How Hot is too Hot and How Cold is too Cold?

Estimating County-Level Relationships between Temperature and Mortality in California Counties

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Abstract

The relationship between temperature and mortality and particularly its geographical variability remains an understudied topic in demography and epidemiology. While many studies have investigated excess mortality during episodes of extreme heat, less attention has been devoted to understanding how mortality responds to temperatures between the extremes. Even fewer studies investigate how the relationship between temperature and mortality varies geographically and which factors explain this variability. This study aims to fill this gap starting with California counties, with the goal of extending the analysis to all counties in the United States.

Introduction

Because of climate change, the frequency, duration, and intensity of heat waves, episodes of elevated maximum and minimum temperatures for consecutive days, are increasing (Perkins-Kirkpatrick and Lewis 2020). The association between extreme heat and mortality has been documented across different settings. Groups at particularly high risk from these events include older adults and racial/ethnic minorities (Kosatsky 2005; Whitman et al. 1997). Typically, the mortality impact extends beyond deaths officially classified as heat-related and it is generally agreed that excess mortality measures provide a more complete assessment of the total impact. For example, while in the United States approximately 700 deaths each year are classified as heat-related (ICD-10 code T67) (Vaidyanathan 2020), estimates of excess deaths attributable to heat vary from 1,400 for all US counties (Khatana, Werner, and Groeneveld 2022b) to 5,608 for just 297 counties representing 61.9% of the United States population in 2000 (Weinberger et al. 2020).

Despite the abundance of case studies investigating the effect of single heat waves, in particular the Chicago heat wave of 1995 (Semenza et al. 1996; Whitman et al. 1997) and the West Europe heat wave of 2003 (Kosatsky 2005), our understanding of the consequences of extreme temperatures for mortality outside of these episodes is still limited. In the United States, spatial heterogeneity in the relationship between temperature and mortality has only recently been examined and only indirectly by modeling temperature effects as a function of county-level characteristics (Khatana et al. 2022b). Additionally, most existing studies focus on a subset of administrative units, typically chosen based on population size, and focus on urban areas (Curriero et al. 2002a; Schinasi et al. 2020; Zanobetti and Schwartz 2008).

Understanding the relationship between high temperatures and mortality at a more granular scale and outside of urban areas is crucial to quantify the potential impact of a warmer climate induced by climate change on mortality over the next decades. Additionally, if age and race/ethnicity specific estimates of the effect of high temperatures on mortality could be constructed, population estimation and projection methods could be used to understand where vulnerability is and will be higher. Finally, the availability of spatially and temporally fine-grained data on the impact of high temperature on mortality would allow for a comprehensive investigation of the factors associated with more severe or less severe effects.

This project builds on the existing literature and investigates the relationship between temperature and all-cause mortality in 58 California counties in 2014-2019. It makes use of a Bayesian hierarchical model adapted from Alexander et al. (2017) and Bryant and Zhang (2020) augmented with a flexible temperature component to model county-level relationships between minimum monthly temperature and mortality. The model is then used to compute the number of deaths attributable to deviations from minimum mortality temperatures.

Background

Historical Episodes

One of the most studied episodes of heat and mortality is the heat wave that affected Western Europe in August 2003. For France, Toulemon and Barbieri (2008) estimate 15,000 deaths over a period of just two weeks, an increase in mortality of approximately 35% (Toulemon and Barbieri 2008). The main urban areas in Italy, exhibited an 15.2% increase in mortality, with close to 20,000 deaths estimated nationally (Conti et al. 2005). Spain had a similar toll with estimated excess deaths between 6,595 and 8,648, corresponding to an increase in mortality between 7.9% and 10.6% (Simon et al. 2005). Portugal, Belgium, Switzerland, the Netherlands, Germany, England, and Wales were also affected (Garssen, Harmsen, and Beer 2005; Grize et al. 2005; Johnson et al. 2005; Kosatsky 2005; Nogueira et al. 2005). Across all affected countries, excess mortality was greatest among the very old (Kosatsky 2005). For countries in which excess mortality was examined separately by sex, France, Italy, and Portugal, females experienced greater mortality (Michelozzi et al. 2005; Nogueira et al. 2005; Pirard et al. 2005). Finally, in the four Italian cities, in which this aspect was investigated, areas with lower SES experienced higher excess mortality (Michelozzi et al. 2005).

In the United States, the Chicago heat wave of July 1995 caused approximately 696 deaths, for a mortality increase of 31% over the month of July (Whitman et al. 1997). Like for the 2003 Western Europe heat wave, mortality was higher among the elderly. However, the sex gap was reversed with males having higher risk of experiencing a heat related death. Non-Hispanic Blacks suffered higher excess mortality rates compared to non-Hispanic Whites, while mortality appears to have been much lower among Hispanics (but the evidence is inconclusive). Being confined to bed and living alone were the strongest risk factors of heat-related death, while having air conditioning and access to transportation were the most protective factors (Semenza et al. 1996).

Other important historical episodes include the Northeast and Upper Midwest heat wave of 1966, with an increase in mortality of 56% in Saint Louis and of 36% in New York (Schuman 1972), the July 1980 heat wave in the Midwest and the Great Plains, with a 57% increase in mortality in Saint Louis, of 67% in Kansas City, but only of 10% in rural Missouri (Jones et al. 1982), and the heat wave of June 1981 in Portugal (Garcia, Nogueira, and Falcão 1999), with a 47% increase in mortality.

Estimating Temperature-Related Mortality

The mortality consequences of heat waves can generally be studied by comparing observed death counts with expected or baseline counts in the counterfactual scenario in which no heat wave had occurred. Typically, mortality for the days in which the heat wave occurred is compared with the average mortality of previous years for the same period. Alternatively, a model for daily, weekly, or monthly mortality is estimated using pre-event data and the model's predictions are used as the baseline. While different methods, choice of reference years, and model specifications lead inevitably to different estimates, the results are usually comparable for cases in which a short prediction interval is used (Toulemon and Barbieri 2008). This approach, however, is not suited for examining the effect of temperature on mortality outside of heat waves and does not generalize well to the study of multiple episodes of elevated temperatures, each requiring a different baseline.

For these cases, researchers have relied on two sets of methods. The first one is the time-stratified case-crossover design (Maclure 1991). In this design, temperature on the day of death (case day) and as relevant, preceding days, is compared with the temperature on control days on which the death did not occur. The case-crossover design naturally controls for potential confounding factors that are time-invariant or that vary slowly over time, for example, ethnicity, socio-economic status, smoking, healthcare, and obesity. The strength of this method is in its ability to model and control for individual level factors making identification of heat related deaths robust to confounders. The main drawback of this method is that it requires individual level information, which is not always available, and that is not well suited to capture harvesting effects (periods of lower mortality following mortality crises). Despite these limitations, this method has been used to study the relationship between heat and mortality in England and Wales (Bennett et al. 2014), California (Basu, Feng, and Ostro 2008; Basu and Ostro 2008), Philadelphia (Schinasi et al. 2020), and other nine US cities (Zanobetti and Schwartz 2008). The second set of methods relies on modeling death counts for some geographical units at some level of temporal aggregation (days, weeks, or months) as a function of temperature (and other predictors). These models can be affected by the presence of confounders that covary with temperature, additionally, they do not permit the identification of single deaths as heat related but rather the attribution of a given number of deaths to temperature effects. An additional weakness is that exposure to heat is measured imperfectly, especially when larger spatial units and coarser temporal units are used. Despite these limitations, these methods are substantially less demanding in terms of data, only requiring aggregate death counts. Additionally, they can be used to test the presence and strength of harvesting effects by examining how the association between temperature and mortality changes when longer vis-à-vis shorter periods of time are used. For these reasons, they have been used widely both in the UK (Armstrong et al. 2011) and in the US (Basu et al. 2008; Khatana et al. 2022b).

Disparities in Heat-Related Mortality

The effect of heat waves on mortality is not the product of environmental factors alone, but it's rather due to a combination of social, structural, policy, and environmental factors (Klinenberg 2015). This observation extends to other natural disasters and has been made very early in the context of floods by Gilbert F. White (White 1945). More generally, natural disasters need to be understood as the interaction of biophysical events with human society. In this perspective it becomes clear that both characteristics of the biophysical event (like maximum temperature during a heat wave) and of the society it affects (like a dense urban population) will determine the impact of the disaster (White, Kates, and Burton 1993). As a society is not simply the sum of the individuals that belong to it (Durkheim 1952), individual characteristics alone are probably inadequate to explain how a community fares during a natural disaster (Klinenberg 2015; Smoyer 1998). Community-level contextual variables should thus be used to complement individual level variables to explain geographic variation in heat-related mortality.

The most stable empirical regularities regarding disparities in heat-related mortality is that older individuals are disproportionately affected (Jones et al. 1982; Kosatsky 2005; Rey et al. 2007; Schuman 1972; Whitman et al. 1997; Zanobetti et al. 2012). However, this regularity is not always present, and it is not clear that an age gradient exists within the 65+ age group. For example, in their analysis of heat-related mortality of England and Wales, Bennett and colleagues found a moderate old-age gradient for females but none for males (Bennett et al. 2014). For the United States, Khatana and coauthors found a weaker association between high temperature and mortality among the adults aged 65+ compared to adults aged 20-64 (Khatana, Werner, and Groeneveld 2022a). Similarly, in their analysis of nine California counties, Basu and Ostro found that the increase in mortality associated with a 10°F increase in mean daily temperature was smaller for the very old (85+) compared to the elderly aged 65+ and 75+ (Basu and Ostro 2008).

Heat related mortality at younger ages has received less attention. Some studies reported a U-shape relationship between age and mortality with young and working age adults exhibiting the lowest heat-related mortality rates and higher mortality for the very young (<5) and the elderly (65+) (Basu and Ostro 2008; Garcia et al. 1999). Consistently with these results, the rigorous study of high temperatures and infant mortality conducted by Schinasi and colleagues in Philadelphia showed that infants are a subpopulation that is particularly vulnerable to heat (Schinasi et al. 2020). Nevertheless, there was no evidence of excess child or infant mortality during the 2003 Western Europe heat wave (Kosatsky 2005).

The evidence regarding gender disparities is not clearcut. Females were found to be affected more severely than males in Saint Louis and New York in 1966 (Schuman 1972) and in Portugal 1981 (Garcia et al. 1999) and but not in Chicago 1995 (Whitman et al. 1997). The study of California by Basu and colleagues found no gender differentials (Basu and Ostro 2008). Finally, Khatana and coauthors found a significant relationship between heat and mortality only for males (Khatana et al. 2022b). Overall, it seems that unobserved factors might be confounding the relationship between sex and heat mortality.

Disparities in heat related mortality between urban and rural areas have rarely been studied. However, in cases in which this aspect has been examined, results are contradictory. For the 2003 heat wave in Spain, Martínez Navarro and colleagues have found similar mortality impacts in rural areas as in provincial capitals (Martínez Navarro, Simón-Soria, and López-Abente 2004). Similarly, investigating the general relationship between heat and mortality in England and Wales Bennett and colleagues find no evidence that rural versus urban status is associated with the effect size (Bennett et al. 2014). However, in their study of the 1980 heat wave in Missouri, Jones and coauthors found much lower mortality in rural areas compared to the cities of Saint Louis and Kansas City (Jones et al. 1982). Examining all counties in the United States, Khatana and colleagues find no relationship between heat and mortality in nonmetropolitan counties (Khatana et al. 2022b).

In the US, racial disparities in heat-related mortality have been documented. During the Chicago heat wave of 1995 excess heat mortality was 50% higher among non-Hispanic Blacks compared to non-Hispanic Whites (Whitman et al. 1997). Similarly, in California the heat-related increase in mortality was twice as high among non-Hispanic Blacks compared to non-Hispanic Whites (Basu and Ostro 2008). Heat related mortality for the Hispanic population has been found to be low or non-existent (Basu and Ostro 2008; Whitman et al. 1997). Regarding the role of SES, a study of the 2003 heat wave in Italy found higher excess mortality in areas of the cities of Rome and Turin with lower socioeconomic level (Michelozzi et al. 2005). However, no relationship between deprivation and heat-related mortality was observed in England and Wales outside of heat waves (Bennett et al. 2014). Both factors deserve more attentions and should be investigated in more detail.

Harvesting

As we have seen, extreme heat has been associated with higher all-cause and cause-specific mortality in different settings. However, as for many mortality shocks, there has been a debate regarding the net effect of heat on mortality (Toulemon and Barbieri 2008; Valleron and Boumendil 2004). While the number of lives lost as a consequence of heat waves is relatively easy to quantify, estimating the years of life lost is more challenging. If extreme temperature mostly affected very frail individuals at older ages, the so called harvesting or frailty effect, we would expect to observe a decline in mortality following the heat wave, with a relatively modest loss of years of life. However, defining harvesting is complicated and detailed characteristics on heat-related deaths which would allow to investigate this phenomenon are hard to collect.

Overall, despite the attention given to the harvesting effect in the literature, the evidence that this phenomenon plays a large role in explaining excess mortality during heat waves is scant. The rigorous analysis conducted by Toulemon and Barbieri for the 2003 heat wave in France concluded that at most one third of the observed excess deaths could be attributed to harvesting (Toulemon and Barbieri 2008). Summarizing the series of studies investigating the impact of the 2003 heat wave in different European countries Kosatsky similarly concluded that there was no evidence of harvesting except for England and Wales (Kosatsky 2005). Recent theoretical results by Goldstein can help explain these results (Goldstein 2023).

Data and Methods

To compute death counts for each county-month and age group, I use individual-level death record files for 2014-2019 obtained from the National Center for Health Statistics (NCHS) under a data user agreement. These records contain information on sex, age, race, ethnicity, county, day of death, and cause of death (ICD-10 codes). In contrast with publicly available data, these records are complete and are not subject to suppression. I group deaths by county, month, and age groups <1, 1-4, 5-14, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, and 85+. Population counts to be used as denominators for mortality rates are also available through the NCHS and were provided to me jointly with the death record files. Data on the average, maximum, and minimum temperature by county and month are available through the National Centers for Environmental Information. In a preliminary exploration, I identified minimum monthly temperature as the best variables to model temperature effects on mortality, this is consistent with the results of another paper that conducted a similar analysis (Schinasi et al. 2020).

Let us denote the death counts for county s, time (in months) t, and age group a as $D_{a,s,t}$, and with $E_{a,s,t}$ the corresponding exposure in person-years. Finally, we denote with $m_{a,s,t}$ the mortality rate (deaths divided by exposure) for the same unit. I model death counts as Poisson distributed with mean $m_{a,s,t} \cdot E_{a,s,t}$. Then, I model the log mortality rate as a linear function of three age components derived from the singular value decomposition (SVD) of a matrix with Census Division-month mortality curves. Finally, to capture excess mortality due to high temperatures, I added a cubic spline with four degrees of freedom for minimum monthly temperatures for each of the broader age groups 0-4, 5-24, 25-54, 55-74, and 75+. I chose these groups based on the findings regarding age discussed in the background section. In this way the effect of high temperature is allowed not only to change the level of mortality but also to affect its age distribution. Here is the model in compact form:

$$D_{a,s,t} \sim Poisson\left(m_{a,s,t} \cdot E_{a,s,t}\right)$$

$$\log\left(m_{a,s,t}\right) = \beta_a + \beta_s + \beta_t + \sum_{b=1}^{B} \beta_{Temp,b,s} \cdot B_b\left(Temp(t,s)\right)$$

$$\beta_s \sim Normal(0, \sigma_s)$$

$$\beta_t = Trend_t + Season_m$$

$$Trend_t \sim Normal(Trend_{t-1}, \sigma_t)$$

$$Trend_t \sim Normal(Trend_{t-1}, \sigma_t)$$

$$\beta_{Temp,b,s} \sim Normal(\beta_{Temp,b}, \sigma_b)$$

The model includes a coefficient for each age group, each assigned a non-informative prior. The underlying age structure is assumed to be the same for all counties (an assumption I am going to relax as a next step). Figure 1 shows the estimated age-mortality curves for all counties. The model also includes county-specific intercepts with a hierarchical prior to induce global smoothing. Time is modeled as the sum of a trend component, modeled as a first order random walk (RW1), and a seasonal component, modeled with month-specific intercepts. As with age, the underlying time component is assumed to be the same for all counties (an assumption I am going to relax as a next step). Figure 2 shows the estimated trend, seasonality, and overall time components. Values past the 40th month are forecasted Finally, the effect of minimum monthly temperature on mortality is modeled with six B-splines (knots placed at equally spaced quantiles) with county-specific coefficients to which I assigned a hierarchical prior to induce global smoothing. Figure 3 shows the six splines.

I fit the model using the R implementation of Stan, which implements Hamiltonian Monte Carlo (Stan Development Team 2023). I examined trace plots and convergence metrics for all parameters and verified that they all showed satisfactory convergence.

Results

Before looking at the estimated temperature-mortality curves, we need to assess the model's fit to the data. We start from age. Figure 4a examines estimated age-mortality curves for four counties (chosen because they are at the 1st, 25th, 75th, and 100th percentiles in the population distribution). Three curves are presented, the observed one (black dotted line), the underlying one as estimated by the model (orange line), and the one obtained by simulating death rates from the model and then computing the corresponding log mortality rates (red line). The shaded area around the red line represents the 80% posterior interval. Despite the rather strong assumption of equal age-mortality curves (shape-wise) for all counties, the model seems to fit the observed curves nicely. Figure 4b moves to time and similarly shows that the despite the strong assumption of equal time effects across counties the model has a reasonable performance. However, we start to see that the fit is not very good for Yuba County. In this figure I also used the model to forecast mortality rates from the 41st month onward, obtaining plausible results. The final exhibit to judge the model fit is Figure 5 that displays observed and model-simulated annual average crude mortality rates for all counties. Figure 5 shows that the geographical structure was well reconstructed with global smoothing pooling the counties with very high and very low mortality closer to the mean. It should be noted the model combines regularization of the mortality estimates together with the estimation of the temperature effect in a single model-fitting exercise. The alternative approach of smoothing mortality curves first and then estimating the temperature effect, as adopted in Khatana et al. (2022a) is less desirable as it runs the risk of producing overconfident estimates for sparsely populated areas.

Having established that the model provides a good fit for the observed mortality rates, we can now look at the estimated temperature-mortality curves in Figure 6. The top panel of Figure 6 reveals a J-shaped relationship between temperature and mortality with minimum monthly temperature above and below the minimum mortality temperature of ~13 degrees Celsius associated with increases in mortality. The shape of the curve is in line with that documented in other studies (Curriero et al. 2002b; Gasparrini et al. 2015; Kunst, Looman, and Mackenbach 1993), with residual confounding potentially explaining the larger effect at colder temperatures reported some studies (Curriero et al. 2002b; Kunst et al. 1993). The bottom panel in Figure 6 goes beyond the average temperature-mortality curve and shows all the county-specific curves. We can see that both the strength and the shape of the relationship between temperature and mortality exhibit a high level of variability, in line with other studies that examined geographical heterogeneity (Gasparrini et al. 2015).

In Figure 7, I used the estimated temperature-mortality curves to compute the crude death rate associated with temperatures above or below the minimum mortality temperature for all counties. We can see that there is considerable variability in the degree to which mortality is affected by non-optimal temperatures. Counties in the North and the East of California exhibit higher temperature related mortality, while California's large metro counties in the coastal area display lower values. Beyond variability, we should also note that temperature-related mortality appears to be rather low if compared with all-cause mortality. Indeed, while the range in Figure 7 vary from 0 to 20 temperature-related deaths every 100,000 residents, the range for all-cause mortality in Figure 5 varies from 400 to 1,600 deaths. This suggests that overall, temperature-related mortality is a small fraction of all-cause mortality. The final set of results, presented in Figure 8, converts the temperature-related mortality rates computed in Figure 7 to actual number of annual temperature-attributable deaths. I estimate that a total of 1,700 annual deaths are attributable to non-optimal temperatures in California. Clearly, more populated regions contribute more deaths with Los Angeles and Inland Empire alone contributing 44.3% of all deaths. However, population is not the only factor explaining the geographic variation. For example, the San Francisco has about 700,000 more residents than the Inland Empire region but has less than half of its temperature-related deaths. To understand whether the estimated number of deaths was coherent with previous estimates for the US I applied the average temperature-related mortality rate to the US population and obtained 17,000 annual deaths. A similar exercise carried out on the results of Weinberger and colleagues (Weinberger et al. 2020) leads to 9,000 deaths attributable to temperatures above the county-optimum, implying a similar number of deaths attributable to temperature.

Discussion and Next Steps

Relying on analyses conducted on mostly urban areas to estimate the effect of heat on mortality might prove misleading. Because of the urban heat island effect, the elevated population density, and other urban-specific factors, heat could potentially be more detrimental in large cities than in smaller towns or rural areas. Similarly, focusing on the effects of extreme events such as the 2003 Western Europe heat wave might lead us to overestimate the consequences of high temperatures outside of these extreme events. In this paper I adapt the model developed by Alexander et al. (2017) for modeling age-specific mortality by county-year. In doing so, I follow the approach used in the recent works of Khatana et al. (2022) but: 1) I integrate demographic knowledge into the models, and 2) I integrate smoothing of mortality curves and estimation of temperature effects within a unique Bayesian model. With the caveat that I only examine California counties for the period 2014-2019, I find a significant association between temperature and mortality at both low and high temperatures.

This work has some clear limitations. The use of a county-level analysis rather an individual-level one trades precise identification of a causal effect for the possibility of estimating an effect even for counties with few death. By estimating separate mortality curves for each county-month, the approach used in this project effectively controls for time invariant caracteristics of counties as well as time trends uncorrelated with high temperature. In this sense, the results are thus robust to the presence of time-invariant confounders and should not be affected by the presence of diverging trends between counties exposed to high temperatures and those that are not. Methods that rely on individual level data such as time-stratified case-crossover designs (Maclure 1991) are very powerful tools to eliminate individual level confounders, and would generally be preferred. However, these methods are unsuitable for areas with smaller populations, and thus lower death counts. Additionally, they are prone to overestimating the effect of heat on mortality because do not account for harvesting effects.

The next steps of this project include replacing the minimum temperature with an indicator that combines temperature and humidity, which would be a better measure of perceived heat. In the same spirit, an indicator for the length of time for which the minimum or maximum temperature was observed might help approximate the intensity of exposure, and thus better capture the effect of temperature on mortality. I will also work on relaxing the model assumptions by introducing separate age and time parameters for each county. Another direction for expanding the project is to model mortality rates separately by race/ethnicity (as I foreshadowed in the introduction). Given the previous findings that racial/ethnic minorities are exceptionally vulnerable to heat related mortality, it is crucial to quantify these disparities. Finally, I hope to extend the model to more states and a longer period to capture a wider range or temperatures.

References

Armstrong, B. G., Z. Chalabi, B. Fenn, S. Hajat, S. Kovats, A. Milojevic, and P. Wilkinson. 2011. "Association of Mortality with High Temperatures in a Temperate Climate: England and Wales." *Journal of Epidemiology and Community Health* 65(4):340–45. doi: 10.1136/jech.2009.093161.

Basu, Rupa, Wen-Ying Feng, and Bart D. Ostro. 2008. "Characterizing Temperature and Mortality in Nine California Counties." *Epidemiology* 19(1):138–45.

Basu, Rupa, and Bart D. Ostro. 2008. "A Multicounty Analysis Identifying the Populations Vulnerable to Mortality Associated with High Ambient Temperature in California." *American Journal of Epidemiology* 168(6):632–37. doi: 10.1093/aje/kwn170.

Bennett, James E., Marta Blangiardo, Daniela Fecht, Paul Elliott, and Majid Ezzati. 2014. "Vulnerability to the Mortality Effects of Warm Temperature in the Districts of England and Wales." *Nature Climate Change* 4(4):269–73. doi: 10.1038/nclimate2123.

Conti, Susanna, Paola Meli, Giada Minelli, Renata Solimini, Virgilia Toccaceli, Monica Vichi, Carmen Beltrano, and Luigi Perini. 2005. "Epidemiologic Study of Mortality during the Summer 2003 Heat Wave in Italy." *Environmental Research* 98(3):390–99. doi: 10.1016/j.envres.2004.10.009.

Curriero, Frank C., Karlyn S. Heiner, Jonathan M. Samet, Scott L. Zeger, Lisa Strug, and Jonathan A. Patz. 2002a. "Temperature and Mortality in 11 Cities of the Eastern United States." *American Journal of Epidemiology* 155(1):80–87. doi: 10.1093/aje/155.1.80.

Curriero, Frank C., Karlyn S. Heiner, Jonathan M. Samet, Scott L. Zeger, Lisa Strug, and Jonathan A. Patz. 2002b. "Temperature and Mortality in 11 Cities of the Eastern United States." *American Journal of Epidemiology* 155(1):80–87. doi: 10.1093/aje/155.1.80.

Durkheim, Emile. 1952. *Suicide : A Study in Sociology*. 2nd ed. New York: Free Press.

Garcia, Ana Cristina, Paulo Jorge Nogueira, and José Marinho Falcão. 1999. "Onda de calor de Junho de 1981 em Portugal: efeitos na mortalidade." *Revista Portuguesa de Saúde Pública* Vol. Temático Nº 1-Clima e saúde:67–77.

Garssen, J., C. Harmsen, and J. De Beer. 2005. "The Effect of the Summer 2003 Heat Wave on Mortality in the Netherlands." *Eurosurveillance* 10(7):13–14. doi: 10.2807/esm.10.07.00557-en.

Gasparrini, Antonio, Yuming Guo, Masahiro Hashizume, Eric Lavigne, Antonella Zanobetti, Joel Schwartz, Aurelio Tobias, Shilu Tong, Joacim Rocklöv, Bertil Forsberg, Michela Leone, Manuela De Sario, Michelle L. Bell, Yue-Liang Leon Guo, Chang-fu Wu, Haidong Kan, Seung-Muk Yi, Micheline de Sousa Zanotti Stagliorio Coelho, Paulo Hilario Nascimento Saldiva, Yasushi Honda, Ho Kim, and Ben Armstrong. 2015. "Mortality Risk Attributable to High and Low Ambient Temperature: A Multicountry Observational Study." *Lancet (London, England)* 386(9991):369–75. doi: 10.1016/S0140-6736(14)62114-0.

Goldstein, Joshua. 2023. "In Disaster's Wake: Heterogeneity and Mortality After a Shock."

Grize, Leticia, Anke Huss, Christian Schindler, Charlotte Braun-Fahrländer, and Oliver Thommen. 2005. "Heat Wave 2003 and Mortality in Switzerland." *Swiss Medical Weekly* 135(1314):200–205. doi: 10.4414/smw.2005.11009.

Johnson, H., S. Kovats, G. McGregor, J. Stedman, M. Gibbs, and H. Walton. 2005. "The Impact of the 2003 Heat Wave on Daily Mortality in England and Wales and the Use of Rapid Weekly Mortality Estimates." *Eurosurveillance* 10(7):15–16. doi: 10.2807/esm.10.07.00558-en.

Jones, T. Stephen, Arthur P. Liang, Edwin M. Kilbourne, Marie R. Griffin, Peter A. Patriarca, Steven G. Fite Wassilak, Robert J. Mullan, Robert F. Herrick, H. Denny Donnell Jr, Keewhan Choi, and Stephen B. Thacker. 1982. "Morbidity and Mortality Associated With the July 1980 Heat Wave in St Louis and Kansas City, Mo." *JAMA* 247(24):3327–31. doi: 10.1001/jama.1982.03320490025030.

Khatana, Sameed Ahmed M., Rachel M. Werner, and Peter W. Groeneveld. 2022a. "Association of Extreme Heat and Cardiovascular Mortality in the United States: A County-Level Longitudinal Analysis From 2008 to 2017." *Circulation* 146(3):249–61. doi: 10.1161/CIRCULATIONAHA.122.060746.

Khatana, Sameed Ahmed M., Rachel M. Werner, and Peter W. Groeneveld. 2022b. "Association of Extreme Heat With All-Cause Mortality in the Contiguous US, 2008-2017." *JAMA Network Open* 5(5):e2212957. doi: 10.1001/jamanetworkopen.2022.12957.

Klinenberg, Eric. 2015. *Heat Wave : A Social Autopsy of Disaster in Chicago /*. Second edition. University of Chicago Press.

Kosatsky, T. 2005. "The 2003 European Heat Waves." *Eurosurveillance* 10(7):3–4. doi: 10.2807/esm.10.07.00552-en.

Kunst, Anton E., Casper W. N. Looman, and Johan P. Mackenbach. 1993. "Outdoor Air Temperature and Mortality in the Netherlands: A Time-Series Analysis." *American Journal of Epidemiology* 137(3):331–41. doi: 10.1093/oxfordjournals.aje.a116680.

Maclure, M. 1991. "The Case-Crossover Design: A Method for Studying Transient Effects on the Risk of Acute Events." *American Journal of Epidemiology* 133(2):144–53. doi: 10.1093/oxfordjournals.aje.a115853.

Martínez Navarro, Ferran, Fernando Simón-Soria, and Gonzalo López-Abente. 2004. "Valoración Del Impacto de La Ola de Calor Del Verano de 2003 Sobre La Mortalidad." *Gaceta Sanitaria* 18(4):250–58.

Michelozzi, P., F. de Donato, L. Bisanti, A. Russo, E. Cadum, M. DeMaria, M. D'Ovidio, G. Costa, and C. A. Perucci. 2005. "The Impact of the Summer 2003 Heat Waves on Mortality in Four Italian Cities." *Eurosurveillance* 10(7):11–12. doi: 10.2807/esm.10.07.00556-en.

Nogueira, P. J., J. M. Falcão, M. T. Contreiras, E. Paixão, J. Brandão, and I. Batista. 2005. “Mortality in Portugal Associated with the Heat Wave of August 2003: Early Estimation of Effect, Using a Rapid Method.” *Eurosurveillance* 10(7):5–6. doi: 10.2807/esm.10.07.00553-en.

Perkins-Kirkpatrick, S. E., and S. C. Lewis. 2020. “Increasing Trends in Regional Heatwaves.” *Nature Communications* 11(1):3357. doi: 10.1038/s41467-020-16970-7.

Pirard, P., S. Vandentorren, M. Pascal, K. Laaidi, A. Le Tertre, S. Cassadou, and M. Ledrans. 2005. “Summary of the Mortality Impact Assessment of the 2003 Heat Wave in France.” *Eurosurveillance* 10(7):7–8. doi: 10.2807/esm.10.07.00554-en.

Rey, Grégoire, Eric Jougla, Anne Fouillet, Gérard Pavillon, Pierre Bessemoulin, Philippe Frayssinet, Jacqueline Clavel, and Denis Hémon. 2007. “The Impact of Major Heat Waves on All-Cause and Cause-Specific Mortality in France from 1971 to 2003.” *International Archives of Occupational and Environmental Health* 80(7):615–26. doi: 10.1007/s00420-007-0173-4.

Schinasi, Leah H., Joan Rosen Bloch, Steven Melly, Yuzhe Zhao, Kari Moore, and Anneclaire J. De Roos. 2020. “High Ambient Temperature and Infant Mortality in Philadelphia, Pennsylvania: A Case-Crossover Study.” *American Journal of Public Health* 110(2):189–95. doi: 10.2105/AJPH.2019.305442.

Schuman, Stanley H. 1972. “Patterns of Urban Heat-Wave Deaths and Implications for Prevention: Data from New York and St. Louis during July, 1966.” *Environmental Research* 5(1):59–75. doi: 10.1016/0013-9351(72)90020-5.

Semenza, Jan C., Carol H. Rubin, Kenneth H. Falter, Joel D. Selanikio, W. Dana Flanders, Holly L. Howe, and John L. Wilhelm. 1996. “Heat-Related Deaths during the July 1995 Heat Wave in Chicago.” *New England Journal of Medicine* 335(2):84–90. doi: 10.1056/NEJM199607113350203.

Simon, F., G. Lopez-Abente, E. Ballester, and F. Martinez. 2005. “Mortality in Spain during the Heat Waves of Summer 2003.” *Eurosurveillance* 10(7):9–10. doi: 10.2807/esm.10.07.00555-en.

Smoyer, Karen E. 1998. “Putting Risk in Its Place: Methodological Considerations for Investigating Extreme Event Health Risk.” *Social Science & Medicine* 47(11):1809–24. doi: 10.1016/S0277-9536(98)00237-8.

Stan Development Team. 2023. “Stan Modeling Language Users Guide and Reference Manual, 2.32.” Retrieved April 27, 2023 (//mc-stan.org).

Toulemon, Laurent, and Magali Barbieri. 2008. “The Mortality Impact of the August 2003 Heat Wave in France: Investigating the ‘Harvesting’ Effect and Other Long-Term Consequences.” *Population Studies* 62(1):39–53.

Vaidyanathan, Ambarish. 2020. "Heat-Related Deaths — United States, 2004–2018." *MMWR. Morbidity and Mortality Weekly Report* 69. doi: 10.15585/mmwr.mm6924a1.

Valleron, Alain-Jacques, and Ariane Boumendil. 2004. "Épidémiologie et canicules : analyses de la vague de chaleur 2003 en France." *Comptes Rendus Biologies* 327(12):1125–41. doi: 10.1016/j.crvi.2004.09.009.

Weinberger, Kate R., Daniel Harris, Keith R. Spangler, Antonella Zanobetti, and Gregory A. Wellenius. 2020. "Estimating the Number of Excess Deaths Attributable to Heat in 297 United States Counties." *Environmental Epidemiology* 4(3):e096. doi: 10.1097/EE9.0000000000000096.

White, Gilbert F. 1945. *Human Adjustments to Floods; a Geographical Approach to the Flood Problem in the United States ...* Chicago, Ill.,.

White, Gilbert F., Robert W. Kates, and Ian Burton. 1993. "The Environment As Hazard." *Routledge & CRC Press*. Retrieved February 20, 2022 (https://www.routledge.com/The-Environment-As-Hazard/Burton-Kates-White/p/book/9780898621594).

Whitman, S., G. Good, E. R. Donoghue, N. Benbow, W. Shou, and S. Mou. 1997. "Mortality in Chicago Attributed to the July 1995 Heat Wave." *American Journal of Public Health* 87(9):1515–18. doi: 10.2105/AJPH.87.9.1515.

Zanobetti, Antonella, Marie S. O'Neill, Carina J. Gronlund, and Joel D. Schwartz. 2012. "Summer Temperature Variability and Long-Term Survival among Elderly People with Chronic Disease." *Proceedings of the National Academy of Sciences* 109(17):6608–13. doi: 10.1073/pnas.1113070109.

Zanobetti, Antonella, and Joel Schwartz. 2008. "Temperature and Mortality in Nine US Cities." *Epidemiology (Cambridge, Mass.)* 19(4):563–70. doi: 10.1097/EDE.0b013e31816d652d.

Tables and Figures

Figure 1: Estimated Age-Mortality Curves for the 58 California Counties

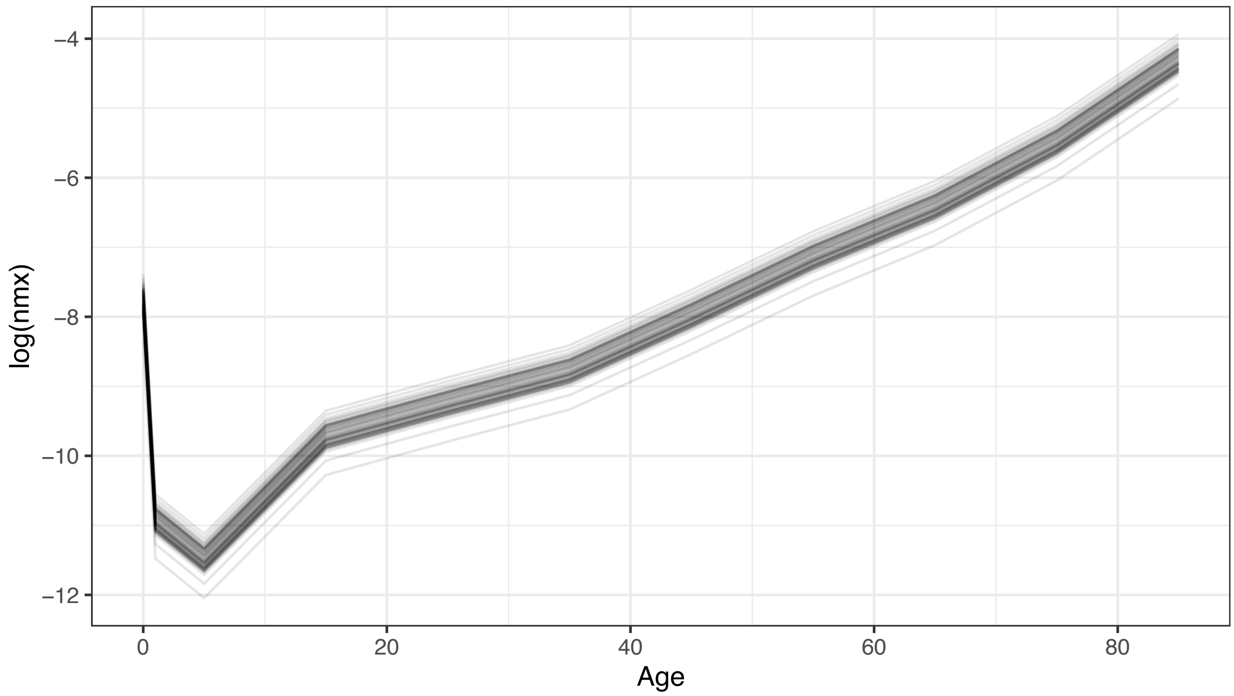
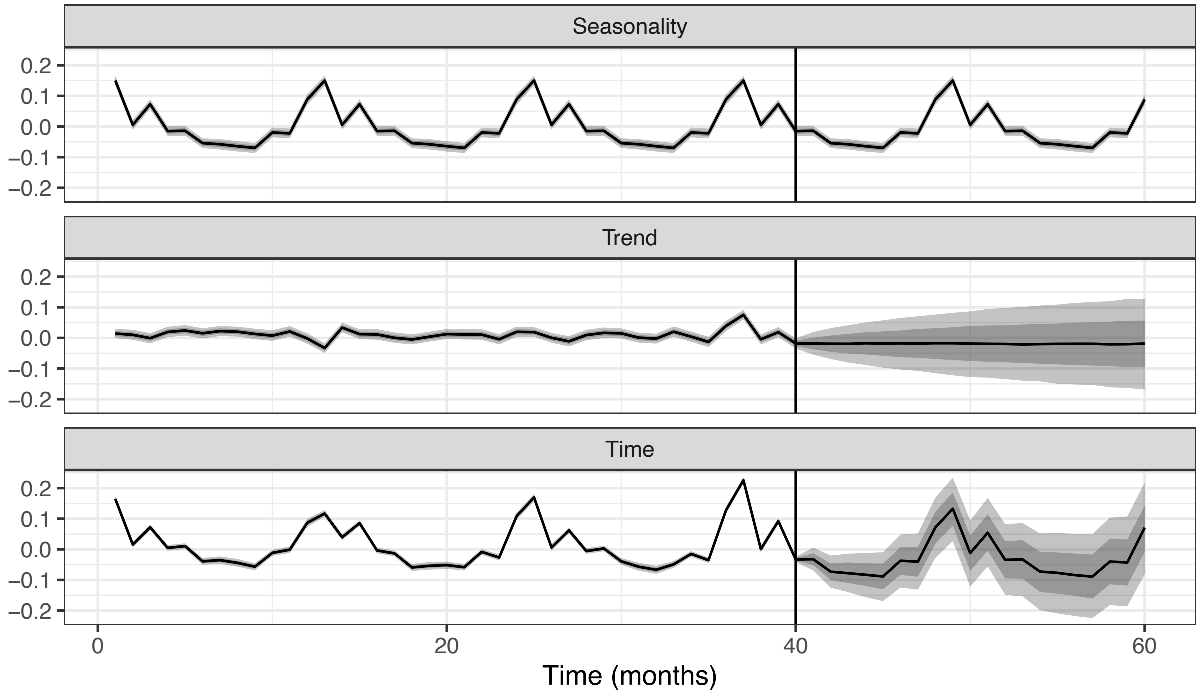


Figure 2: Estimated Time Trend, Seasonality Component, and Overall Time Effect



Notes: the light gray intervals represent 80% posterior intervals while the dark gray intervals represent 50% posterior intervals.

Figure 3: B-Splines for Minimum Monthly Temperature

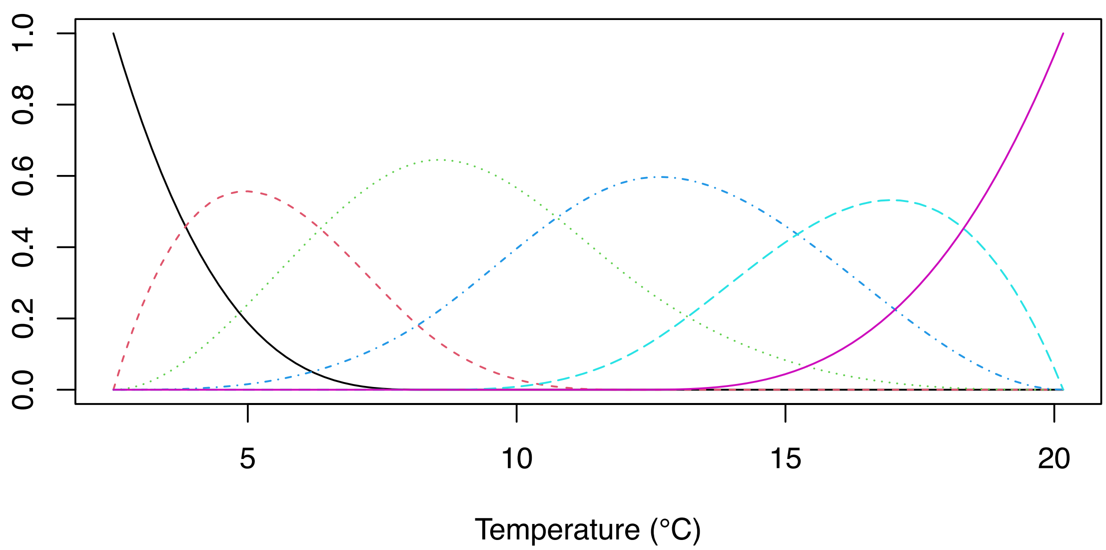
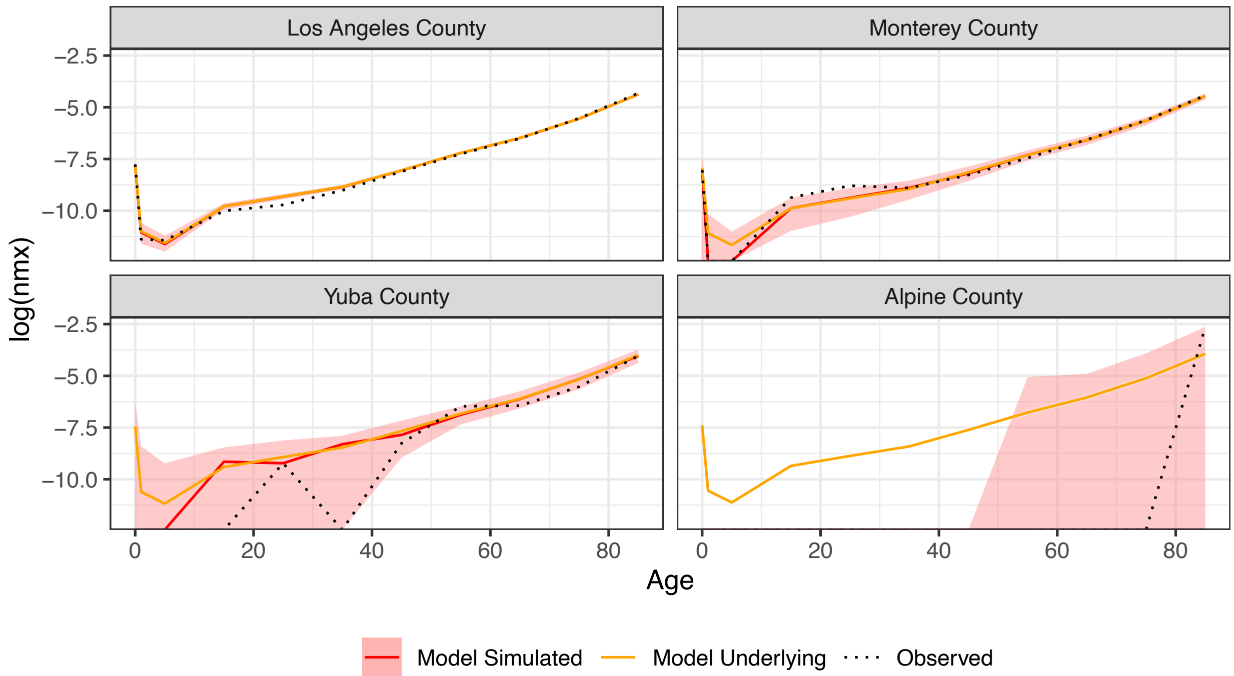
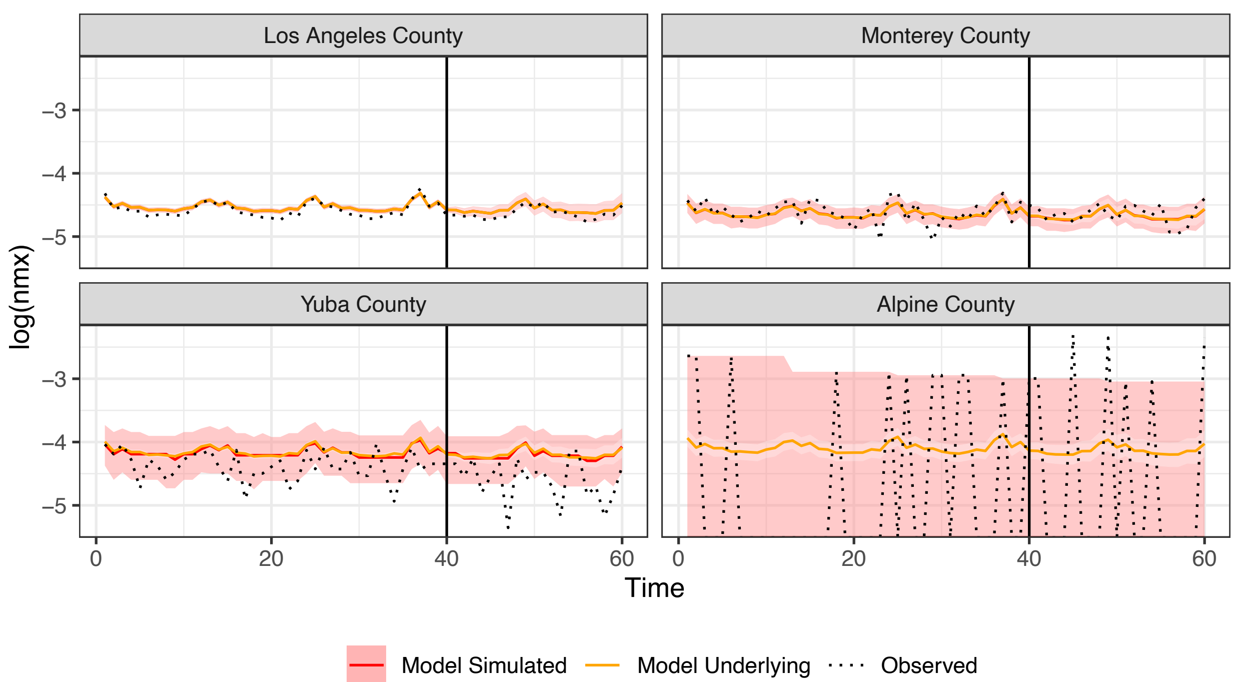


Figure 4a: Evaluating Predicted Age-Specific Mortality Rates Against Observed Ones for Los Angeles County and Nevada County



Notes: the red intervals represent 80% posterior intervals.

Figure 4b: Evaluating Predicted Age-Specific Mortality Rates Against Observed Ones for Los Angeles County and Nevada County



Notes: the red intervals represent 80% posterior intervals.

Figure 5: Observed and Predicted Average Log-Mortality Rates for the Period 2014-2019 for All California Counties.

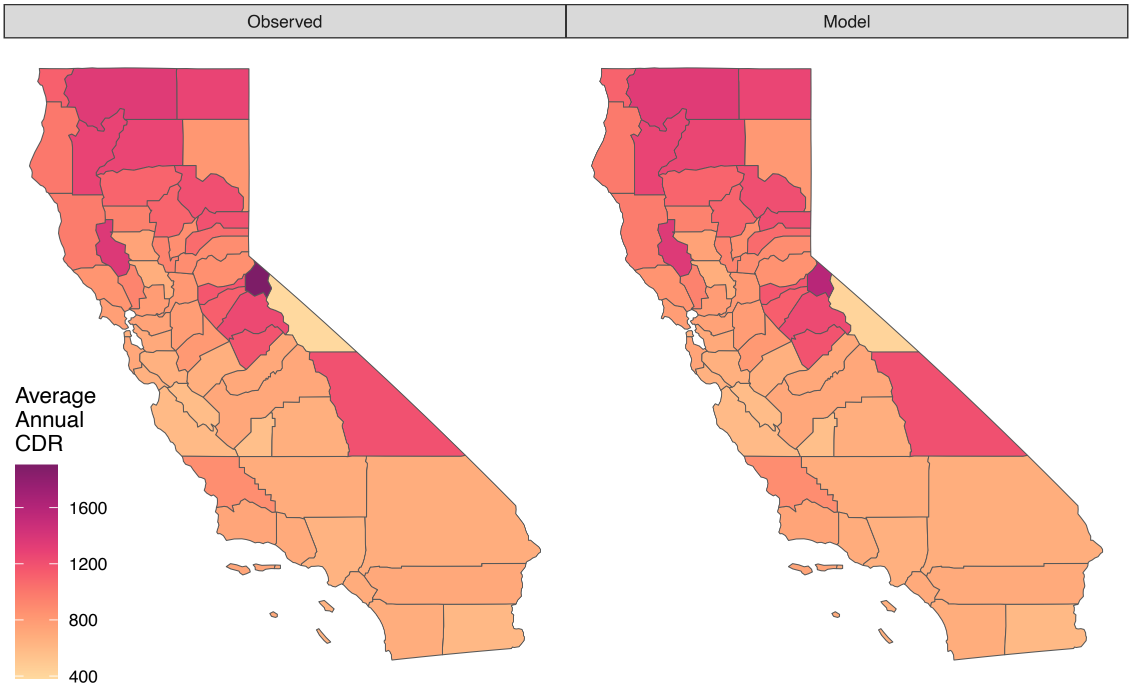
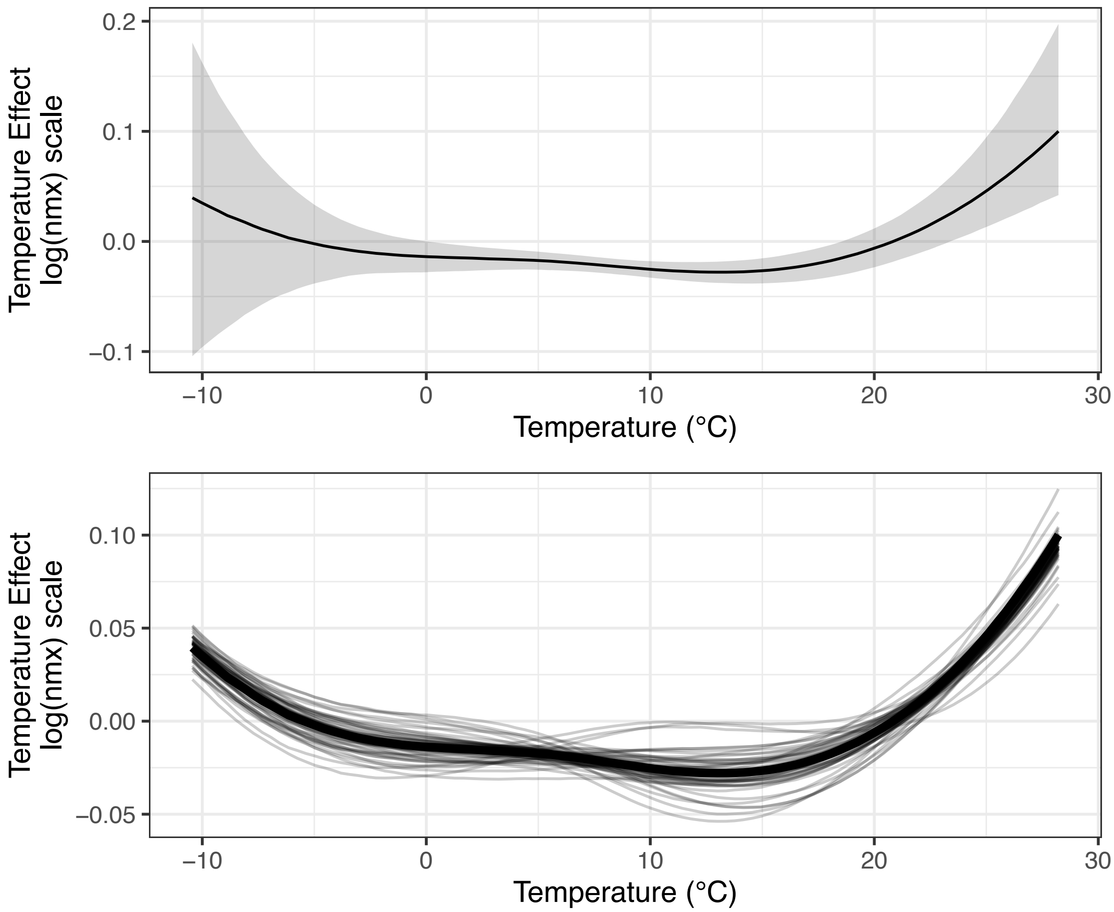


Figure 6: Estimated Relationship between Minimum Monthly Temperature and Mortality by Broad Age Groups.



Notes: the light gray intervals represent 80% posterior intervals.

Figure 7: Estimated Relationship between Minimum Monthly Temperature and Mortality by Broad Age Groups.

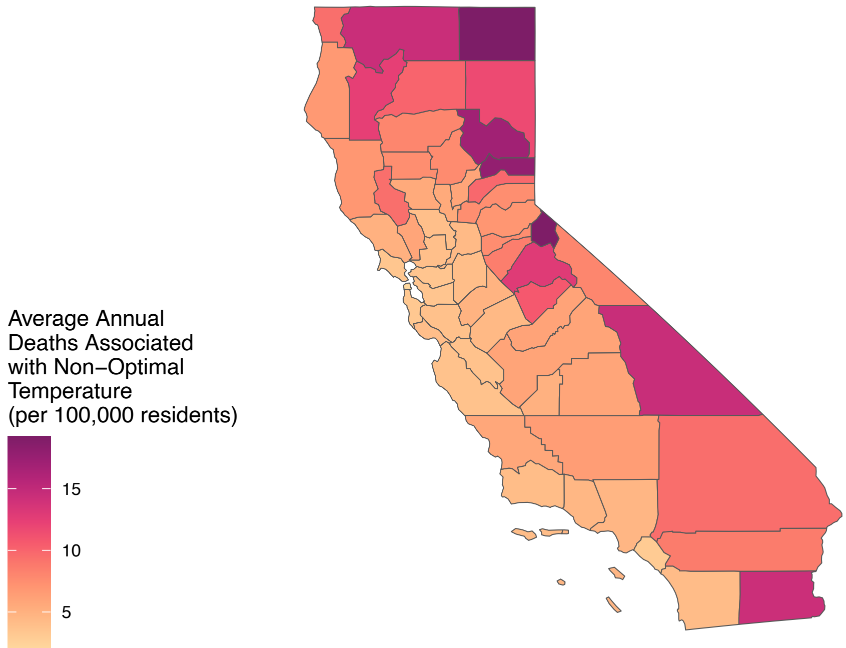


Figure 8: Estimated Relationship between Minimum Monthly Temperature and Mortality by Broad Age Groups.