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Ambient temperature and added heat wave effects on hospitalizations in California from 1999 to 2009

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ABSTRACT

Investigators have examined how heat waves or incremental changes in temperature affect health outcomes, but few have examined both simultaneously. We utilized distributed lag nonlinear models (DLNM) to explore temperature associations and evaluate possible added heat wave effects on hospitalizations in 16 climate zones throughout California from May through October 1999–2009. We define heat waves as a period when daily mean temperatures were above the zone- and month-specific 95th percentile for at least two consecutive days. DLNMs were used to estimate climate zone-specific non-linear temperature and heat wave effects, which were then combined using random effects meta-analysis to produce an overall estimate for each. With higher temperatures, admissions for acute renal failure, appendicitis, dehydration, ischemic stroke, mental health, non-infectious enteritis, and primary diabetes were significantly increased, with added effects from heat waves observed for acute renal failure and dehydration. Higher temperatures also predicted statistically significant decreases in hypertension admissions, respiratory admissions, and respiratory diseases with secondary diagnoses of diabetes, though heat waves independently predicted an added increase in risk for both respiratory types. Our findings provide evidence that both heat wave and temperature exposures can exert effects independently.

1. Introduction

Associations of high temperatures or heat waves with mortality and morbidity from a number of illnesses have been well-documented in scientific literature (Astrom et al., 2011; Basu, 2009; Johnson et al., 2005; Kravchenko et al., 2013). However, surveillance and media reporting of heat wave impacts have often focused on explicitly diagnosed heat-related illnesses (HRI; e.g. heat stroke) and mortality. Making case determinations regarding the direct or indirect role of heat relies on professional judgement using both narrow heat illness definitions (e.g. hyperthermia) and limited knowledge regarding the specific circumstances of the incident (Donoghue et al., 1997). Consequently, heat-related health impacts are often underreported. For example, following the 2006 heat wave in California, researchers estimated approximately 600 heat-related deaths using epidemiological methods, almost four times greater than what was reported by the Coroner's office (Hoshiko et al., 2010; Ostro et al., 2009). More intense, frequent, and longer heat waves are predicted, both statewide and globally (Allen et al., 2012; Gershunov et al., 2009; Gershunov and Guirguis, 2012; Meehl and Tebaldi, 2004; Solomon et al., 2007), heightening the importance of adequately defining health-threatening heat waves and identifying impacted health outcomes so that appropriate preventative measures can be implemented.

Existing heat wave definitions vary by temperature metrics, thresholds, and duration (Anderson and Bell, 2011; D'Ippoliti et al., 2010; Gasparrini and Armstrong, 2011; Hajat et al., 2006; Keellings and Waylen, 2014; Kent et al., 2014; Smoyer, 1998), and no consensus exists on which best predict morbidity. One reason is that thresholds of concern may be different in milder climate regions or early in warm seasons due to regional or temporal acclimatization (Baccini et al., 2008; Gasparrini et al., 2016; Guirguis et al., 2014; Hajat et al., 2002; Lee et al., 2014; Tobias et al., 2012; Xiao et al., 2015). Nonetheless, few investigators have attempted to define heat waves based on timing in the summer within a varying climate, using month-specific thresholds (D'Ippoliti et al., 2010; Schifano et al., 2009). This method helps account for population acclimatization by defining region-specific heat

Abbreviations: AIC, Akaike information criterion; DLNM, distributed lag nonlinear models; MI, myocardial infarction; ZCTA, zip code tabulation area; $PM_{2.5}$, particulate matter with aerodynamic diameter less than or equal to 2.5 µm; CI, confidence interval; OR, odds ratio; GAM, generalized additive model; O_3, ozone; NO_2, nitrogen dioxide; SO_2, sulfur dioxide; CO, carbon monoxide

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waves that account for varying temperatures throughout the warm season (Anderson and Bell, 2009).

Most studies of heat waves and morbidity have considered specific major heat waves without adjusting for temperature (Kaiser et al., 2007; Li et al., 2015; Weisskopf et al., 2002; Ye et al., 2011). Quantifying the impact of heat waves in addition to temperature allows us to specifically capture effects of prolonged days of heat after parsing out the effects of high daily temperature, and allows for the identification of the highest risk outcomes during long durations of high temperatures. Additionally, some health impacts may be sensitive to high or even moderate temperatures independent of duration (Gasparrini et al., 2015; Gronlund et al., 2014; Yang et al., 2016) and merit vigilance regardless of the presence of a heat wave. Identifying these different relationships would benefit illness prevention efforts by allowing for better targeting and implementation of extreme heat and heat wave warnings towards at-risk populations, as well as enhancing the ability to anticipate heat care utilization during such periods. While a few studies have used this approach in studying morbidity outcomes (Gronlund et al., 2014; Xu et al., 2014a), most investigations have focused on mortality (Anderson and Bell, 2009; Chen et al., 2015; Egondi et al., 2015; Hajat et al., 2006; Zeng et al., 2014) which can differ from morbidity due to the severity of mortality causes.

In this study, we explored different definitions of heat waves to estimate their associations with hospitalizations across 16 climate zones of California during the warm season from 1999 to 2009. Because of California's diversity of population and climate zones, studying region-specific heat waves is essential, after defining what constitutes a heat wave. We examined temperature-hospitalization relationships, with particular interest in the added effect of heat waves on these relationships, using distributed lag non-linear models (DLNM) which allow for examination of lagged and cumulative effects. We also considered the possibility of confounding by air pollution and effect modification by age or race/ethnicity group, as well as area differences in effect that might arise due to acclimatization or other regional factors.

2. Materials and methods

2.1. Exposure

The study period spanned years 1999 through 2009, with focus on the warm (May 1–October 31) season because of our interest in heat waves and higher temperatures. Daily minimum and maximum temperatures were derived from gridded data on a 12 km by 12 km grid throughout California (Maurer et al., 2002). Because these were the only metrics available, daily mean temperatures were estimated as the average of the minimum and maximum values. The relative humidity measurements were abstracted from the National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis data (Mesinger et al., 2006), with gridded data available at a 32 km by 32 km spatial resolution. Exposure data was assigned to each zip code tabulation area (ZCTA) and then aggregated into 16 climate zones where each ZCTA was weighted based on its population size. Climate zone boundaries were provided by the California Energy Commission (CEC), which classified 16 areas based on weather, energy use, and other climatic factors (California Energy Commission, 2015).

To test for potential confounding by air pollutants, we utilized data for carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), ozone (O_3), as well as particulate matter less than 2.5 µm in aerodynamic diameter ($PM_{2.5}$) provided by the California Air Resources Board (California Air Resources Board, 2011). Gaseous pollutants were measured as daily one-hour maxima, while $PM_{2.5}$ is typically measured every third or sixth day depending on the location and timing of the year and provided as a 24-h average. Only climate zones with $PM_{2.5}$ above a specific threshold of observations over the study period (25% for climate zones 3, 4, 11, 15, and 16 and 50% for climate zones 6–10, 12, and 13) were included. For all pollutants, one monitor was chosen for each climate zone based on completeness of data and population coverage within 20 km based on population-weighted zip code centroid.

2.2. Health-outcome data

We obtained data for all hospitalizations in California from the Office of Statewide Health Planning and Development (OSHPD) Patient Discharge Data (PDD) spanning 1999–2009. Only unscheduled hospitalizations at acute care facilities were included. Variables of interest included zip code, date of hospital admission, day of the week, counts for each health outcome category, age groups 0–5, 6–18, 19–64, and 65 years and older) and race/ethnicity (White non-Hispanic, Black non-Hispanic, Asian non-Hispanic, and Hispanic). The following primary diagnoses were evaluated, as listed in the International Classification of Disease codes, 9th Revision, Clinical Modification: acute myocardial infarction (MI) (410), acute renal failure (584), appendicitis (540–542), cardiac dysrhythmias (427), cardiovascular disease (CVD) (390–459), dehydration/volume depletion (276.5), diabetes (250), diverticulitis (562), essential hypertension (401), heat illness (992), intestinal infectious disease (1–9), ischemic heart disease (410–414), ischemic stroke (433–436), mental health (290–319), non-infectious enteritis (558) and all respiratory diseases (460–519). These outcomes were chosen because prior studies had linked them or related outcomes to temperature (Bunker et al., 2016; Li et al., 2015). We also examined visits listing diabetes (250) as a secondary diagnosis for all respiratory diseases and all CVD each as primary diagnoses, as diabetes has been implicated in conferring susceptibility to heat-related morbidity (Bunker et al., 2016; Schifano et al., 2009). In sensitivity analyses of respiratory subgroups, we considered acute (460–466, 480–488) and chronic (470–478, 490–519) diagnoses. Outcome data were aggregated into daily counts for 16 climate zones to correspond with the heat wave and temperature metrics. Repeat visits by the same individual were counted as separate, unique visits due to an inability to differentiate specific individuals in this dataset. For each outcome, we only included climate zones that had at least 20 hospitalizations per year.

2.3. Model selection/data analysis

We created a number of heat wave definitions using the distributions for the mean, minimum and maximum temperature. For each temperature variable, we calculated a 95th percentile cutoff specific to each climate zone over the study period. We also devised month-specific 95th percentile cutoffs as a possible way to account for acclimatization. Periods of at least two consecutive days above these cutoffs were identified, and days within these periods, exclusive of the first day of the period, were designated as heat wave exposure days. All other days, including the first day of the heat wave period, were designated non-heat wave exposure days.

We applied time-series methods for analysis. DLNM utilizing generalized additive models (GAM) with a quasi-Poisson link function were used to predict the climate zone-specific daily counts for hospitalizations at day t with (1) distinct cross-basis terms for the binary heat wave indicator variable ($Cb.HW_{t,l}$) and continuous temperature ($Cb.temp_{t,l}$); (2) a natural spline over the range of study dates for time trend (time); (3) an indicator for day of the week (DOW_t); and (4) a linear term for relative humidity (RH_t).

$$LnE[Y_t] = \alpha + \beta Cb.\, HW_{t,l} + \gamma Cb.\, temp_{t,l} + NS(time, df) + \delta DOW_t + \varepsilon RH_t$$

The quasi-Poisson link function was used to account for over-dispersion in the data. Cross-basis terms for heat wave and temperature modeled the daily exposures-response relationships using binary and spline terms, respectively. Simultaneously, these cross-bases modeled their lag relationships from 0 to 3 (l) using a natural spline with an