Response to Mitchell et al – Relevant and Robust Data for Climate Change Risk Assessment

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Time-series studies, which are commonly used to analyse associations of temperature with mortality, can inform short-term planning but have limited relevance to how changes in temperature over longer-time periods influence human health. They also cannot account for how populations adapt to their local climate, that for example people in Phoenix have adapted to temperatures which Chicago would engender extreme situations and cause thousands of deaths. Our study,[1] and another recent analysis,[2] used innovative designs and large quantities of data to overcome these inherent limitations of time-series analysis in informing long-term risk assessment. In particular, the anomaly metric used in our analysis is both intuitive and consistent with how populations experience and respond to weather patterns in the long term. Therefore, our study has made a major advance in making epidemiological analysis relevant for long-term risk assessment. A second methodological innovation of our work is to leverage variation over both space and time, versus each alone, to infer the size of associations. This approach has been used in studies of air pollution[3,4] and cardiovascular risk factors[5] because spatiotemporal inference is more efficient and robust than using variation in either dimension alone.

As incorrectly stated by Mitchell and colleagues, computational considerations had no influence on the choice to analyse monthly mean temperature. Rather, in addition to anomaly in mean temperature, we analysed and reported in the paper metrics of extreme temperature including (1) the 90th percentile (°C) of daily mean temperatures; (2) number of days in a month above the long-term 90th percentile of average temperature for each state and month; and (3) number of episodes of 3+ day episodes above the long-term 90th percentile of average temperature for each state and month. The estimated rate ratios of the temperature anomaly based on daily means were robust to the addition of alternative measures of anomaly, whereas the coefficients of the additional measures were generally not statistically significant and with large credible intervals. This may be because empirically changes in heat waves are explained by simple shifts in mean temperature.[6]

We used a (log-)linear association, consistent with other analyses of injuries.[2,7] Further, the anomaly metric used in our paper has a much smaller size range (<8°C across all states and months in our data) than the range of absolute temperatures (>40°C in our data). Finally, having age- and month-specific coefficients gives our model the flexibility to infer different effect sizes in cold and warm months and for different age groups, as seen in Figure 4 of our paper. Our computer code is available on an open access basis (http://globalenvhealth.org/code-data-download/) and can be used to consider alternative functional forms.

Our statistical model by design adjusts for environmental, social, and meteorological factors that are specific to month, state and state-month through the use of corresponding random intercepts. The potential unmeasured confounding factors would be those with anomalies similar to those of the average monthly temperature in each state, such as air pollution, which is not associated with injury mortality. As for other meteorological factors, anomalous temperature in USA is not significantly correlated with anomalous cloud cover based on data from ERA5, nor with precipitation.[7] Further the association between temperature and transport injury is robust to adjustment for precipitation.[7] Therefore, the most plausible explanation for our findings is a causal effect from anomalous temperature.

To illustrate the public health significance of the findings, we applied our estimated rate ratios to a fixed temperature anomaly (1.5 and 2 degrees) and 2016 age- and sex-specific death rates, carefully reported as an "anomalously warm year". The choice of counterfactual exposure in our illustrative example is similar to analyses for air pollution[4,8] and for virtually every other risk factor[9] which use either a constant change in exposure or a constant level of exposure as counterfactual exposure. Full climate change risk assessment, as done for other risk factors,[10] requires three inputs: (i) spatially and temporally coherent projections of temperature; (ii) spatially and temporally coherent projections of population; and (iii) spatially, temporally and epidemiologically coherent projections of age-, sex- and cause-specific death rates,[11] because death rates from each disease and injury change due to factors other than climate – as seen in secular trends of deaths from various injuries in Figure 2 of our paper. The innovative scope of our work, i.e. analysing the complete range of intentional and unintentional injuries by age group and sex, and its methodological innovations provide a relevant and robust basis for such analyses.

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