Mobility data to aid assessment of human responses to extreme environmental conditions

Mobile phone-derived human mobility data are now publicly available in support of tracking the effect of interventions to control community spread of SARS-CoV-2.[1–3] Previous work leveraged mobility data that used to be proprietary to examine responses to extreme events including wildfires and hurricanes.[4] With increased availability of mobility data, re-highlighting the added value it provides to informing policy aimed at minimising negative health outcomes is worthwhile. For example, mobility data are particularly well suited to assess the effectiveness of heat or smoke early-warning systems promoting collective or individual behavioural actions captured by population-level stay-at-home data. As opposed to hospitalisation or mortality data[5] that becomes available years later, mobility data are generally immediately available[6] and readily useable for real-time evaluation studies.

As an example, we applied county-level mobility data in the USA to reveal the power of this application during various extreme environmental conditions including hurricanes, wildfire smoke, and winter weather (figure). We de-seasonalised daily, county-level, stay-at-home metrics provided by Facebook's Data for Good Movement Range Maps[6] to remove the weekly cycle[7] and present data as anomalies by subtracting the long-term median for the period June 21, 2020, to July 18, 2021. This period follows the cessation of stay-at-home orders due to COVID-19 in the country.

The 2020 Atlantic hurricane season was the most active since 1851 with 30 named storms. Concerns mounted regarding the risks posed by hurricane landfalls to communities struggling to contain COVID-19.[8] Using mobility data from Puerto Rico and Louisiana, we found exposure to a hurricane corresponds with decreased mobility as people sheltered in place (figure A).

The US West Coast had an unprecedented wildfire season in 2020, precipitated by long-term drying of overstocked fuels, anthropogenic and dry lightning ignitions coinciding with strong downslope winds, and heatwaves. In September, 2020, air quality in Oregon and Washington was degraded by local wildfires and regional transport from California wildfires. Hazardous-level $PM_{2·5}$ concentrations triggered warning systems that advised avoiding outdoor activity, leading to reduced mobility (figure B).

Winter weather can also reduce mobility. During the winter of 2020–21, Texas had three winter weather events with corresponding decreases in mobility (figure C). The largest mobility decrease occurred during the February, 2021, cold spell and a subsequent energy crisis that caused millions to lose power and water for days.

Under normal circumstances, human mobility reductions during extreme events indicate a successful response by limiting exposure to a hazardous environment. Amid a pandemic, assessing the balance of environmental and disease risks and their respective burdens on public health and health care remains difficult.[9] One compounding impact comes from air pollution when poor air quality coincides with extreme heat. A potentially non-negligible fraction of the population spends substantial time in workplaces or schools where quality air filtration provides a healthier environment indoors than their home environment. COVID-19-related school and workplace closures meant these populations remained at home. Populations in older, poorly sealed homes without air conditioning or those unable to afford air filtration systems or run their air conditioning are exposed to both the effects of poor air quality and heat. Differential exposure combined with increased home-bound populations, especially those affected by heat, during pollution episodes might increase health impact disparities. Census tract-level mobility data, rather than county-level mobility data, might facilitate examination of responses across socioeconomic and demographic categories.

The availability of mobility data provides novel insight into human movement patterns in response to environmental hazards. For example, these data offer an approach to assessing the real-time effectiveness of existing early-warning systems during extreme events. Commonly, increased stay-at-home behaviour reduces risk by limiting exposure to extreme conditions. However, unique situations arise when compounded with complications introduced by a pandemic and environmental factors including poor air quality and

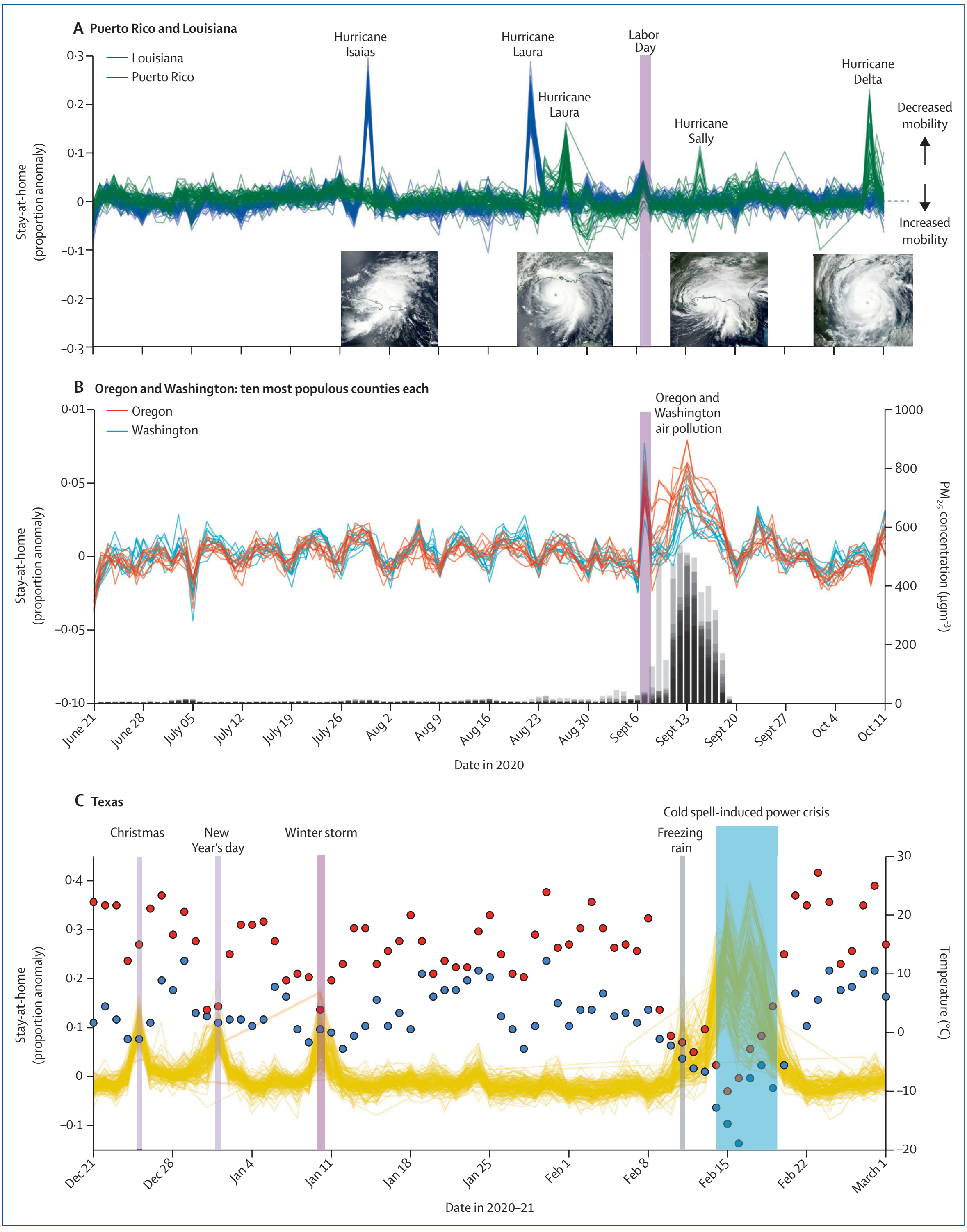

***Figure:* Time series of deseasonalised anomalies of the stay-at-home metric in Puerto Rico and Louisiana (A), the ten most populous counties in each of Oregon and Washington (B), and Texas (C)**

Positive values on the left y axis on all plots imply decreased mobility. Vertical bars and labels show key holiday periods and times of weather events. In panel B, $PM_{2.5}$ observations are shown for 14 Environment Protection Agency locations in these states on the right y axis, with darker bars indicating more observation stations reporting. In panel C, the dots show maximum (red) and minimum (blue) temperatures from Dallas-Fort Worth Airport on the right y axis.

heat. Physical distancing, an accepted non-pharmaceutical intervention in reducing community spread of SARS-CoV-2,[1] is restricted in indoor settings, potentially conflicting with heat illness-prevention measures like cooling centres.[9]

Our brief examination of mobility responses to extreme environmental conditions highlights the importance of secondary uses of mobility data made available by private entities. These data can support accountability or early-warning system effectiveness studies. It also enables hypothesis testing, such as whether behavioural responses to poor air quality vary with pollution type (eg, visible particulate matter *vs* invisible ozone) and how communities respond to other environmental extremes like heatwaves. To sample across larger demographics, we recommend global aggregation of mobility data of the highest resolution possible to a centralised dataset. Finally, we recommend applying mobility data to assess extreme weather impacts on health outcomes and assessments of communication strategies to identify best practices to provide clear and consistent messaging, especially to vulnerable populations.[10]

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