How Heat Influences Human Mobility: A Comparative Analysis of Alternative Heat-Stress and Mobility Indices

Geo-Social

IOWA

Sriaditya Pendyala[1], Caglar Koylu, PhD[2]

[1]The Quarry Lane School, Dublin, CA; [2]School of Earth, Environment, and Sustainability, University of Iowa, Iowa City, IA

Introduction

- Due to climate change, higher temperatures are becoming more common across densely populated metropolitan statistical areas (MSAs) in the United States[7].
- Extreme heat changes the spatial pattern of human movement[1,8]; these changes in mobility are broadly measured via flows, activity spaces, entropy, and spatial clustering[7,5,4].
- "Feels like" temperature is captured through several such heat-stress indices such as the Heat Index (HI), Wet-Bulb-Globe-Temperature (WBGT), and Universal Thermal Climate Index (UTCI)[7].
- Current literature is split on the type of heat-stress index to use; the United States uses HI, Europe uses UTCI[7], and militaries & government agencies use WBGT.
- Due to the disparities between these indices and their usage[2], it is important to understand how they differ with respect to measuring mobility.

Objectives

- Assess how extreme heat restructures the types of flows between tracts using mobility metrics.
- Examine the magnitude and direction of change in mobility based on the choice of heat stress index.
- Understand the extent to which different heat indices are qualitatively and quantitatively similar.

Data Collection

- Data was spatially and temporally bound to May 1 - Sep 30 of 2019 (153 days) and Maricopa County (895 census tracts)
- Aggregated Safegraph mobility data at the daily census tract level was collected[8]
  - All flows where the origin or destination is Maricopa County were included
  - Metrics are calculated on each tract-day
- Heat-stress index data was collected at the hourly census tract level[7]
  - Data was processed into a daily max for each tract-day
  - Heat-stress indices that produced unattainable temperatures were adjusted to the 95th percentile of the respective index.

Method A: Mapping Heat Stress Indices

- The chosen heat stress indices correlate very strongly with each other due to the similarity in which they represent "feels like" temperature, and the geographical location Phoenix, Arizona.

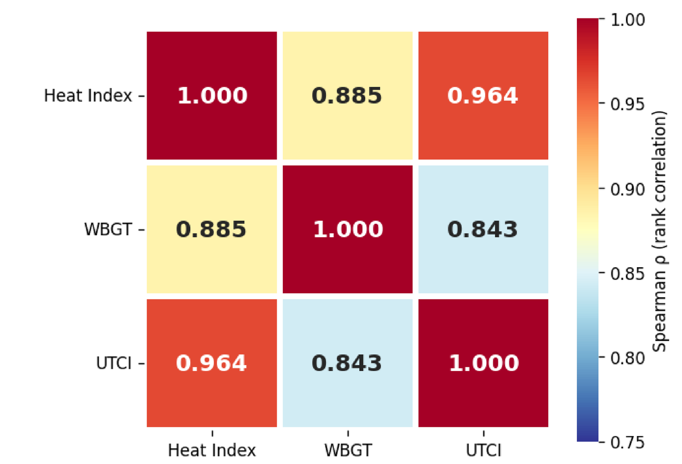

Fig 1. Spearman ρ for heat indices on daily-max from May –Sep 30 2019

- The distribution shows us monthly variations in heat.
- Fig 3: Strong spatial clustering between maps.

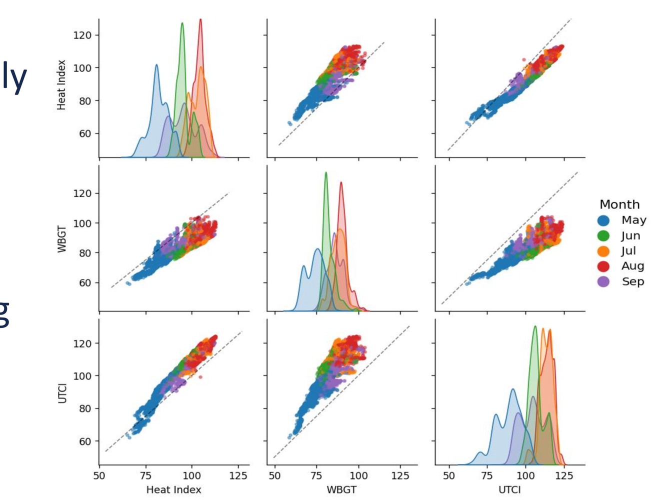

Fig 2. Scatterplot matrix of heat stress indices on each tract-day and their corresponding distributions. Heat depicted temporally.

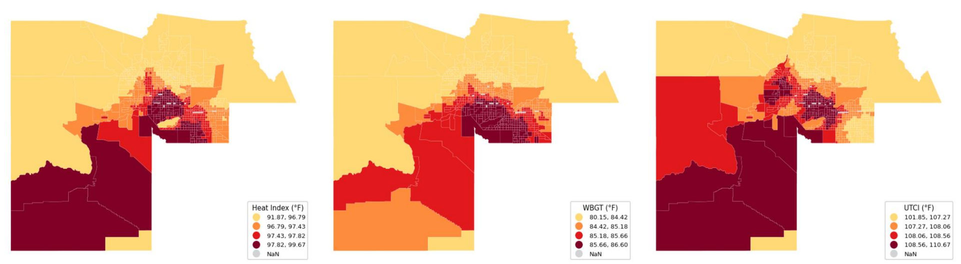

Fig 3. Choropleth maps of Maricopa County at tract level; left to right: HI, WBGT, UTCI; 153 day period-median quartiles. Heat depicted spatially.

Method B: Measuring Mobility Metrics

- Mobility can be visualized via traces of flows between tracts.

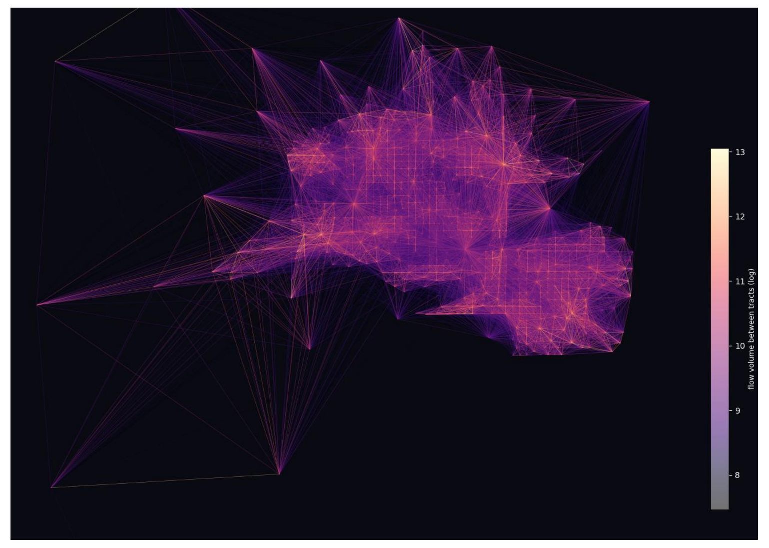

Fig 4. Top 20% Flows by Volume in Maricopa County. Edges Represent Flows log-scaled. Nodes Represent Centroids of Tracts

- Metrics that capture spatial nuances can be calculated with flow data; some key metrics we will observe are:
  - *Weighted Clustering Coefficient (WCC)*: gives the strength and cohesion of neighboring nodes

$$WCC_i^w = \frac{1}{s_i(k_i-1)}\sum_{j,h}\frac{(w_{ij}+w_{ih})}{2}a_{ij}a_{ih}a_{jh}$$

  - *In-degree & Out-degree:* gives the number of connected tracts based on inflow and outflow.

$$Degree_i = \sum_{j\neq i} a_{ij}$$

  - *Inflow, Outflow, Within-flow:* gives the volume of flows into, out of, and within a tract

$$Inflow_i = \sum_{j\neq i}^{n} flow_{ji} \qquad Outflow_i = \sum_{j\neq i}^{n} flow_{ij} \qquad Withinflow_i = flow_{ii}$$

  - Outflow Weighted Radius of Gyration (OWRg): is the typical travel radius weighted for the volume of flows.

$$OWR_g(i) = \sqrt{\frac{\sum_{j=1}^{n}(d_j - l_{wc})^2}{n}}$$

Method C: Fixed Effects Model

$$y_{it} = \beta \cdot (heat\ index)_i + \alpha_i + \varepsilon_{it} + \gamma_{dow(t)}$$

- y is some metric on tract *i* on day *t*
- β is how much some metric (adjusted to a % of metric's typical value in Fig 5.) changes per 1 SD (adjusted to per 10°F) of change in some index.
- α is the intercept for tract *i*
- ε is the error on tract *i* on day *t*
- γ is the day-of-the-week pattern that can be controlled

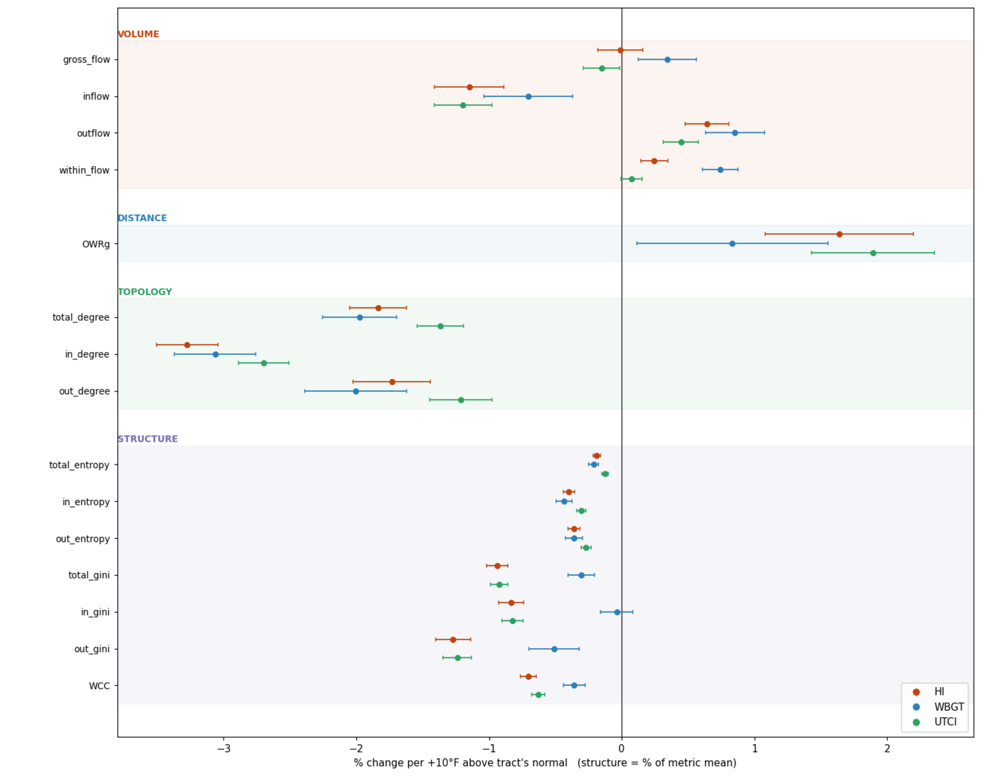

Fig 5. The % change from a tract's typical value for every +10°F on an index captured in a 95% CI for β where tract and day-of-week are Fixed Effects. Phoenix MSA 2019 May 1 to Sep 30.

- We use a fixed effects model to account for implicit variability within the tract and index.
- We aggregate the demeaned data for average y and average heat-index and run regressions for each tract-metric pair.
- The regression produces a 95% CI for β for each tract metric pair.
- The error epsilon is negligible

Spatial & Temporal Analyses of Divergences in Heat Indices

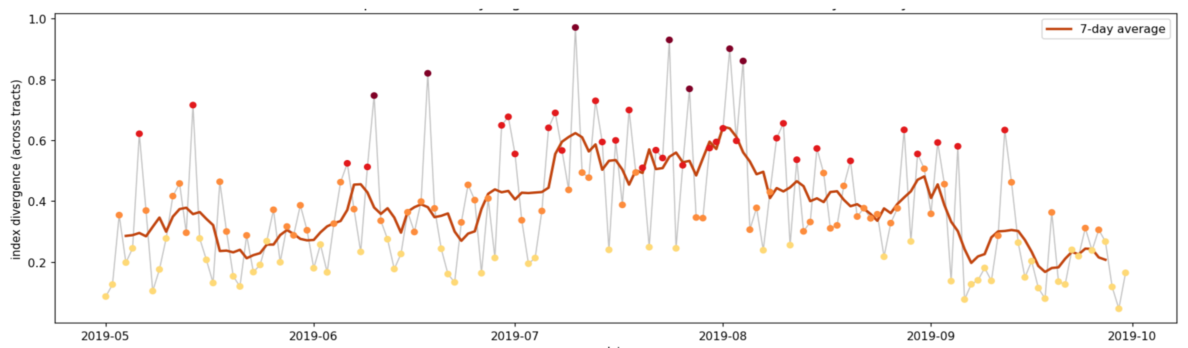

Fig 7. Divergence vs Time; Smoothed 7 Day Line Graph in Red

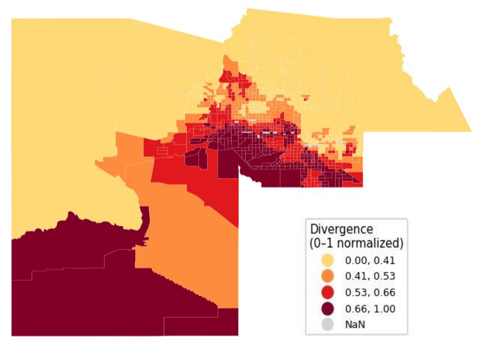

Fig 6. Index Divergence Per Tract; Min-Max Normalized and Split into Quartiles

- The divergence increases most during the monsoon season in Phoenix due to greater variability in meteorological conditions
- Divergence is calculated using an average of Spearman's ρ pairs

$$Divergence = 1 - \frac{\rho^{HI,WBGT} + \rho^{HI,UTCI} + \rho^{UTCI,WBGT}}{3}$$

- Divergence is greatest in urban tracts due to high aridity and lower elevation.

Results & Conclusion

- Studies that use UTCI will have consistently smaller magnitude changes in mobility compared to studies that use HI; European studies would measure smaller changes in mobility compared to American studies.
- Distance traveled from home increases due to a decreasing volume of shorter inter-tract and within-tract flows
- Communities will become less tightly knit; flows will concentrate between fewer denser urban areas due to decreasing flows between outer tracts.
- Due to how similar the 3 indices are, they perform nearly identically on each metric with a few exceptions.
  - Indices perform the same for measuring the volume of flows
  - Index choice matters most for measuring short distance flows and the directional-frequency of flows
- WBGT consistently separates itself from UTCI and HI which shows that it is the least similar to UTCI and HI; metrics calculated with WBGT would produce noticeably different results compared to HI & UTCI.

Future Works

- Observe how index-choice matters over other MSAs that aren't under constant heat-stress
- Assess how distinct meteorological factors (dry air-temperature, humidity, wind, etc...) individually contribute to variations in human mobility.

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