

**Supporting Information for**

**Trends and Disparities of Dangerous Humid Heat Exposure Among  
Incarcerated People in the United States**

Cascade Tuholske, Victoria D. Lynch, Raenita Spriggs, Anne E. Nigra, Robbie M. Parks

Corresponding Authors: Cascade Tuholske and Robbie M. Parks

Email: [cascade.tuholske1@montana.edu](mailto:cascade.tuholske1@montana.edu) and [robbie.parks@columbia.edu](mailto:robbie.parks@columbia.edu)

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### *Incarceration Data.*

We use carceral facility (referring to prisons, jails, and other carceral facilities) locational boundaries (polygon latitudinal and latitudinal coordinates) and population data from the Homeland Infrastructure Foundation-Level Data (HIFLD), produced by the United States Department of Homeland Security (1). We included 4,078 operational and populated prisons, jails, and carceral facilities including ICE detention centers, juvenile or geriatric facilities, and halfway houses in the continental United States in our analysis. Of these, there were 232 federal, 1,606 state, 2,142 county, and 73 local facilities. Twenty-five (0.6% of total) carceral facilities did not fall into these categories and were classed as 'other'. Texas was the state with the single most prisons and jails (411 or 10.1% of total). In total, in 2018, there were 2,032,647 incarcerated people in included prisons and jails, of which 187,847 were in federal, 1,202,930 in state, 604,699 in county, 25,267 in local, and 11,904 in other. Texas was also the state with the single most incarcerated people (233,601 or 11.5% of total). The single largest prison by population was Cook County Jails, IL, with 8,216 incarcerated people.

### *Climate Data.*

The Parameter-elevation Relationships on Independent Slopes Model (PRISM) dataset from Oregon State University provides high-resolution (4 km grids) daily  $T_{\max}$  and maximum vapor pressure deficit ( $VPD_{\max}$ ) from 1981 - to near present (2). As described in (3-5), mean fields are produced by interpolating data from a dense network of weather stations with a spatial-weight regression model that uses landscape features like elevation and aspect to predict daily meteorological conditions across the continental United States (CONUS). PRISM data has been well-validated and shown to be well-suited for heat-related epidemiological research in the United States (5). The 4-km dataset is freely available.

### *Daily $WBGT_{\max}$ Estimates.*

$T_{\max}$  and  $VPD_{\max}$  mean fields were converted to approximated indoor or shaded  $WBGT_{\max}$  following the procedure described in (6,7). First,  $VPD_{\max}$  are converted to daily minimum relative humidity fields described in (5). Next, we combine  $T_{\max}$  and  $RH_{\min}$  to create daily maximum heat index ( $HI_{\max}$ ) mean fields following the U.S. National Weather Service's procedure (8). The full heat index equation is provided in our code (Data, Materials, and Software Availability). To calculate  $HI_{\max}$  for each day, we use  $T_{\max}$  and  $RH_{\min}$  to best align relative humidity at the time the daily maximum temperature occurs during a given diurnal cycle (5).

We then use the quadratic relationship identified by (9) between  $HI_{\max}$  and  $WBGT_{in}$  to convert  $HI_{\max}$  values to an approximated  $WBGT_{\max}$  (eq. 1).

$$WBGT (^{\circ}C) = -0.0034HI^2 + 0.96HI - 34 (^{\circ}F) \text{ (eq. 1)}$$

Outdoor wet bulb globe temperature ( $WBGT_{out}$ ) is a linear combination of wet bulb temperature ( $T_w$ ), black globe temperature ( $T_g$ ) and dry bulb temperature ( $T_d$ ) (eq 2), whereas indoor wet bulb globe temperature ( $WBGT_{in}$ ) combines only  $T_w$  and  $T_g$  (eq 3) (21). Both require in-situ field instruments to correctly measure (21, 22), though several methods exist to approximate  $WBGT_{out}$  from meteorological data (22).

$$\text{WBGT}_{\text{out}} = 0.7T_w + 0.2T_g + 0.1T_a \text{ (eq. 2)}$$

$$\text{WBGT}_{\text{in}} = 0.7T_w + 0.3T_g \text{ (eq. 3)}$$

We recognize that our  $\text{WBGT}_{\text{max}}$  approximation assumes fixed wind speeds ( $0.5 \text{ m s}^{-1}$ ) and neglects radiated heat of  $\text{WBGT}_{\text{out}}$ . But given that incarcerated Americans spend the preponderance of their time indoors and that most carceral facilities lack AC (7, 8),  $\text{WBGT}_{\text{in}}$  is appropriate to measure how humid heat exposure and changed across carceral facilities in the continental United States. Further, WBGT thresholds are used by multiple organizations, including ISO and the US National Institute for Occupational Safety & Health (NIOSH), to identify occupational risks related to heat stress (12).

#### *Calculating humid heat exposure and trajectories of change metrics*

For each carceral facility, we calculated the number of days in each year during 1982-2020 that were greater than  $28^\circ\text{C}$   $\text{WBGT}_{\text{max}}$  ( $n_{\text{days}_{\text{year}}}$ ). We first assigned the average number of days per year  $\text{WBGT}_{\text{max}}$  exceeded  $28^\circ\text{C}$  from 2016 - 2020. Then, we measured exposure during 2016 - 2020 by multiplying the number of incarcerated people housed at each carceral facility in 2018 by the average number of days  $\text{WBGT}_{\text{max}}$  exceeded  $28^\circ\text{C}$  from 2016 - 2020.

To calculate the disparities between carceral facilities with the rest of the state, we calculated state-level estimates for  $n_{\text{days}_{\text{year}}}$  by aggregating across counties in each state in each year using county-level population weights derived from the NCHS Vintage 2020 bridged-race dataset during 1990 - 2019 (11) and from the US Census Bureau prior to 1990 (12). We then made a population-weighted estimate of the state-level carceral facility value for  $n_{\text{days}_{\text{year}}}$  and subtracted the estimate calculated for the entire state to obtain the annual estimated disparity in exposure to humid heat days in each year of study in each state.

To estimate trajectories of change in dangerous humid heat, we performed a linear regression of  $n_{\text{days}_{\text{year}}} \sim \text{year}$  to estimate the change in  $n_{\text{days}_{\text{year}}}$  per year from 1982 - 2020. Using this fitted linear regression for each carceral facility, we then used the estimated parameter ( $\beta$ ) multiplied by the number of years between 1982-2020 (37 years) to estimate the fitted change in number of humid heat days.

#### **Supporting Information References**

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