be associated with increases in mortality and morbidity (Benmarhnia et al., 2015; Sheridan et al., 2009; Xu et al., 2016; Cheng et al., 2019). Specifically, high heat events have revealed increased risk of hospitalization for various diagnoses including cardiovascular disease, acute renal failure, dehydration, heat illness and respiratory disease (Ebi et al., 2004; Phung et al., 2016; Ponjoan et al., 2017; Knowlton et al., 2009; Guirguis et al., 2018). For example, 16,166 excess emergency department visits and 1182 excess hospitalizations occurred in California during a heat wave that affected much of the state in July 2006 (Knowlton et al., 2009). As the severity, frequency and duration of extreme heat events continue to increase due to climate change, the burden of heat on morbidity and mortality will be exacerbated (Sheridan et al., 2009; Sheridan and Allen, 2018; Guo et al., 2018). Consequently, continued research studying the health impacts of ambient heat is crucial to inform policy action to reduce the magnitude of these effects.

Although acute heat-related illness from high ambient temperature occurs in various climates and countries around the world, these impacts are largely preventable. Early warning systems have been implemented in various cities globally, which activate measures to protect the population from negative health impacts during extreme heat events (Lowe et al., 2011; Matthies and Menne, 2009). Typically, measures include media releases, dissemination of heat advice to vulnerable populations (Price et al., 2018, 2013; White-Newsome et al., 2014; McGregor et al., 2015), provision of portable water in public of places, advice on food hygiene, preparation and storage and other targeted interventions (Lowe et al., 2011). Some studies have shown that these actions as part of heat warning systems can be effective in reducing morbidity and mortality on hot days (Price et al., 2018; McGregor et al., 2015; Vaidyanathan et al., 2019; Benmarhnia et al., 2019; Benmarhnia et al., 2016), while the effectiveness of National Weather alerts has been shown to be inconsistent (Weinberger et al., 2018).

Many studies have investigated health impacts associated with various heat waves definitions (Xu et al., 2016; Tong et al., 2010; Kent et al., 2013; Chen et al., 2015; Xu et al., 2019; Liss et al., 2017). Defining heat wave days could be particularly useful to identify the set of meteorological criteria for triggering early warning systems. Such criteria can include temperature thresholds (e.g. percentiles exceeding the norm), temperature metrics (maximum or minimum temperatures) or duration, for example. Some studies (Gasparrini et al., 2015; Benmarhnia et al., 2014; Berko et al., 2014) highlighted that both the amplitude of the risk (e.g. measured as a risk ratio) and the prevalence of the exposure associated with a heat event are important for anticipating public health impacts.

Other studies found that the heat-health relationship varies greatly by geography (Gasparrini et al., 2015; Curriero et al., 2002). This is mostly due to variations in meteorological conditions and micro-climates (Schinasi et al., 2018) or population composition (Benmarhnia et al., 2017; Hondula and Barnett, 2014; Hondula et al., 2013). A comprehensive county-level analysis across counties of the United States highlighted significant variability in health impacts for different identified thresholds for heat-alert criterions (Vaidyanathan et al., 2019). Such differences can be substantial even at a smaller scale level such as within a city or a county (Li et al., 2015; Toloo et al., 2014). Therefore, adopting a single criterion for a whole county may not provide an accurate picture of the small scale variation of the observed health effects and will fail to maximize the potential effectiveness of heat warning systems.

San Diego County, California is a unique region to investigate such small scale variations because it has 3 predominant climate zones: coastal, inland, and desert (Thrower and Bradbury, 1977), spanning approximately 4500 mile^2 and a resident population of 3.3 million (SANDAG, 2017). Due to this heterogeneity, we propose using separate heat wave definitions for each unique climate zone within the county and hypothesize that health burden will differ by the temperature distribution and measure used. A previous study (Guirguis et al., 2018) found that in the County, health impacts occur at lower temperatures in coastal locations compared to inland locations.

A previous study published in 2018 quantified, on the relative scale, the health impacts of ambient temperatures at numerous thresholds levels, within the same three climate zones in San Diego (Guirguis et al., 2018). This previous analysis's main objective was to explore how prevalence of living in a residence with air conditioning impacted the association of heat and hospitalizations for the previous listed conditions and whether the association was modified by age, ethnicity, income, and home ownership. This study will build on these prior analyses and focuses on informing early warning systems by examining the heat-health relationship within the three climate zones compared to the entire county climate thresholds to indicate the importance of local heat wave definitions within one county.

In this paper, we propose an approach that compares various heat events to identify actionable to maximize public health benefits. We considered heat waves and extreme heat events for each unique climate zone within the county to evaluate whether the health burden differed by the temperature distribution and measure used. We also quantified the discrepancy in attributable number of a range of heat-related illnesses when comparing county-level and climate zone-level heat event classifications.

2. Materials and methods

2.1. Climate data

Temperature data were downloaded from a dataset that includes data from National Ocean and Atmosphere Administration Cooperative Observer (NOAA COOP) stations across the United States (NOAA, 2017). The climate data was processed for San Diego County, including maximum temperature and minimum temperature from 1999 to 2013. For the analyses, only the months of June to October were analyzed. The data were subset into three micro climate zones: coastal, inland, and desert, as defined by the California Energy Commission (California S, 2017) (Fig. 1).

Various heat event classifications were modeled for the three geographical regions. Criteria consisted of a combination of percentiles, temperature metrics and duration of extreme heat. Heat waves and 1-day extreme heat events were defined using daily maximum and minimum temperature metrics. Four percentiles were considered as heat wave thresholds for each temperature metric: 90, 92.5, 95, and 97.5. One day and two consecutive heat wave days were considered. Classifications included definitions using the distribution for the entire county and for each climate zone for the 18 criteria for heat waves and extreme heat events in order to quantify the importance of locally-defined heat wave definitions (72 definitions in total). For example, when defining heat waves and extreme heat events for the county level, a day would be considered a heat wave or extreme heat event if the temperature was above the 90th percentile of the temperature distribution for the entire county. Alternatively, when considering climate zone level definitions, a day would be considered a heat wave or extreme heat event day if the temperature exceeded the 90th percentile for the temperature distribution of that specific climate zone.

2.2. Hospitalization data

Unscheduled hospitalizations at acute care facilities in San Diego County that occurred in the months of May 1st to October 31st from 1999 to 2013 were obtained from the Office of Statewide Health Planning and Development Patient Discharge Data at the climate zone and county level. The outcome variable was described as a hospitalization with a primary diagnosis for any heat-related illness (ICD-9 992.0–992.9), including dehydration (276.5), heat cramps (992.2), heat exhaustion (992.3, 992.4 and 992.5), and heat stroke (992). Such specific outcomes are useful and sensitive as an indicator of the response to extreme heat, but may underestimate the overall burden associated with extreme heat, which can include other outcomes of several other ICD codes such as fluid and electrolyte disorder or acute kidney failure (Bobb et al., 2014; Hopp et al., 2018). Included in the health data was the patient's zip code of residence. Hospitalizations were assigned by aggregating these residential zip codes into the three climate zones, coastal, inland, and desert.

2.3. Data analysis

For each heat event classification, we first aimed at obtaining comparable set of heat events and non-heat wave events which resemble each other in regard to time-varying confounders including long term and seasonal patterns (year, month, day of the week) while allowing for non-linear forms, i.e. by adding a quadratic term. We also considered temperature lag variables that ranged from 1 to 4 day lags.

We used a propensity score matching approach to analyze the health impacts of heat wave events (Austin, 2011). Propensity scores were generated using logistic regression with one of the heat event classifications as the dependent variable and identified confounders as predictors. This generation of propensity scores was repeated for each of the 18 different heat event measurements using the entire County and by climate zone classifications. A one-to-one propensity score matching was then completed for each of the heat events classifications. The

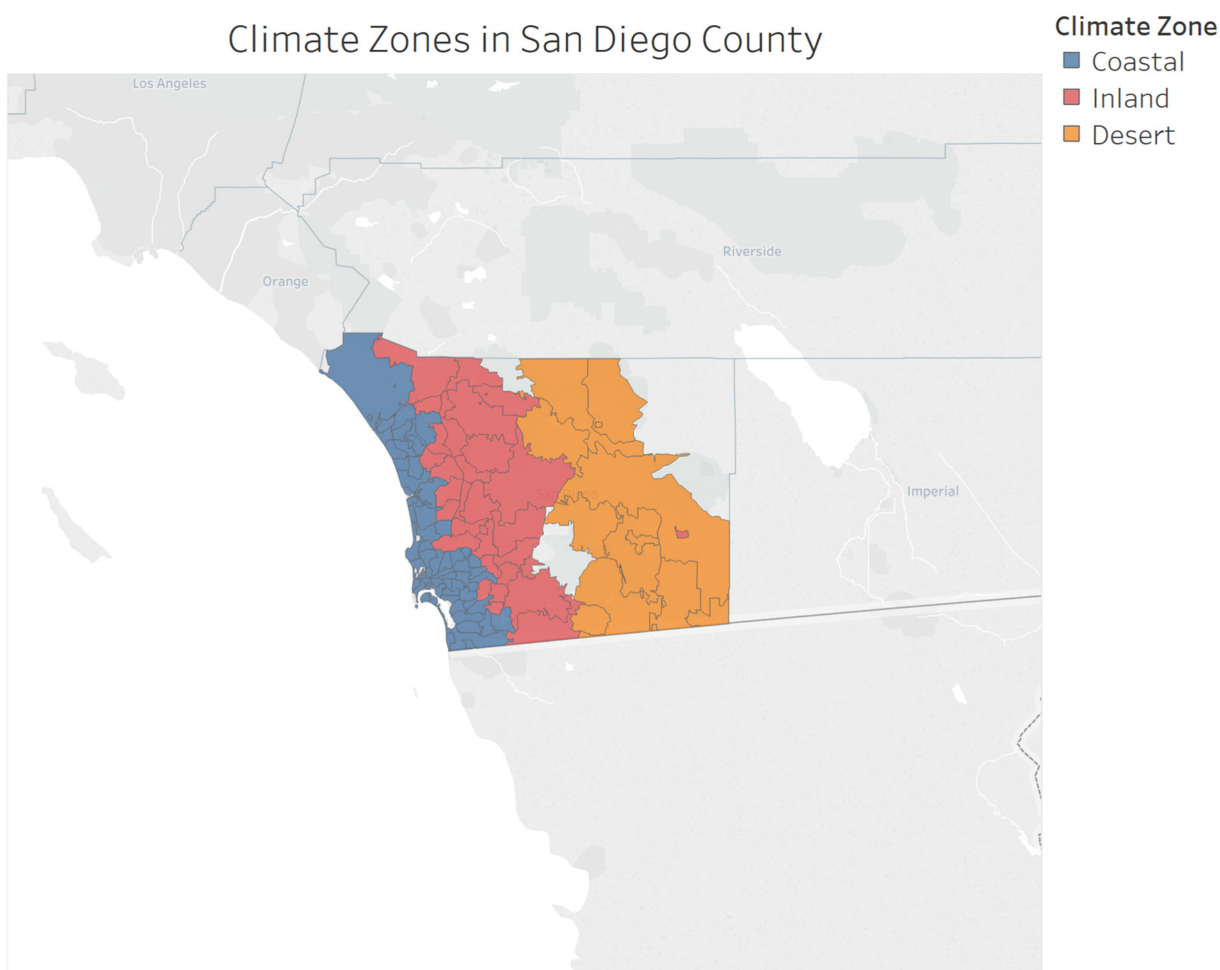

Fig. 1. Map of San Diego County, separated by climate zone.

matching was executed utilizing the *onetomanymatch* macro (Parsons, 2004). This macro uses the Greedy method of matching cases to controls. More specifically, a case is matched to a control via the "best" match, or by the propensity score with the greatest matching digits. Once a control is selected for a case, it is not considered for any other cases in the dataset.

Subsequently, after matching was completed, conditional general linear models with a Poisson distribution and log link function was run per the PROC GENMOD command in SAS to assess the relationship between heat-related illness hospitalizations and each heat event classification. The strata statement within the PROC GENMOD procedure was used to account for the matched data. Relative risks (RR) and their 95% confidence intervals were estimated from this analysis. We then estimated the absolute number of heat-related illnesses attributable to each heat wave definition (Vaidyanathan et al., 2019; Benmarhnia et al., 2014). The population attributable fraction (PAF) was derived from both the relative risk (RR-1/RR). This was then multiplied by the prevalence of heat event days and the average number of heat-related illness hospitalizations. Previous work has showed that both the relative and absolute scales are important to report as they may not systematically coincide (Gasparrini et al., 2015; Benmarhnia et al., 2014; Nori-Sarma et al., 2019). Analyses were executed for each zone (coastal, inland, desert) individually and for the entire county separately.

3. Results

Overall, there were a total of 11,708 hospitalizations in all three climate zones. The coastal region observed 7890 hospitalizations, the inland region experiences 3709, and the desert region had 109 heat-related hospitalizations. Results of the study reveal heterogeneity in the number of heat wave days in each climate zone when using the heat wave definitions based on the county-wide temperature distribution in comparison to the desert, inland and coast specific temperature distributions (Table 1). For example, when 90th percentile heat wave thresholds were calculated from county-wide distributions, the frequency of exceedance was much higher for the hottest desert zone 3 (exceeded on 540 days) compared to the cooler coastal zone 1 (exceeded on only 28 days). When calculated using zone-specific temperature distributions, 90th percentile thresholds were exceeded on 276 days for each zone. The temperature threshold differed across heat wave measurements. When considering all definitions using the maximum temperature metric, the lowest threshold was 29.11 °C for 1-day extreme heat events at the 90th percentile in zone 1 while the highest threshold was 36.55 °C for the zone-specific 2-day heat waves at the 97.5th percentile in zone 3 (Table 1).

Fig. 2 shows attributable hospitalizations and relative risks associated with all heat wave definitions (using both county-wide and zone-specific meteorological data). In the coastal zone, the highest number of attributable hospitalizations estimated was 355 when considering one day extreme heat events at the 90th percentile using maximum temperature, while the lowest number of attributable hospitalizations was 3 when considering 1-day extreme heat events and 2-day heat waves at the 97.5th percentile of minimum temperature (Table S1). A sensitivity analysis was performed to examine the effects of longer heat waves of three and four consecutive in length. The 90th percentile of maximum temperature was used for this analysis as it is the heat wave measurement with the greatest difference in attributable hospitalizations when using the zone-specific or county-wide definition (Fig. 3). These results showed similar trends to shorter heat waves, with high variation in attributable hospitalizations by climate zone when considering climate-zone specific measurements (Table S4).

The relationship between relative risks and attributable hospitalizations differed substantially across the climate zones and the heat wave definitions (Fig. 2). Heat waves and extreme heat events with the highest RR (Tables S2 and S3) were not necessarily associated with the highest attributable hospitalizations. When focusing on zone-specific definitions, it appears that those defined based on the 90th or 92.5th percentiles were associated with the highest burden of attributable hospitalizations in all zones (Table S1). Heat waves and extreme heat events defined based on maximum temperature were systematically more impactful in zone 1 while in zones 2 and 3 those defined both with maximum and minimum temperatures had the most impact on burden of hospitalizations.

We also observed important differences in the number of attributable hospitalizations between the heat waves and extreme heat events based on the temperature distribution of the entire county compared to those determined by the zone-specific temperature measurements (Fig. 3). The largest discrepancy between the two criteria occurred with the 1-day extreme heat event definition using the 90th percentile of maximum temperatures: a difference from county-level and climate-zone level of 193 attributable heat-related hospitalizations when comparing the zone-specific definition to the overall county-level definition (Fig. 2).

4. Discussion

In this paper, the importance of defining heat waves using sub-regional meteorological data was shown by highlighting the large

Table 1
Comparing zone-specific and city-wide temperature thresholds and number of days for each heat wave, May–September 1999–2013.

Heat wave measurement	Climate zone in San Diego County					
	Zone 1-coastal		Zone 2-inland		Zone 3-desert	
	By county/zone		By county/zone		By county/zone	
	# days	Temp. threshold (°C)	# days	Temp. threshold (°C)	# days	Temp. threshold (°C)
Max. temperature, 90th percentile, 1 day in length	276/28	33.4/29.1	276/261	33.4/33.2	276/540	33.4/34.7
Max. temperature, 92.5th percentile, 1 day in length	207/23	33.9/29.8	207/187	33.9/33.7	207/410	33.9/35.1
Max. temperature, 95th percentile, 1 day in length	138/14	34.6/30.7	138/120	34.6/34.3	138/280	34.6/35.7
Max. temperature, 97.5th percentile, 1 day in length	69/8	35.7/31.9	69/61	35.7/35.5	69/138	35.7/36.6
Min. temperature, 90th percentile, 1 day in length	276/561	17.8/18.8	276/215	17.8/17.5	276/50	17.8/15.6
Min. temperature, 92.5th percentile, 1 day in length	207/429	18.2/19.1	207/159	18.2/17.9	207/33	18.2/16.1
Min. temperature, 95th percentile, 1 day in length	138/292	18.7/19.6	138/104	18.7/18.4	138/18	18.7/16.7
Min. temperature, 97.5th percentile, 1 day in length	69/142	19.5/20.2	69/61	19.5/19.3	69/49	19.5/17.6
Max temperature, 90th percentile, ≥2 days in length	234/24	33.4/29.1	257/218	33.4/33.2	259/205	33.4/34.7
Max temperature, 92.5th percentile, ≥2 days in length	171/19	33.9/29.8	184/147	33.9/33.7	188/136	33.9/35.1
Max temperature, 95th percentile, ≥2 days in length	104/12	34.6/30.7	116/76	34.6/34.3	126/70	34.6/35.7
Max temperature, 97.5th percentile, ≥2 days in length	44/7	35.7/31.9	55/38	35.7/35.5	58/33	35.7/36.6
Min. temperature, 90th percentile, ≥2 days in length	258/213	17.8/18.8	256/212	17.8/17.5	253/49	17.8/15.6
Min. temperature, 92.5th percentile, ≥2 days in length	188/156	18.2/19.1	184/156	18.2/17.9	181/33	18.2/16.1
Min. temperature, 95th percentile, ≥2 days in length	109/98	18.7/19.5	116/100	18.7/18.4	111/18	18.7/16.7
Min. temperature, 97.5th percentile, ≥2 days in length	54/54	19.5/20.2	54/56	19.5/19.3	56/4	19.5/17.6

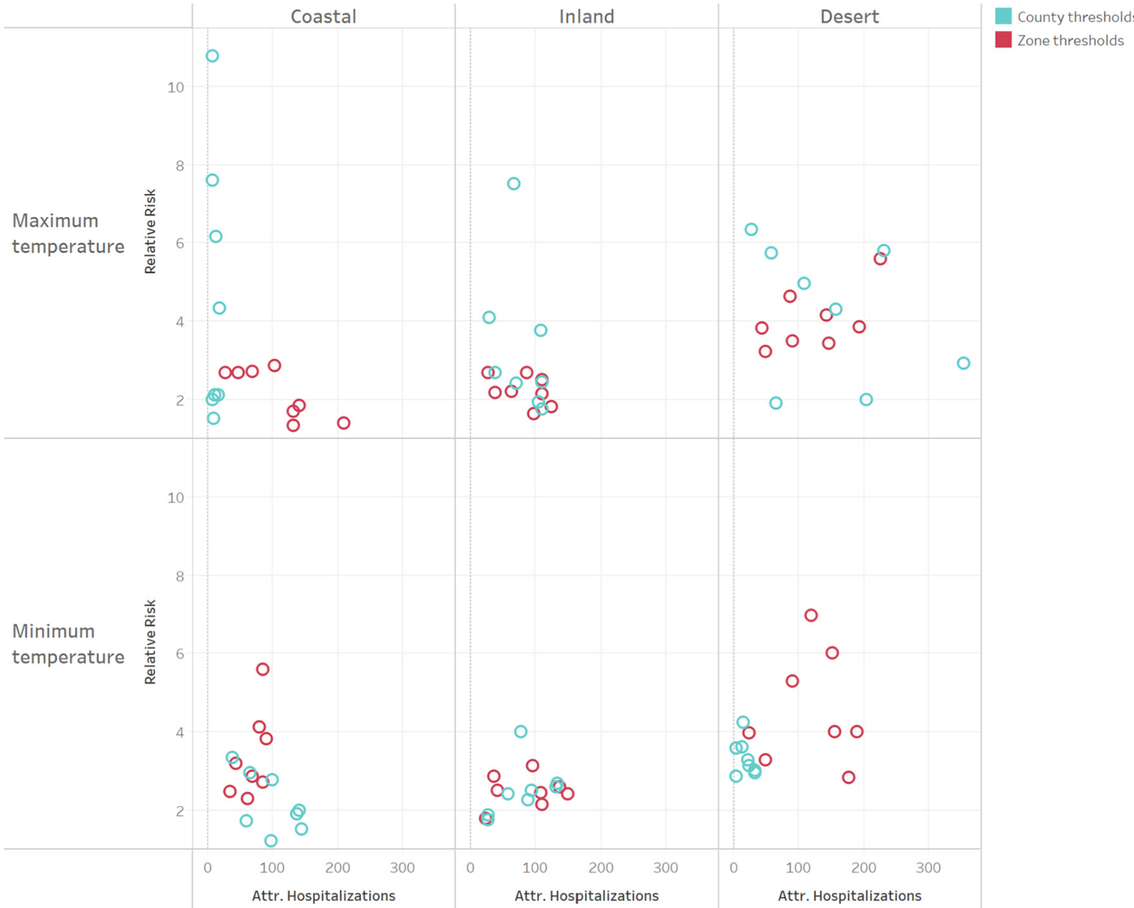

Fig. 2. Scatterplot of attributable hospitalizations and relative risk using temperature distribution for entire county and temperature distribution by climate zone.

discrepancies in the number of attributable hospitalizations when comparing zone-specific to county-wide temperature distributions. These results indicate that adopting a single criterion for an entire region may not provide an accurate picture of the observed health effects due to substantial differences in climate patterns or population characteristics. Instead, using local meteorological data, more precise modeling can

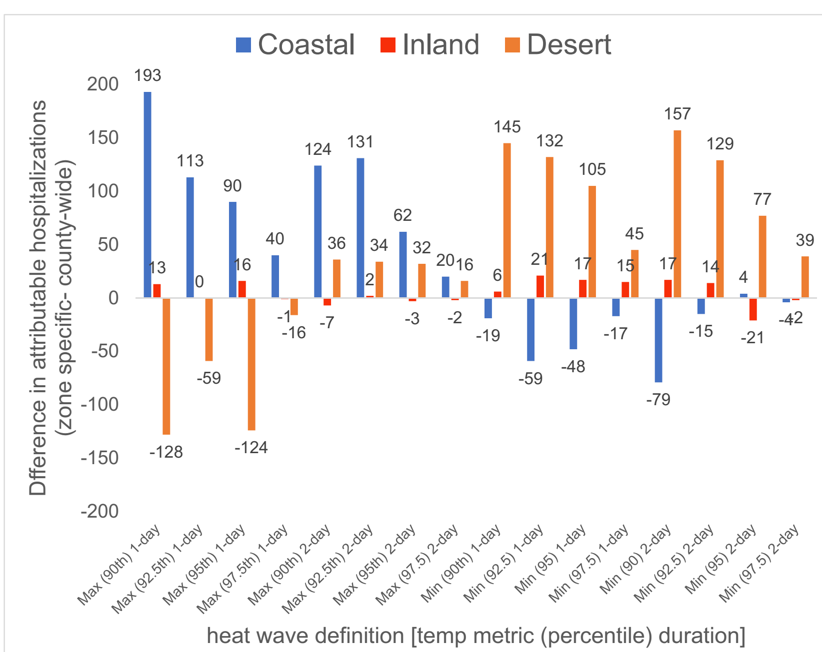

Fig. 3. Differences in attributable hospitalizations for heat waves using zone-specific temperature distribution and county-wide temperature distribution in San Diego County, 1999–2013.

substantially improve early heat warning systems within large administrative jurisdictions.

Our results show that the health burden of ambient temperature differs vastly by measurement used for heat waves or extreme heat events. This finding is consistent with previous research showing that heterogeneous heat wave definitions can result in substantial differences in estimated health outcomes (Tong et al., 2010; Kent et al., 2013; Anderson and Bell, 2009). For example, Tong et al. (2010) compared ten heat wave definitions to determine which is the best predictor of health impacts in Brisbane, Australia, and found that small changes in heat wave definitions could lead to substantial changed in health impacts (Tong et al., 2010). Kent et al. (2013) conducted a similar analysis in Alabama, USA and revealed that relative heat wave index measures had stronger associations with preterm births and non-accidental deaths (Kent et al., 2013). The variation in the impacts according to heat wave measurement in our results agrees with the literature on this topic. However, most of the previous literature aimed to reveal which definition for heat waves and extreme heat events are the best predictors of health impacts for an entire city or region (Xu et al., 2016). Campbell et al. (2019) did consider the heat waves using a relative measure of temperature using historical data for each location and found increases in emergency department hospitalizations in Tasmania, Australia (Campbell et al., 2019); however they did not calculate these estimates with overall measures as a comparison. Our study explores this with further depth to understand how these definitions can differ within a city or county, and understand the extent of the misclassification occurring between climatic zones when using one regional temperature distribution. Instead of testing various definitions on a regional level, our results can be used to inform the most appropriate heat wave and extreme heat definition at the local level.

The previous 2018 study found coastal residents were more susceptible to heat-related hospitalizations than inland residents (Guirguis et al., 2018). Also, the coastal region saw health impacts at lower temperatures thresholds compared to inland locations. These results align with our findings that persons living in the coastal region were observed to experience heat-related illness at lower temperature than the inland and desert climate zones.

Our results show that using the same temperature threshold for the all zones of the San Diego County fails to reveal the range of the impacts. These definitions may capture distinct types of heat waves, or meteorological events, which may present differently over the various subregions of the county. This has been documented in summer, when specific meteorologically distinct events are expressed in different climate regions, such as the coast or desert (Clemesha et al., 2018). For example, the higher health impact of heat waves and extreme heat events defined by maximum temperature in zone 1 may be because of the Santa Ana winds that are associated with hot temperatures along the coast (Guzman-Morales et al., 2016). Utilizing one county level heat wave definition fails to consider the risks of these unique heat wave expressions which differ by zones within the county.

There are many examples of heat waves that only express themselves over the coast or deserts of Southern California (Austin, 2011). The estimated number of patients admitted for heat-related illness attributable to heat waves showed vastly different results when climate zones were considered individually rather than when the heat wave were measured based on the temperature distribution for the entire county. The average county estimations either drastically overestimated or underestimated hospital admissions, except for zone 2 — the transitional zone between coast and desert. Heat wave definitions that incorporate geographical and weather/climate criteria should be contextualized to a local scale to improve the accuracy of heat warning systems and hospital preparedness. This has long been recognized in San Diego County, which motivated an improved warning system that accounts for local variation in climatology and provides tiered heat alerts for different levels of population vulnerability (NWS, https://www.wrh.noaa.gov/wrh/heatrisk/?wfo=sgx).

The activation of early warning systems is often based on identified thresholds and therefore is based on binary criteria. However, our results show that these should be built around local epidemiologic evidence and in collaboration with emergency management stakeholders (McGregor et al., 2015). This approach should by nature and needs to be complementary to long-term measures such as greening and other climate adaptation strategies (Chun and Guldmann, 2018; Stone et al., 2013). Yet, it also possible to consider graduated alert systems with different levels associated with different actions such as the one implemented in the heat alert system in Montreal, Canada (Price et al., 2013) or in air quality indexes implemented in the United States (US) (see https://airnow.gov/index.cfm?action=aqibasics.aqi).

Subsequently, an additional important finding of this paper is the variation revealed when considering scales for the contrast measures. These results demonstrate distinctions in the health effects when using an attributable risk compared to relative risk. The majority of previous literature comparing heat wave definitions relies on relative risk to estimate the health impacts. However, a heat wave definition that best mitigates its health impacts on a population may not correspond to the highest relative risk as this measure does not take into account the occurrence of the heat waves. For example, although an extreme heat wave may have a stronger health burden, by occurring less frequently, the impact may be less severe than for a heat wave that is experienced more regularly.

Additionally, we show that heat wave and extreme heat definitions based on maximum temperature measurements resulted in the greatest number of attributable heat-related hospital admissions. Yet, while heat waves based on the minimum temperature metric contributed the least amount of attributable hospitalizations, the associated burden in zones 2 and 3 was significant. This highlights that it may be beneficial in some cases to consider a combination of criteria using both minimum and maximum metrics when planning an early heat warning system. High minimum temperatures can reflect high nighttime temperatures which often reflect high humidity events, which have been shown to be particularly harmful for health (Gershunov et al., 2009).

A limitation of this study was that we focused only on heat waves occurring during summer months (May through October). Yet, extreme heat events with health impacts can occur throughout the year in Southern California, (Kalkstein et al., 2018) and a further analysis could be conducted focusing on off-summer heat events, as well as specific meteorological types of heat waves. Additionally, humidity, which has been shown to be associated with health effects and heat waves was not included as a covariate, but elevated minimum temperature has been shown to be correlated with high humidity events (Gershunov et al., 2009). In addition, investigating a smaller subset of zones led to small sample sizes, which reduced the power and precision of the relative and attributable health risks. Also, we have no data on population mobility across climate zones in San Diego; we assumed that patients visit a hospital within their climate zone. Lastly, although it was beyond the scope of this study, we hope to explore the potential harvesting effect for various definitions of heat waves and extreme heat in future work.

While we identified variation in the burden associated with many heat wave definitions, we were not able to assess the drivers of such variations. Such drivers could for example include demographics, socioeconomic status and behavioral and contextual factors, such as the social isolation, chronic illness, and outdoor occupations. These factors have been shown to increase vulnerability to heat effects (Benmarhnia et al., 2015; Gronlund, 2014). Understanding spatial variation of these vulnerabilities may have important implications for refining heat warning systems' specific actions to reduce heat risk.

This study used hospital discharge data in San Diego County to show how various heat wave events can predict a significantly different health burden when considering locally derived heat wave thresholds. The results demonstrate that variations in heat event criteria, including climate zone, temperatures, and duration, produce significantly different risk estimates. This work highlights the importance of selecting the most appropriate risk measures when investigating the effects of heat waves on public health. Utilizing a county-level threshold will not capture the full extent of these health impacts and therefore will not be adequate in mitigating these effects. Activating heat warning systems based on locally defined thresholds that are selected based on their prediction of the attributable risk promotes greater accuracy in informing these systems, and ultimately greater alleviation of the health impacts of heat.

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CrediT authorship contribution statement

Sara McElroy: Conceptualization, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Lara Schwarz:** Conceptualization, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Hunter Green:** Data curation, Writing - review & editing. **Isabel Corcos:** Writing - review & editing. **Kristen Guirguis:** Data curation, Writing - review & editing. **Alexander Gershunov:** Writing - review & editing, Funding acquisition. **Tarik Benmarhnia:** Supervision, Conceptualization, Writing - original draft, Writing - review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.137678.

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