Anomalous temperature and intentional and unintentional injury mortality in the USA

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Abstract

There is limited data on how temperature deviations from long-term norms affect deaths from different injuries. Here, we used mortality and temperature data from 1980 to 2016 in the USA and a Bayesian spatio-temporal model to estimate how anomalous temperatures affect deaths from different intentional (transport, falls and drownings) and unintentional (assault and suicide) injuries by age group, sex and month. We estimated that a 1°C anomalously warm year would be associated with 941 (95% credible interval 831-1,053) additional injury deaths in the contiguous USA. 87% of deaths would occur in males, mostly in adolescent to middle ages. These excess deaths would comprise of increases in drowning, transport injuries, assault and suicide, offset partly by a decline in deaths from falls in older ages. The findings demonstrate the need for public health interventions against injuries during periods of anomalously high temperatures, especially as they increase with global climate change.

Introduction

The potential health impacts of anthropogenic climate change are one of the key drivers for efforts to mitigate greenhouse gas emissions and for pursuing adaptation measures (Haines & Ebi, 2019; McMichael et al., 2006; Smith et al., 2015)**.** Current assessments of the health effects of climate change largely focus on parasitic and infectious diseases, and cardiorespiratory and other chronic diseases (Gasparrini et al., 2017; Haines & Ebi, 2019; Huang et al., 2011; McMichael et al., 2006; Smith et al., 2015; Watts et al., 2018). Less research has been conducted on injuries (Burke et al., 2018; Orru & Åström, 2017; Rey et al., 2007), especially in a consistent way across injury types and demographic subgroups of the population, even though death rates from injuries vary seasonally (Parks, Bennett, Foreman, Toumi, & Ezzati, 2018; Rau, 2004), which means that temperature may play a role in their pathogenesis. Our aim was to evaluate how deaths from various injuries may be affected by changes in temperature that could arise as a result of global climate change in a national study.

We used vital registration data on all injury deaths in the contiguous USA from 1980 to 2016, with information on sex, age at death, underlying cause of death and state of residence. During this period, 4,006,454 boys and men and 1,757,862 girls and women died from an injury in the contiguous USA (i.e., excluding Alaska and Hawaii), accounting for 9.2% and 4.2% of all male and female deaths respectively. 95.6% of male injury deaths and 93.9% of female injury deaths were in those aged 15 years and older, and over half (52.6%) of male injury deaths were in those aged 15-44 years (Figure 1). In contrast with males, there was less of an age gradient in females after 15 years of age.

Results

Injuries from transport, falls, drownings, assault, and suicide accounted for 79.0% of injury deaths in males and 72.1% in females. The remainder were from a heterogeneous group of "other unintentional injuries" (Figure 1), within which the type of injury that led to death varied by sex and age group. Transport was the leading injury cause of death in women younger than 75 years and men younger than 35 years. Between 35 and 74 years of age, more men died of suicide than any other injury. Above 75 years of age, falls were the largest cause of death in both men and women.

There was a decline in age-standardised death rates of three out of five major injuries (transport, drownings and assault) from 1980 to 2016, although assault deaths have shown a recent increase since 2014 (Figure 2). In contrast, age-standardised death rates from falls increased over time while those from suicide initially decreased followed by an increase to surpass 1980 levels. The largest overall decline over time was for transport deaths, which declined by over 50% from 1980 to 2016. Age-standardised death rates for transport injuries and drownings peaked in summer months but deaths from other major injuries did not have clear seasonal patterns.

With few exceptions,(Burke et al., 2018; Shi, Kloog, Zanobetti, Liu, & Schwartz, 2015) current climate change risk assessments typically extrapolate from changes in mortality in relation to daily temperature (Basu, 2009; Gasparrini et al., 2015, 2017; Huang et al., 2011; Ye et al., 2012). Climate change, however, will fundamentally modify weather, including seasonal weather patterns, compared to long-term norms, and hence can disrupt long-term adaptation. To mimic the conditions that may arise with global climate change, we developed methodology to examine how deviations from long-term norm temperature may impact injury death rates.

We first defined a measure of anomalous temperature for each state and month relative to long-term norm temperature of the state in that month (Figure 3). In this approach, a state with higher, but more stable, temperature in a specific month has smaller anomalies than one with lower but more inter-annually variable temperature. Average size of anomaly over the study period (1980-2016), a measure of how variable temperatures are around their central state-month long-term norm, ranged from 0.4°C for Florida in September, to 3.4°C for North Dakota in February (Figure 4). The average size of anomaly had a median value of 1.2°C across all states and months, with 27% less than 1°C and 90% less than 2°C (Figure 4). Temperature anomalies were largest in January and December and smallest in August and September. They were larger in northern and central states than in southern and coastal ones.

We then analysed the association of monthly injury death rates with anomalous temperature using a Bayesian spatio-temporal model, described in Methods. The model accounted for systematic variations in death rates across states and months, through state-, month- and state-month-specific random intercepts, and for their long-term trends. These terms together remove the effects of space and time varying factors other than temperature that affect injuries. Analyses were done separately by injury type, sex and age group. We used the resultant risk estimates and the age-sex-specific death rates from each injury in 2016, to calculate additional deaths if each month in each state were +1°C above its long-term norm, by type of injury, sex, age group, state and month.

Based on these calculations, there would be an estimated 941 (95% credible interval 831, 1,053) excess injury deaths, equivalent to 0.47% of all injury deaths in 2016, in each year in which each month in each state were +1°C above its long-term norm (Figure 5). Deaths from drowning, transport, assault and suicide would be predicted to increase, partly offset by a decline in deaths from falls in middle and older ages and in winter months (Figure 5). Most excess deaths would be from transport injuries (448) followed by suicide (315). 87% of the excess deaths would occur in males and 13% in females. 80% of all male excess deaths would occur in those aged 15-64 years, who have higher rates of deaths from transport injuries. In those aged 85 years and older, there would be an estimated decline in injury deaths, because deaths from falls are expected to decline in a warmer year.

Proportionally, deaths from drownings are predicted to increase more than those of other injury types, by as much 8.3% (7.3, 9.3) in men aged 15-24 years (Supplementary Figure 1); the smallest proportional increase was that of assault and suicide (less than 2% in all age and sex groups). There was a larger percent increase in transport deaths for males than for females, especially in young and middle-ages (~e.g., 1.25% (0.90, 1.60) for 25-34 year old men versus 0.23% (-0.28, 0.76) for women of the same age) (Supplementary Figure 1).

Discussion

While there are no previous studies of how deviations of monthly temperature from long-term norm are associated with injury mortality, our results are broadly in agreement with those that have analysed associations with absolute temperature and for specific injury types. A study of suicide in US counties over 37 years (1968-2004) estimated that 1°C higher monthly temperature would lead to a 0.7% rise in suicides (Burke et al., 2018), compared to our findings of 0.44-1% in males and 0.39-1.47% in females in different ages. In a study of six French heatwaves during 1971-2003, mortality from unintentional injuries rose by up to 4% during a heatwave period compared to a non-heatwave baseline (Rey et al., 2007). A study of daily mortality from all injuries from Estonia found a 1.24% increase in mortality when daily maximum temperature went from the 75th to 99th percentile of long-term distribution (Orru & Åström, 2017).

That anomalously warm temperature influences deaths from drowning, although not previously quantified, is highly plausible because swimming is likely to be more common when monthly temperature is higher. The higher relative and absolute impacts on men compared with women may reflect differences in behaviour. For example, over half of swimming deaths for males occur in natural water, compared to about quarter for females (Xu, 2014), which may lead to a larger rise in the former in warmer weather. Similarly, the decline in deaths from falls, which are mostly in older ages, may be because falls in older people are more likely to be due to slipping on ice than in younger ages (Ambrose, Paul, & Hausdorff, 2013; Bobb et al., 2017; Kelsey et al., 2010).

The pathways from anomalous temperature to transport injury are more varied. Firstly, driving performance deteriorates at higher temperatures (Daanen, Van De Vliert, & Huang, 2003; Mackie & Hanlon, 1976; Wyon, Wyon, & Norin, 1996; Zlatoper, 1991). Further, alcohol consumption increases during warm temperature anomalies (Opinium, 2018), potentially also explaining why teenagers, who are more likely than other age groups to crash while intoxicated (Voas, Torres, Romano, & Lacey, 2012), experience a larger proportional rise in deaths from transport than older ages when temperatures are anomalously warm. Lastly, warmer temperatures generally increase road traffic in North America (Datla, Sahu, Roh, & Sharma, 2013; H.-J. Roh, Datla, & Sharma, 2013; H.-J. Roh, Sahu, Sharma, Datla, & Mehran, 2016; H. J. Roh, Sharma, & Sahu, 2016); With more people generally outdoors in warmer weather (Graff Zivin & Neidell, 2014), this could lead to more fatal collisions.

Pathways linking anomalously high temperatures and deaths from assault and suicide are less established. One hypothesis is that, similar to transport, more time spent outdoors in anomalously warmer temperatures leads to an increased number of face-to-face interactions, and hence arguments, confrontations, and ultimately assaults (Glaeser, Sacerdote, & Scheinkman, 1996; Rotton & Cohn, 2003). These effects could be compounded by the greater anger levels linked to higher temperatures (Anderson, 1989; Baron & Bell, 1976). Regarding suicide, higher temperature has been hypothesised as associated with higher levels of distress in younger people (Majeed & Lee, 2017). Nonetheless, links between temperature and mental health requires further investigation (Berry, Waite, Dear, Capon, & Murray, 2018), including whether the relationship varies by age and sex, as indicated by our results.

The major strength of our study is that we have comprehensively modelled the association of temperature anomaly with injury by type of injury, month, age group and sex. Our measure of temperature anomaly internalises long-term historical experience of each state, and is closer to what climate change may bring about than solely examining daily episodes, or average temperature to which people have adapted. To utilise this metric, we integrated two large disparate national datasets on mortality (US vital statistics) and meteorology (ERA-Interim (Dee et al., 2011)), and developed a bespoke Bayesian spatio-temporal model. A limitation of our study is that, like all observation studies, we cannot rule out confounding of results due to other factors, although it is unlikely that such factors will have the same anomalies as temperature, even if their average space and time patterns are the same.

Our work highlights how deaths from injuries are currently susceptible to temperature anomalies and could also be modified by rising temperatures resulting from climate change, unless countered by social and health system interventions that mitigate these impacts. Though absolute impacts on mortality are modest, some groups, especially men in young to middle-ages, will experience larger impacts. Therefore, a combination of public health interventions that broadly target injuries in these groups – for example targeted messaging for younger males on the risks of transport injury and drowning – and those that trigger in relation to forecasted high temperature periods – for example more targeted blood alcohol level checks – should be a public health priority.

Materials and methods

Data

We used data on deaths by sex, age, underlying cause of death and state of residence in the contiguous USA from 1980 to 2016 through the National Center for Health Statistics (NCHS) (https://www.cdc.gov/nchs/nvss/dvs_data_release.htm) and on population from the NCHS bridged-race dataset for 1990 to 2016 (https://www.cdc.gov/nchs/nvss/bridged_race.htm) and from the US Census Bureau prior to 1990 (https://www.census.gov/data/tables/time-series/demo/popest/1980s-county.html). We calculated monthly population counts through linear interpolation, assigning each yearly count to July.

The underlying cause of death was coded according to the international classification of diseases (ICD) system (9th revision from 1980 to 1998 and 10th revision thereafter). The 5.7 million injury deaths fell into six categories: transport, falls, drownings, assault, suicide and an aggregate set of other unintentional injuries. We report the results of all of these categories except other unintentional injuries (1,329,200 deaths or 23% of total injury deaths during 1980-2016), because the composition of this aggregate group varies by sex, age group, state and time.

We obtained data on temperature from ERA-Interim, which combines predictions from a physical model with in-situ and satellite measurements.(Dee et al., 2011) We used gridded four-times-daily estimates at a resolution of 80 km to generate monthly population-weighted temperature by state throughout the analysis period.

Anomalous temperature metric

To calculate the magnitude of temperature anomaly by state and month, we first calculated 30-year (long-term) norm temperatures (from 1980-2009) for each month in each state. We calculated for 30 years because it is the duration used in climate assessments (Wallace & Hobbs, 2006). We subtracted these long-term norm temperatures from respective monthly temperature values to generate a temperature anomaly time series for each month and year in each state (Figure 3). The temperature anomaly metric measures the extent that temperature experienced in a specific month, year and state is warmer or cooler than the long-term norm to which the population of each state has acclimatised. These values can be different for different months in the same state, and different states in the same month.

Statistical methods

We formulated a Bayesian spatio-temporal model to estimate the effect of temperature anomaly on injury deaths rates. The outcome was deaths from several types of injury. We carried out all analyses separately by sex and age group (0-4 years, 10-year age groups from 5 to 84 years, and 85+ years) because injury deaths rates vary by age group and sex (Lozano et al., 2012; Parks et al., 2018; Rau, 2004), as might their associations with temperature.

We modelled the number of deaths in each year as following a Poisson distribution:

$$deaths_{state-time} \sim Poisson(death\ rate_{state-time} \cdot population_{state-time})$$

with log-transformed death rates modelled as a sum of components that depend on location (state) of death, month of year, overall time (in months) and temperature anomaly:

$$\begin{aligned} \log(deaths_{state-time}) = \\ \alpha_0 + \beta_0 \cdot time + \\ \alpha_{state} + \beta_{state} \cdot time + \\ \alpha_{month} + \beta_{month} \cdot time + \\ \zeta_{state-month} + \\ \nu_{time} + \\ \gamma_{month} \cdot Anomaly_{state-time} + \\ \varepsilon_{state-time} \end{aligned}$$

The model contained terms that represent the overall level and trend in mortality, with α_0 as the common intercept and β_0 the common time slope. Death rates also vary by month, which may be partly related to temperature and partly due to other monthly factors; monthly variations tend to be smooth across adjacent months (Parks et al., 2018). Therefore, we allowed each month of the year to systematically have a different mortality level and trend, with α_{month} the month-specific intercept and β_{month} the month-specific time slope. We used a random walk for the month terms to smooth the coefficients, widely used to characterise smoothly varying associations (Rue & Held, 2005). The random walk had a cyclic structure, so that December was adjacent to January.

We also included state random intercepts and slopes for death rates, with α_{state} as the state-specific intercept and β_{state} the state-specific time slope. These terms measure deviations of each state from national values, and allow variation in level and trend in mortality by state. In addition, death rates in neighbouring states may be more similar than in those further away, modelled using a Conditional Autoregressive (CAR) spatial model (Besag, 1974). This allows mortality levels and trends of states to be estimated based on their own data as well as using those of their neighbours. The extent to which information is shared between neighbouring states depends on the uncertainty of death rates in a state and the empirical similarity of death rates in neighbouring states. We also included state-month interactions for intercepts and slopes ($\zeta_{state-month}$), to allow variation in mortality levels and trends in a particular state for different months and vice-versa. Non-linear change over time was captured by a first-order national random walk, ν_{time} (Rue & Held, 2005).

Finally, we included a term that relates log-transformed death rate to the above-defined state-month temperature anomaly, $\gamma_{month} \cdot Anomaly_{state-time}$. The coefficients of γ_{month} represent the logarithm of the monthly death rate ratio per 1°C increase in anomaly. There was a separate coefficient for each month which means that an anomaly of the same magnitude could have different associations with injury mortality in different months. As with the month-specific intercepts and trends, we used a cyclic random walk to smooth the coefficient of the temperature anomaly across months. An over-dispersion term ($\varepsilon_{state-time}$) captured the variation unaccounted for by other terms in the model, modelled as $N(0,\sigma_{\epsilon}^2)$. We fitted the models using integrated nested Laplace approximation (INLA), using the R-INLA software, which offers orders of computational efficiency improvement in Bayesian inference compared to traditional MCMC (Rue, Martino, & Chopin, 2009).

We estimated the mortality impact of a national year-round temperature anomaly of 1°C in each month and state, realistic in our lifetimes under current projections of global climate change (IPCC, 2018), as well as within the range of anomaly size experienced by some states (Figure 4). For this calculation, we multiplied the actual death counts for each month, sex, state and age group in 2016 by the corresponding excess relative risk, which was calculated as the exponential of the coefficient of the temperature anomaly term from the above analysis. The uncertainty in our results were obtained from 5000 draws from the posterior marginal of each month's excess relative risk. The reported 95% credible intervals, quoted in brackets where appropriate, are the 2.5th to 97.5th percentiles of the sampled values.

Sensitivity analysis

We conducted sensitivity analyses to assess how much our results might depend on the temperature metric used to generate anomalous temperature. First, instead of building our monthly temperature anomalies based on daily mean temperatures, we used daily maxima and minima. These measures were strongly correlated to those generated from daily means (Supplementary Table 2), and therefore we did not run models using these alternatives.

Together with temperature anomaly based on daily mean temperatures, we also included a second measure of anomaly in the model. The additional measures were related to more extreme anomalous situations:

- temperature anomaly calculated based on 90th percentile (°C) of daily mean temperatures within a month, compared to 30-year (long-term) norm of 90th percentile for each state and month
- number of days in a month above the long-term 90th percentile of norm temperature for each state and month (adjusted for length of month)
- number of 3+ day episodes above the long-term 90th percentile of norm temperature for each state and month (adjusted for length of month)

The correlations among these variables and anomaly based on mean were between 0.60 and 0.89 (Supplementary Table 3). The estimated rate ratios of temperature anomaly based on daily means (i.e., the anomaly measure used in the main analysis) were robust to the addition of alternative measures of anomaly, while the coefficients of the additional measures were generally not significant and with large credible intervals. Therefore, we did not include the alternative additional measures of extreme anomalous temperature in the main analysis.

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Author contributions

All authors contributed to study concept, analytical approach, and interpretation of results. RP, GD and ME collated and organised mortality files. RP performed the analysis, with input from other authors. RP and ME wrote the first draft of the paper; other authors contributed to revising and finalising the paper.

Competing interests statement

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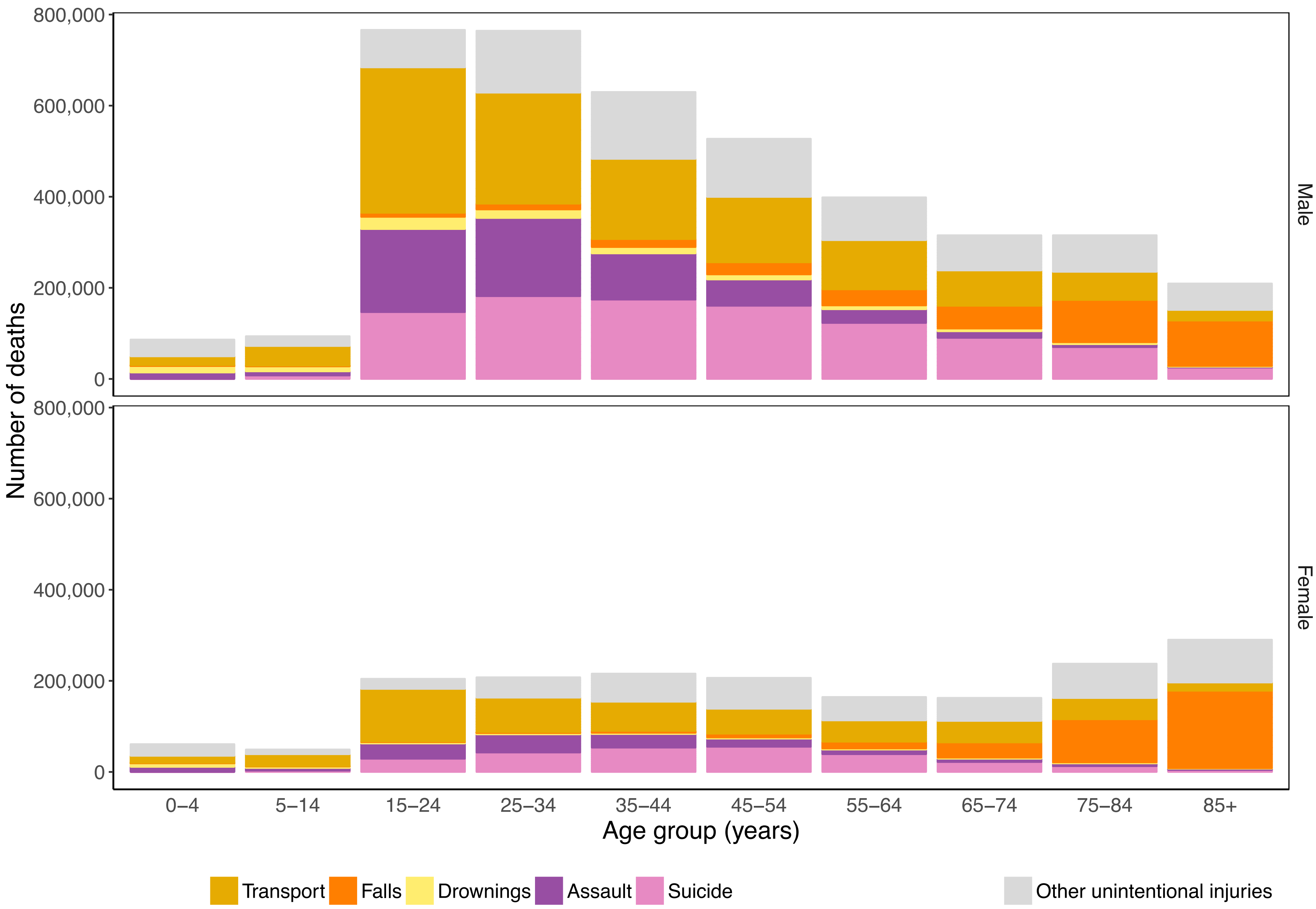
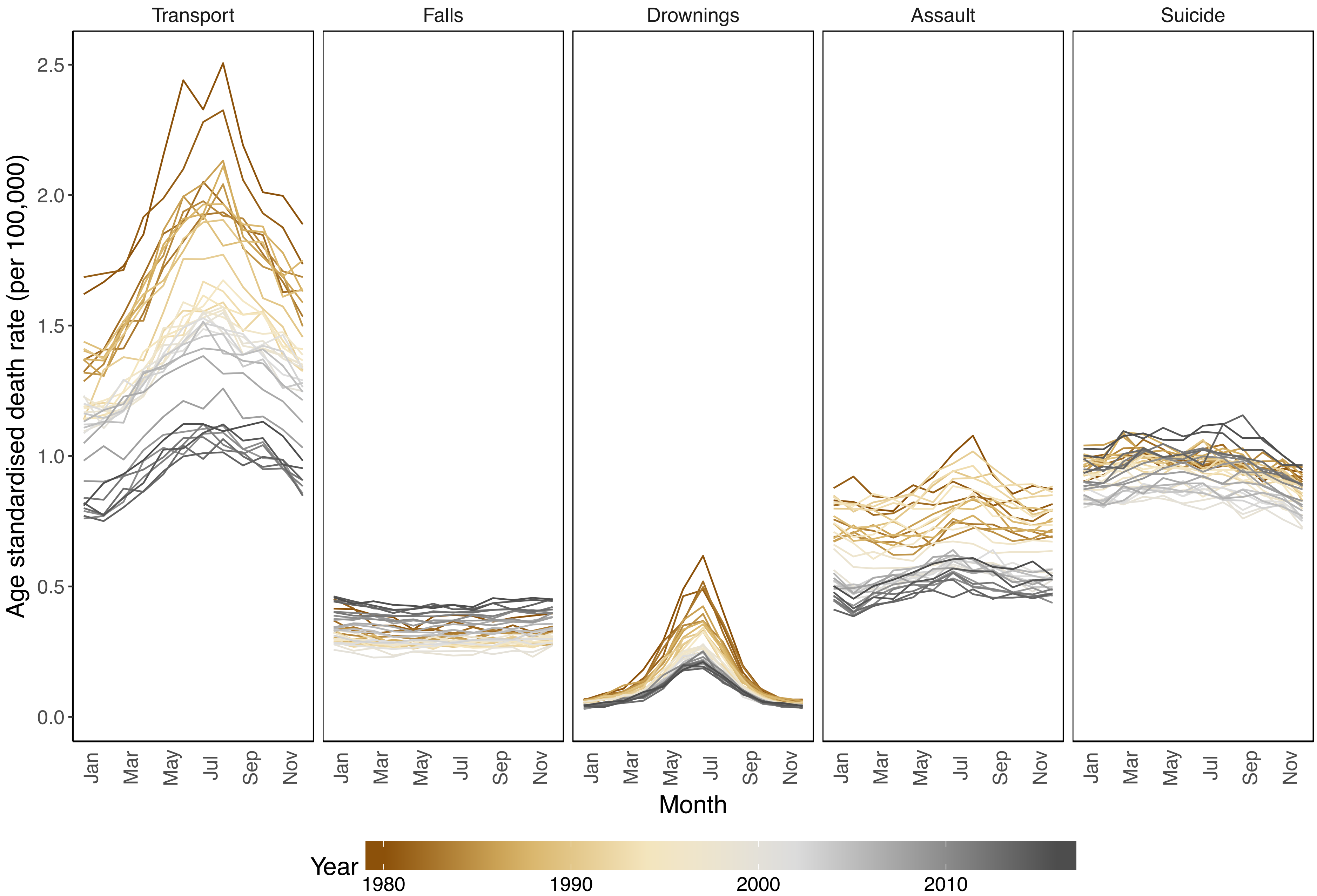
Figure 1. Number of injury deaths, by type of unintentional (transport, falls, drownings, and other) and intentional (assault and suicide) injury, by sex and age group in the contiguous USA for 1980-2016.



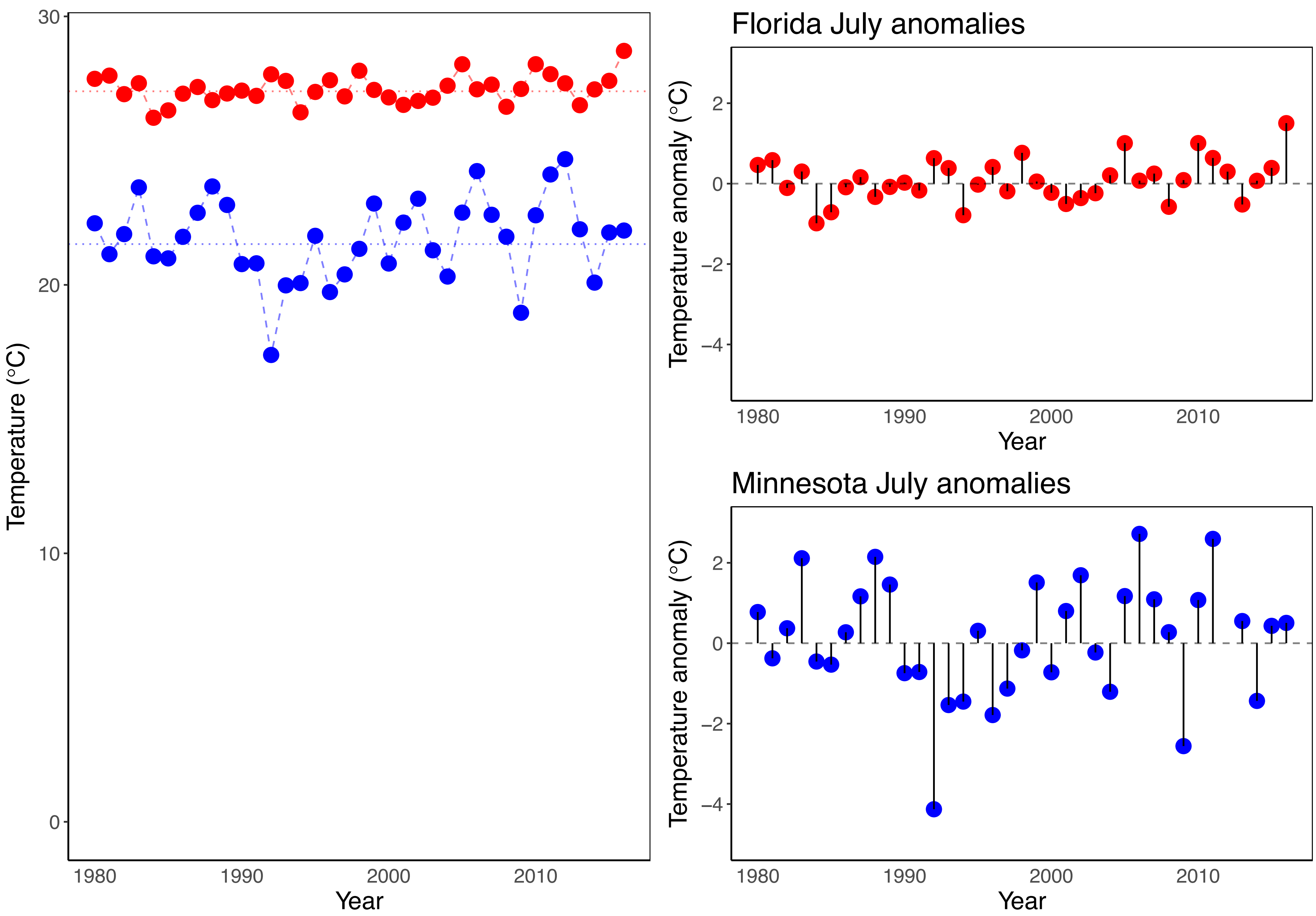
Number of deaths
800,000
600,000
400,000
200,000
0
Male
Female
0–4
5–14
15–24
25–34
35–44
45–54
55–64
65–74
75–84
85+
Age group (years)
Transport
Falls
Drownings
Assault
Suicide
Other unintentional injuries

Figure 2. National age-standardised death rates from 1980 to 2016, by type of injury and month.



Transport
Falls
Drownings
Assault
Suicide
Age standardised death rate (per 100,000)
2.5
2.0
1.5
1.0
0.5
0.0
Jan
Mar
May
Jul
Sep
Nov
Month
Year
1980
1990
2000
2010

Figure 3. Graphic representation of temperature anomaly measure used in the analysis. The graph shows how monthly temperatures in July two example states (Florida in red and Minnesota in blue) (left panel) for 1980-2016 are used to calculate temperature anomalies. As seen, a warmer state like Florida (top right) can have a smaller inter-annual variation in a particular month (here, July) compared with a cooler state like Minnesota (bottom right).



Temperature (°C)
30
20
10
0
1980
1990
2000
2010
Year
Florida July anomalies
Temperature anomaly (°C)
2
0
−2
−4
1980
1990
2000
2010
Year
Minnesota July anomalies
Temperature anomaly (°C)
2
0
−2
−4
1980
1990
2000
2010
Year

Figure 4. Average size of temperature anomaly (°C) from 1980 to 2016, by state and month. The value for each state and month is the mean of the absolute size of anomaly, be it cold or warm, and hence gives an indication of the scale of anomalies around the norm local temperatures.

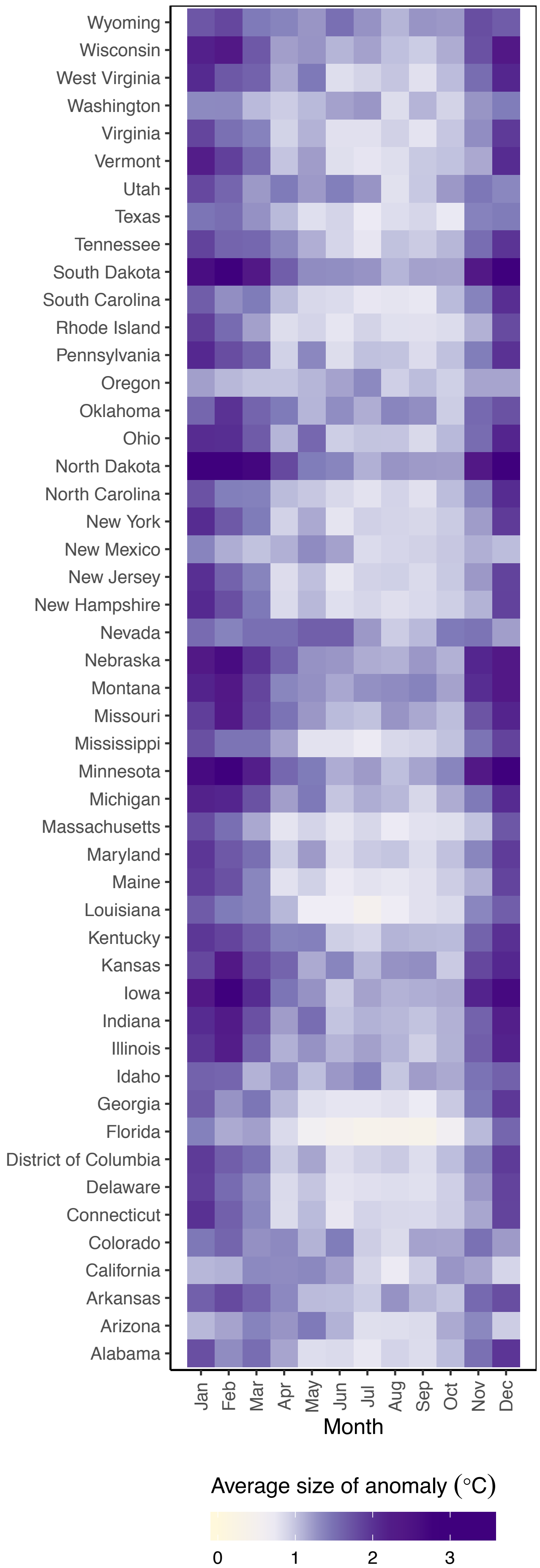
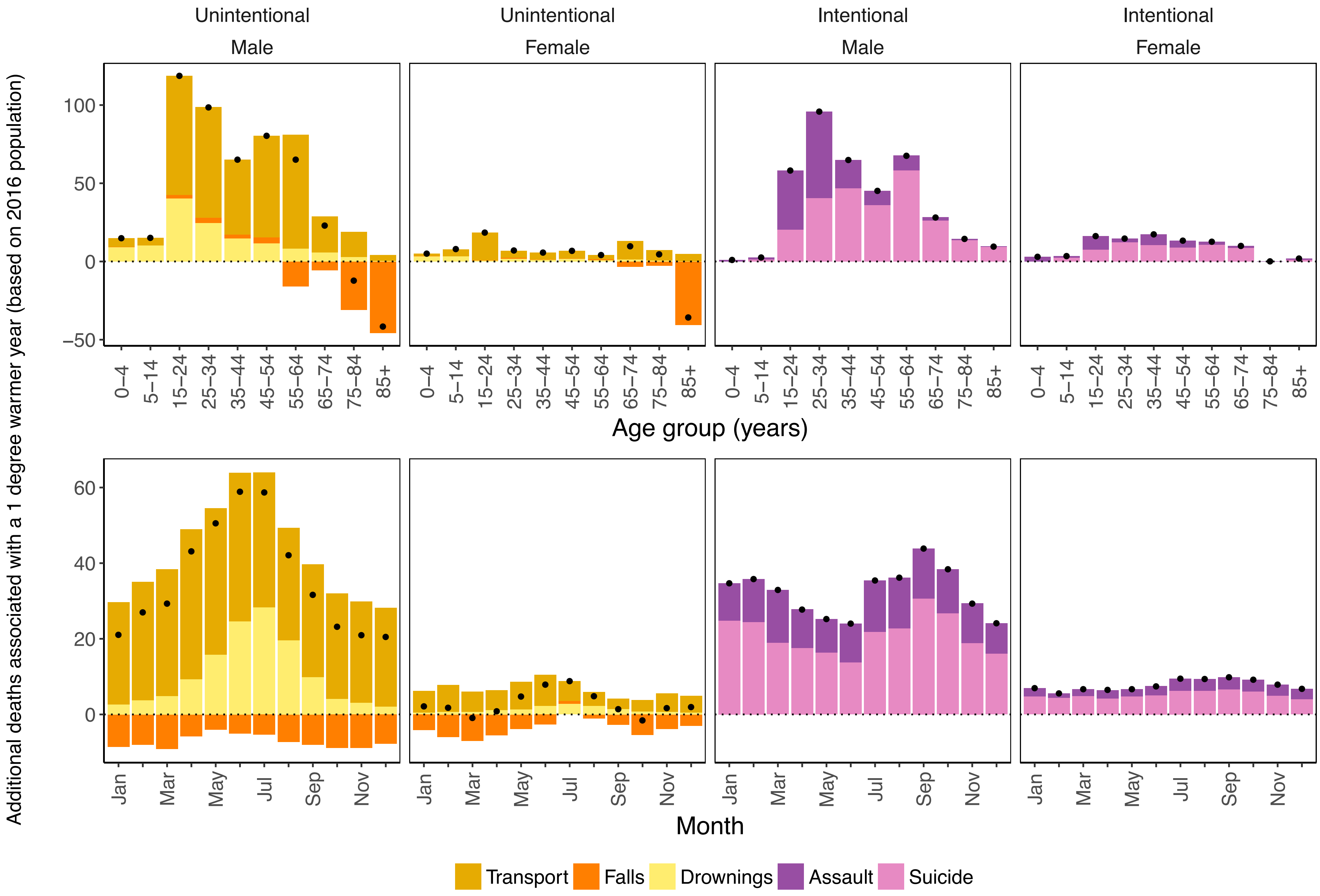
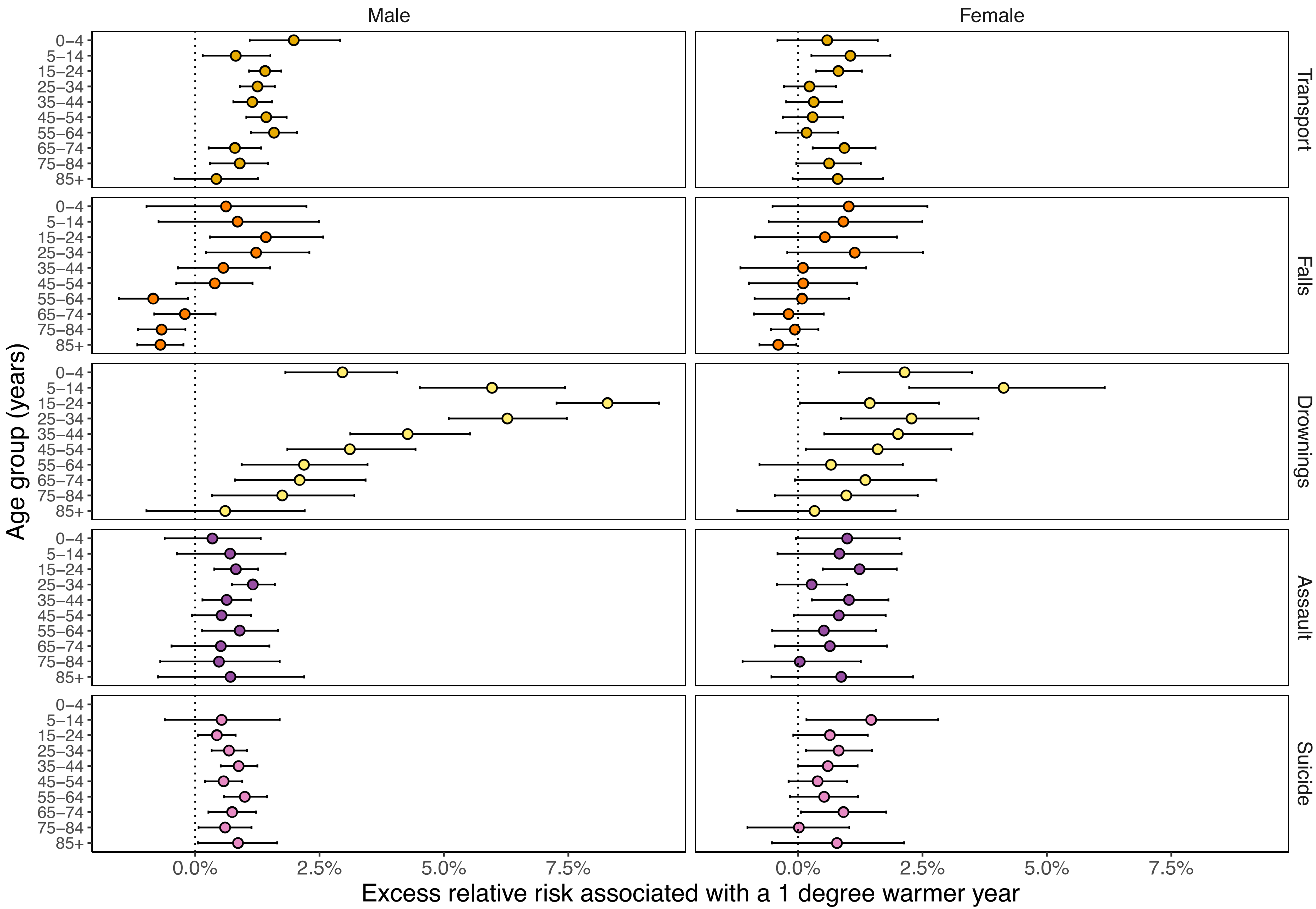

Wyoming
Wisconsin
West Virginia
Washington
Virginia
Vermont
Utah
Texas
Tennessee
South Dakota
South Carolina
Rhode Island
Pennsylvania
Oregon
Oklahoma
Ohio
North Dakota
North Carolina
New York
New Mexico
New Jersey
New Hampshire
Nevada
Nebraska
Montana
Missouri
Mississippi
Minnesota
Michigan
Massachusetts
Maryland
Maine
Louisiana
Kentucky
Kansas
Iowa
Indiana
Illinois
Idaho
Georgia
Florida
District of Columbia
Delaware
Connecticut
Colorado
California
Arkansas
Arizona
Alabama
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
Average size of anomaly (°C)
0
1
2
3

Figure 5. Additional annual injury deaths for the 2016 US population in year in which each month was +1°C warmer compared with 1980-2009 norm temperatures. The top row shows breakdown by type of injury, sex and age group. The bottom row shows the break down by type of injury, sex and month. Black dots represent net changes in deaths for each set of bars.

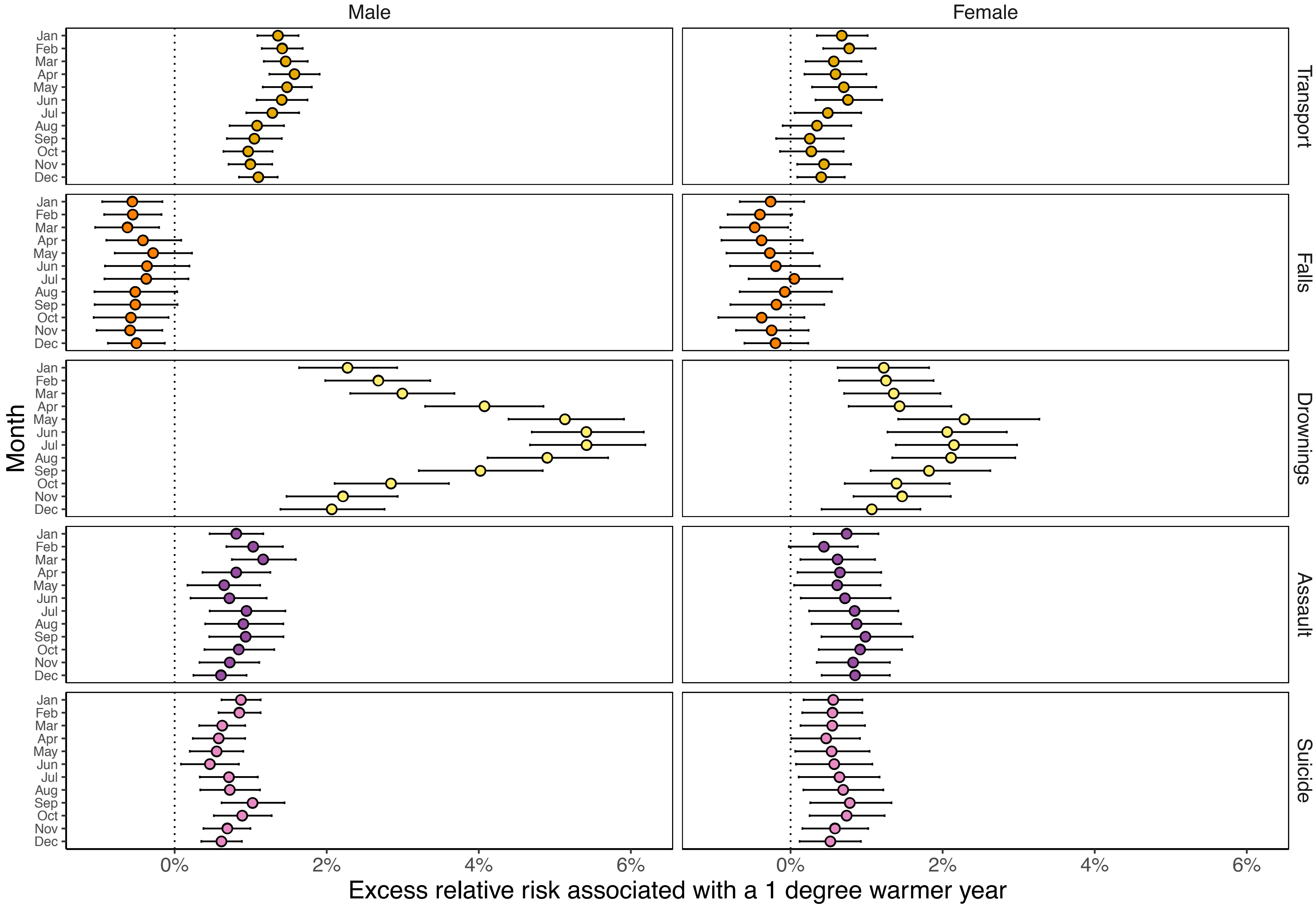

Unintentional
Male
Unintentional
Female
Intentional
Male
Intentional
Female
Additional deaths associated with a 1 degree warmer year (based on 2016 population)
100
50
0
−50
0–4
5–14
15–24
25–34
35–44
45–54
55–64
65–74
75–84
85+
Age group (years)
60
40
20
0
Jan
Mar
May
Jul
Sep
Nov
Month
Transport
Falls
Drownings
Assault
Suicide

Supplementary Figure 1. Percent change in death rates in year in which each month was +1°C compared with 1980-2009 norm temperatures by type of injury, sex and age group.



Male
Female
Transport
Falls
Drownings
Assault
Suicide
Age group (years)
0–4
5–14
15–24
25–34
35–44
45–54
55–64
65–74
75–84
85+
0.0%
2.5%
5.0%
7.5%
Excess relative risk associated with a 1 degree warmer year

Supplementary Figure 2. Percent change in death rates in year in which each month was +1°C compared with 1980-2009 norm temperatures by type of injury, sex and month.



Male
Female
Transport
Falls
Drownings
Assault
Suicide
Month
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
0%
2%
4%
6%
Excess relative risk associated with a 1 degree warmer year

Supplementary Table 1. Injury groups used in the analysis with ICD-9 and ICD-10 codes.

Injury type	ICD-9	ICD-10
All injuries	E800-E999	V0-Y89
Unintentional	E800-E949, E980-E989	V0-V99, W0-99, X0-X59, Y10-Y34, Y40-Y89
Transport	E800-E807, E810-E838, E840-E849	V0-V99
Falls	E880-E888	W0-W19
Drowning	E910-E910	W65-W74
Intentional	E950-E979.9, E990-E999	X60-X99, Y0-Y9, Y35-Y39
Suicide	E950-E959	X60-X84
Assault	E960-E979, E990-E999	X85-X99, Y0-Y9, Y35-Y39

Supplementary Table 2. Correlation coefficients between monthly anomalies generated from daily mean temperature and daily maximum and minimum temperatures. Each correlation coefficient was calculated in each state for each month for 1980-2016, then averaged over all states for each month.

Month	**Mean daily temperature and maximum daily temperature**	**Mean daily temperature and minimum daily temperature**
January	0.98	0.98
February	0.98	0.98
March	0.97	0.97
April	0.97	0.96
May	0.96	0.94
June	0.95	0.92
July	0.97	0.94
August	0.96	0.93
September	0.93	0.91
October	0.91	0.93
November	0.96	0.97
December	0.97	0.98

Supplementary Table 3. Correlation coefficients between anomaly of mean daily temperature and measures of extreme anomalous temperature described in Methods. Each correlation coefficient was calculated in each state for each month for 1980-2016, then averaged over all states for each month.

Temperature variables	Anomaly of mean (main analysis)	Anomaly of 90th percentile	Number of days above long-term 90th percentile	Number of 3+ day episodes above long-term 90th percentile
Anomaly of mean (main analysis)		0.79	0.75	0.6
Anomaly of 90th percentile	0.79		0.89	0.77
Number of days above long-term 90th percentile	0.75	0.89		0.86
Number of 3+ day episodes above long-term 90th percentile	0.6	0.77	0.86	