The Implications of Neighborhood Mobility Networks on Urban Heat Exposure

Noli Brazil
Department of Human Ecology
University of California, Davis

Introduction

Global temperatures are rising at rates never before observed. The 10 warmest years in record have all occurred since 2010, with the last nine years ranking as the warmest years on record (NOAA, 2022). For the United States, nine of the 10 warmest years on record have occurred since 1998, and 2012 and 2016 were the two warmest years on record. The annual number of heat waves is now twice that in the 1980s, and the heat wave season is more than 3 times as long as it was in the 1960s (Klingelhofer, 2023). These rising temperatures carry consequences across multiple domains of well-being, as they increase the risk of other types of disasters such as drought and wildfire, and pose threats to energy and agricultural systems (Perera et al., 2020; Sun et al., 2019). Exposure to extreme heat also substantially affects human health, in both the short and long term (Ebi et al., 2021).

The burden of higher temperatures and extreme heat is not evenly distributed across communities within cities. Research has found that racial/ethnic and socioeconomic disparities in exposure are particularly robust across different US contexts, with greater exposure in lower-income and nonwhite communities, while findings related to age and disability are mixed (Dialesandro et al., 2021; Lindsay, 2023). Much of this research uses neighborhoods as the ecological units shaping these disparities, which aligns with the dominant framework in urban research that identifies neighborhoods as independent institutions affecting resident health and well-being (Sampson, 2012).

The neighborhood effects framework was broadened by the perspective that ecological features shaping spatial inequalities are spatially clustered (Morenoff et al., 2001). Geographic clustering indicates that the heat burden experienced in neighborhoods extends to their extra-local environments. This perspective aligns with urban heat island research which identifies clusters of neighborhoods within cities experiencing extreme heat events (Deilami et al., 2018). Here, temperature is not a discontinuous phenomenon that changes at neighborhood boundaries, but "spills" over to create a cluster of neighborhoods experiencing disproportionate levels of heat exposure.

In the same way that temperature is not contained within neighborhood boundaries, people are also not confined to their residential settings, but travel to neighborhoods across their cities for work, school, errands and leisure. Prior work has shown that residents spend large proportions of time outside of their neighborhoods, this time is often spent in distal areas of the city, and residents of poor and minority neighborhoods travel about as widely across their cities as those of other groups (Brazil, 2020; Jones and Pebley, 2014; Wang et al., 2018). Much of this evidence comes from the rich literature on activity spaces, which shows that people spend a great deal of their day in activities occurring in places outside their home areas (Cagney et al., 2020).

Aggregating these individual trips up to the population level reveals a higher-order, urban network formed by large and consistent flows connecting neighborhoods both near and far.

The implication of this higher-order neighborhood scale is that prior work may be misestimating exposure to extreme heat. On the one hand, residents from higher temperature neighborhoods may be exposed to lower temperatures in the neighborhoods they travel to for daily routines. This is the perspective of the neighborhood effect averaging problem, which posits that taking people's daily mobility into account will lead to an overall tendency toward the mean exposure because exposure levels for people whose residence-based exposures are lower or higher than the mean exposure will tend toward the mean exposure (Kwan, 2018). On the other hand, heat exposure may be similar or greater for residents burdened with high heat exposure in their residential settings. This may be the case if residents from disadvantaged/advantaged neighborhoods travel on average to similarly disadvantaged/advantaged neighborhoods (Brazil et al., 2024).

Prior studies using geolocated cell phone pings, social media posts and job commuting to measure inter-city flows between neighborhoods have examined exposure to a variety of conditions in mobility networks, including crime, air pollution, tree canopy, poverty, segregation, and health outcomes (Brazil, 2022; Candipan et al., 2021; Levy et al., 2020; Moro et al., 2021; Wei et al., 2024). In this study, I add to this burgeoning literature by estimating average heat exposure in the network of neighborhoods linked via daily mobility flows. Using 2018–2019 anonymized mobile phone data from SafeGraph, I construct neighborhood networks based on daily mobility flows for the 100 largest US metropolitan areas. I examine differences in neighborhood exposure to heat and its association with ecological conditions across three neighborhood scales: (1) the residential neighborhood; (2) the neighborhoods bordering the residential neighborhood; and (3) the non-residential and non-adjacent neighborhoods visited by residents. I then examine sociodemographic inequalities in exposure by comparing differences by neighborhood ethnoracial, socioeconomic disadvantage, age and disability composition.

Data

Mobility

Mobility of residents between neighborhoods are based on the location pings of smart phone devices. A flow between neighborhoods *i* and *j* represent the number of trips originating from home neighborhood *i* visiting destination neighborhood *j*. Cell phone location data rely on numerous smart phone apps and were aggregated by SafeGraph (SafeGraph, 2024). SafeGraph provides visit patterns for more than 40 million devices to more than 6 million points of interests. The dataset contains information on the daily number of pings in a destination block group and the residence block group locations of the pings. The analysis includes pings aggregated up to the tract level from November 2018 to November 2019, before the major impact of COVID-19 on travel.

I used SafeGraph data because it provides extensive spatial coverage, with almost all counties represented (Li et al., 2024). Furthermore, SafeGraph data are a widely used standard in large-scale studies of human mobility across many different areas including air pollution and COVID-19 modelling (Brazil, 2022; Marlow et al., 2021). The SafeGraph sample is not a perfect representative subset of the population (Li et al., 2024). Not everyone owns a cellphone, carries one with them, some use alternative forms of communication when travelling, such as burner phones, some people carry multiple devices, some devices are shared across multiple individuals, and some people carry a smart device only some of the time. Nevertheless, the empirical sampling rates in the sample panel are quantitatively close to the expected sampling rates from a large-N random sample (Squire, 2019; Noi et al., 2022).

Temperature

Land surface temperature data come from a nationwide dataset that I constructed with several co-authors (Dialesandro et al. 2021). The dataset is based on Landsat 8 Operational Land Imager (OLI) Tier 1 imagery downloaded from Google Earth Engine (GEE). Using JavaScript-enabled GEE we processed these data to obtain at-sensor (or top-of-atmosphere (TOA)) radiance and surface reflectance. We then used TOA radiance and surface reflectance data to retrieve Land Surface Temperature (LST). Temperature recorded dates were selected for cloud-free periods (which provide the most accurate readings) in the summer season. Similar to Dialesandro et. al (2021), I will explore three temperature scenarios. First, the number of extreme heat days in a given year. This was done by selecting the warmest days available between 2013 and 2018 that coincided with a cloud-free day of Landsat 8 OLI imagery capture. Second, the average summer day temperature based on the average of available Landsat scenes during the study period. Third, the average summer nighttime temperature.

Neighborhood Sociodemographic Characteristics

Data on census tract level demographic and socioeconomic characteristics will be drawn from the 2015-19 American Community Survey (ACS). I will collect data on population size, racial/ethnic composition (percent non-Hispanic white, non-Hispanic black, non-Hispanic Asian, Hispanic and other), age composition (% 65 years old and older) and disability prevalence. Consistent with prior research, I conduct a principal components analysis of the following neighborhood variables to measure neighborhood disadvantage: percentages of poverty, unemployment, single-headed households, public assistance receipt, adults without a high school diploma, adults with a bachelor's degree or higher, and workers who are managers or professionals.

Methods

This study examines differences in neighborhood heat exposure levels across residential, adjacent and network neighborhoods. I run the following fixed-effects regression model to obtain estimates of heat exposure:

$$Heat_{ik} = \beta_0 + \beta_1 X_{ik} + \beta_2 Pop_{ik} + \alpha_k + \epsilon_{ik}$$

where $Heat_{ik}$ is neighborhood measures of heat exposure at the residential, adjacent or network scale for neighborhood i in MSA k, and X_{ik} is the set of sociodemographic variables described above. The parameter α_k is a metro fixed effect, which controls for unobserved metro characteristics; and Pop_{ik} controls for differences in resident total population.

I then examine neighborhood ethnoracial, socioeconomic disadvantage, age and disability differences in exposure to neighborhood heat exposure levels. For race/ethnicity, I calculate the gap in the predicted average exposure levels between white and Asian, Black, and Hispanic neighborhoods, and comparing the gaps across the three neighborhood scales. I construct a categorical variable indicating whether neighborhood *i* in metro *k* is white, Black, Asian, Hispanic or other, with other containing neighborhoods that are either not at or above the 75th percentile in an ethnoracial group, or at or above more than one ethnoracial distribution. For socioeconomic disadvantage, age and disability, I keep the variables as continuous.

Expected Findings

Studies using cell phone pings, job commuting flows, and georeferenced social media posts to capture resident travel have found that neighborhoods are connected to other neighborhoods with similar levels of socioeconomic disadvantage, regardless of distance (Brazil et al., 2024; Moro et al., 2021; Wang et al., 2018). Other phenomena found to be correlated across neighborhood networks include air pollution levels, segregation, crime, and health outcomes including COVID-19 and sexually transmitted diseases (Brazil, 2022; Candipan et al., 2021; Evans et al., 2023; Newmyer et al., 2022; Wang et al., 2018). Given this prior evidence, I hypothesize that heat exposure levels will be equal or greater in the neighborhoods that residents travel to for daily routines compared to their residential and adjacent neighborhoods. Prior work has also shown that exposure to disadvantage is equal or greater for nonwhite network-based neighborhoods compared to their white counterparts (Brazil et al., 2024; Wang et al., 2018). As such, I hypothesis similar network inequalities for heat exposure. Given mixed findings for disability and age in residential-based studies of heat exposure inequality, I hypothesis mixed findings for heat when examining exposure at the network level for these groups.

References

Brazil, N. (2022). Environmental inequality in the neighborhood networks of urban mobility in US cities. *Proceedings of the National Academy of Sciences*, *119*(17), e2117776119.

Brazil, N., Chakalov, B. T., & Ko, M. (2024). The health implications of neighborhood networks based on daily mobility in US cities. *Social Science & Medicine*, *354*, 117058.

Cagney, K. A., York Cornwell, E., Goldman, A. W., & Cai, L. (2020). Urban mobility and activity space. *Annual Review of Sociology*, *46*(1), 623-648.

Candipan, J., Phillips, N. E., Sampson, R. J., & Small, M. (2021). From residence to movement: The nature of racial segregation in everyday urban mobility. *Urban Studies*, *58*(15), 3095-3117.

Deilami, K., Kamruzzaman, M., & Liu, Y. (2018). Urban heat island effect: A systematic review of spatio-temporal factors, data, methods, and mitigation measures. *International journal of applied earth observation and geoinformation*, *67*, 30-42.

Dialesandro, J., Brazil, N., Wheeler, S., & Abunnasr, Y. (2021). Dimensions of thermal inequity: Neighborhood social demographics and urban heat in the Southwestern US. *International journal of environmental research and public health*, *18*(3), 941.

Ebi, K. L., Capon, A., Berry, P., Broderick, C., de Dear, R., Havenith, G., ... & Jay, O. (2021). Hot weather and heat extremes: health risks. *The lancet*, *398*(10301), 698-708.

Evans, M., Graif, C., & Matthews, S. A. (2023). The Role of Infant Health Problems in Constraining Interneighborhood Mobility: Implications for Citywide Employment Networks. *Journal of health and social behavior*, *64*(4), 555-577.

Jones, M., & Pebley, A. R. (2014). Redefining neighborhoods using common destinations: Social characteristics of activity spaces and home census tracts compared. *Demography*, *51*(3), 727-752.

Klingelhöfer, D., Braun, M., Brüggmann, D., & Groneberg, D. A. (2023). Heatwaves: does global research reflect the growing threat in the light of climate change?. *Globalization and Health*, *19*(1), 56.

Kwan, M. P. (2018). The neighborhood effect averaging problem (NEAP): An elusive confounder of the neighborhood effect. *International journal of environmental research and public health*, *15*(9), 1841.

Levy, B. L., Phillips, N. E., & Sampson, R. J. (2020). Triple disadvantage: neighborhood networks of everyday urban mobility and violence in US cities. *American Sociological Review*, *85*(6), 925-956.

Levy, B. L., Vachuska, K., Subramanian, S. V., & Sampson, R. J. (2022). Neighborhood socioeconomic inequality based on everyday mobility predicts COVID-19 infection in San Francisco, Seattle, and Wisconsin. *Science advances*, *8*(7), eabl3825.

Lindsay, S., Hsu, S., Ragunathan, S., & Lindsay, J. (2023). The impact of climate change related extreme weather events on people with pre-existing disabilities and chronic conditions: a scoping review. *Disability and Rehabilitation*, *45*(25), 4338-4358.

Li, Z., Ning, H., Jing, F., & Lessani, M. N. (2024). Understanding the bias of mobile location data across spatial scales and over time: a comprehensive analysis of SafeGraph data in the United States. *Plos one*, *19*(1), e0294430.

Marlow, T., Makovi, K., & Abrahao, B. (2021). Neighborhood isolation during the COVID-19 pandemic. *Sociological Science*, *8*, 170-190.

Morenoff, J. D., Sampson, R. J., & Raudenbush, S. W. (2001). Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence. *Criminology*, *39*(3), 517-558.

Moro, E., Calacci, D., Dong, X., & Pentland, A. (2021). Mobility patterns are associated with experienced income segregation in large US cities. *Nature communications*, *12*(1), 4633.

Newmyer, L., Evans, M., & Graif, C. (2022). Socially connected neighborhoods and the spread of sexually transmitted infections. *Demography*, *59*(4), 1299-1323.

NOAA National Centers for Environmental Information, Monthly Global Climate Report for Annual 2022, published online January 2023, retrieved on September 9, 2024 from https://www.ncei.noaa.gov/access/monitoring/monthly-report/global/202213.

Noi, E., Rudolph, A., & Dodge, S. (2022). Assessing COVID-induced changes in spatiotemporal structure of mobility in the United States in 2020: a multi-source analytical framework. *International Journal of Geographical Information Science*, *36*(3), 585-616.

Perera, A. T. D., Nik, V. M., Chen, D., Scartezzini, J. L., & Hong, T. (2020). Quantifying the impacts of climate change and extreme climate events on energy systems. *Nature Energy*, *5*(2), 150-159.

SafeGraph [WWW Document] (2024). URL https://www.safegraph.com/about (accessed 07.28.24)

Sampson, R. J. (2012). *Great American city: Chicago and the enduring neighborhood effect*. University of Chicago Press.

Squire, R.F. (2019). What About Bias in the SafeGraph Dataset? URL https://www.safegraph.com/blog/what-about-bias-in-the-safegraph-dataset

Sun, Q., Miao, C., Hanel, M., Borthwick, A. G., Duan, Q., Ji, D., & Li, H. (2019). Global heat stress on health, wildfires, and agricultural crops under different levels of climate warming. *Environment international*, *128*, 125-136.

Wang, Q., Phillips, N. E., Small, M. L., & Sampson, R. J. (2018). Urban mobility and neighborhood isolation in America's 50 largest cities. *Proceedings of the National Academy of Sciences*, *115*(30), 7735-7740.

Wei, H., Renson, A., Huang, X., Thorpe, L. E., Spoer, B. R., & Charles, S. L. (2024). Assessing potential benefits of visits to neighborhoods with higher tree canopy coverage using mobility data: Associations with cardiovascular health outcomes in twenty US metropolitan areas. *Health & Place*, *89*, 103299.