

Heat exposure in neighborhood mobility networks for the 100 largest U.S. cities¹

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Introduction

Global temperatures have been increasing over time due to climate change, exerting far-reaching consequences on environmental and human systems (Hansen et al., 2022). This trend is expected to continue, with extreme heat events also increasing in frequency and severity (Tuholske et al., 2021). There is a large body of research which associates exposure to high temperatures to increases in mortality rates, several non-fatal health outcomes, including heat strokes, dehydration, and hospitalizations, and well-being measures, such as loss of labor productivity and decreased learning (Graff Zivin & Neidell, 2014; Heaviside et al., 2017; Park et al., 2020).

Because built environments are commonly hotter than the natural (surrounding) environment, a phenomenon commonly referred to as the urban heat island (UHI) effect, cities have experienced the greatest increases in temperatures (Peng et al., 2012). The UHI effect is not distributed evenly within a city; rather, higher temperatures are concentrated in neighborhoods characterized by concentrated socio-economic disadvantage, particularly in areas with higher proportions of non-white residents (Dialesandro et al., 2021; Hsu et al., 2021; Renteria et al., 2022). The UHI literature has examined these disparities according to the neighborhoods where households reside. For example, Hsu et al. (2021) find that the average person of color lives in a census tract with higher temperatures than non-Hispanic whites in all but 6 of the 175 largest urbanized areas in the United States. However, residents spend large proportions of time outside of their residential settings, 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 (Wang et al., 2019). Accordingly, we hypothesize that measurement of heat exposure should incorporate the neighborhoods where people live, work, play, and otherwise spend time. Prior work reveals that aggregating 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 (Brazil et al., 2025). Understanding the geographic burden of heat exposure must consider this higher-order, neighborhood network, because if residents spend significant time outside of their neighborhoods and travel to neighborhoods beyond those that are geographically adjacent, we are potentially misestimating exposure, and its inequality across racial/ethnic lines (Levy & Bonner, 2025; Sampson & Candipan, 2023).

There may be notable differences in heat exposure between the neighborhoods people visit and their home neighborhoods based on variation in land use and socioeconomic environments. For example, residents of neighborhoods with lower temperatures may visit commercial and industrial areas with material properties that reflect less solar energy, and absorb and emit more of the sun's heat, such as pavement, roofing, sidewalks, roads, buildings, and parking lots; there

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may be lower tree canopy in the neighborhoods in which individuals with lower incomes reside and so they visit neighborhoods with higher tree canopy coverage for outdoor activities (Wang et al., 2021; Wei et al., 2024). These differences in visit patterns and purposes, along with socioeconomic disparities between neighborhoods, can contribute to substantial variation in temperatures even in relatively small geographic areas. Indeed, one study found that air pollution exposure also varies across the places where people spend time, and that residents from poor and minority neighborhoods travel to neighborhoods with more air pollution than do residents from nonpoor and white neighborhoods (Brazil, 2022). In contrast, there may be little to no difference in temperatures between residential and mobility-based neighborhoods. In this case, limited neighborhood networks, influenced by racial disparities in mobility, sustain heat inequities linked to socioeconomic disadvantages in the residential neighborhood (Candipan et al., 2021).

In this study, we construct neighborhood networks based on daily mobility flows for the 100 largest US metropolitan areas using 2018–2019 anonymized mobile phone data from SafeGraph. We examine differences in neighborhood exposure to summer temperatures 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. We then examine ethnoracial and socioeconomic inequalities in exposure by comparing differences by neighborhood composition, and explore heterogeneity by Census region.

Data

Data was collected at the census tract level in the 100 largest metropolitan statistical areas (MSA) in the United States based on 2018 U.S. Office of Management and Budget MSA definitions and total population estimates. The 100 largest MSAs were chosen due to their greater availability of cell phone data. Census tract was used because it is the most common scale for measuring neighborhoods in social science research and provides lower uncertainty of mobility and socioeconomic characteristics relative to lower scales such as the block group (Sampson, 2012).

Mobility flows

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 from multiple cell phone companies to more than 6 million points of interests. Here, a trip is represented as a cell phone device being pinged when an application is in use in a location other than its home neighborhood, where “home” is the location where the mobile device is detected most at night (from 18:00 to 07:00) over a 6-wk period. The data do not uniquely identify individuals but rather provide an anonymized overview of their aggregated movement to protect individual privacy while still providing insights into broader patterns of human mobility. 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 data is not publicly available but is purchased through a paid subscription. 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. SafeGraph did not collect weekly patterns data before 2018. Prior work has shown that SafeGraph-based mobility patterns are broadly consistent before and after the peak of the COVID-19 pandemic, and with patterns for multiple years of other forms of mobility data (e.g., geolocated tweets), demonstrating consistency in mobility patterns observed with a single year of SafeGraph data (Levy et al., 2020; Marlow et al., 2023).

We 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, crime and COVID-19 modelling (Brazil, 2022; Levy et al., 2022). 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

Historical daily ambient temperature data (in degrees Fahrenheit) was obtained from the gridMET dataset, which provides validated and publicly available daily surface fields of maximum temperature and minimum temperature covering the contiguous United States at a resolution of ~ 4 km (1/24th degree). It integrates climate data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) with data from the National Land Data Assimilation System (NLDAS) to generate spatiotemporally continuous surface meteorological forcings (Abatzoglou, 2013). Our heat exposure variable is the census tract mean maximum temperature in the summer months (June-September) of 2018 and 2019.

We construct three variables capturing heat exposure across the following scales: (1) mean maximum summer temperature in neighborhood i (Residential); (2) the average mean maximum summer temperature in neighborhood i 's spatially adjacent neighbors (Adjacent), where neighbor is sharing a border or vertex; and (3) the average mean maximum summer temperature in a neighborhood's mobility flow network weighted by the proportion of trips to each MSA neighborhood (Network). Visits to the same and adjacent neighborhoods are excluded, and thus the corresponding cell values are populated with zeros. We restrict adjacency and network connections to neighborhoods within the same MSA.

Sociodemographic characteristics

Data on census tract level demographic and socioeconomic characteristics were drawn from the American Community Survey (ACS), 5-year 2015-2019 estimates. Ethnoracial data capture resident percent composition based on the following categories: Non-Hispanic white, non-

Hispanic Black, non-Hispanic Asian, Hispanic. 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 (Levy et al., 2020). We also include log population size, percentage of household without a private automobile, percent of residents over 65 years old, and percent of residents with a physical disability.

Methods

We estimate heat exposure across residential, adjacent and network scales using spatial error regression models of the following form:

$$Heat\ Exposure_{ik} = \beta_0 + \beta_1 X_{ik} + \alpha_k + \lambda W \mu_{ik} + \varepsilon_{ik} \quad (1)$$

where $Heat\ Exposure_{ik}$ represents mean maximum summer temperature for neighborhood i and MSA k at the residential, adjacent and network scales as described above, μ_{ik} is spatially autocorrelated error term and W is a row-standardized spatial weights matrix based on Queen contiguity. We predict heat exposure with MSA dummy variables α_k and a vector of covariates (X_{ik}). Percent Black and percent Hispanic were included in Equation 1. Including percent white introduced high multicollinearity.

We next examine ethnoracial and SES differences in heat exposure across residential, adjacent and network scales. We run models including percent Black, Hispanic and white, separately. We also examined neighborhood racial and socioeconomic intersectional disparities in heat exposure risk. Specifically, we ran the same fixed-effects model specified above but interacted the SES indicator with each race/ethnicity variable.

Results

Figure 1 presents regression-adjusted mean summer temperatures with 95% confidence intervals at the residential, adjacent and network scales. The results indicate that heat exposure is similar across all three scales. Mean summer temperatures in the residential environment is slightly higher at 86.7 degrees. Heat exposure in its adjacent areas and the neighborhoods it is connected to via daily mobility flows are slightly lower at 84.5 and 85.8 degrees, respectively.

Figure 2 shows predicted mean summer temperatures and 95% confidence intervals by percent White, Black and Hispanic. We make comparisons between residential and network trends. Regression coefficients for percent White and Hispanic are statistically significant at standard thresholds, with a greater percent White associated with lower temperatures and greater percent Hispanic associated with higher temperatures at both residential and network scales. However, while the slope is smaller at the network scale for percent White, it is greater for percent Hispanic, indicating a reduced heat exposure advantage for White neighborhoods and a greater disadvantage for Hispanic neighborhoods in their network of neighborhoods. Figure 2 also indicates a small decrease in temperature with greater percent Black at both scales; however, the slopes are not statistically significant.

Figure 3 shows the relationship between socioeconomic disadvantage and heat exposure. Greater neighborhood socioeconomic disadvantage is associated with greater heat exposure at the network scale, with a statistically significant slope coefficient. In contrast, greater socioeconomic disadvantage exhibits no association with summer temperature in the residential neighborhood.

Figure 4 presents predicted summer temperatures by racial/ethnic composition interacted with whether a neighborhood is poor or not poor, where poor is defined as percent poverty greater than 30%. Here, we find that the positive relationship between percent Hispanic and summer temperature is present in both poor and nonpoor neighborhoods. In contrast, the negative relationship between percent White and summer temperature is true only for non poor neighborhoods. Percent White in poor neighborhoods exhibits no association with summer temperature in the residential and network environments. Percent Black shows no association at both scales.

Figure 5 shows racial/ethnic results broken down by Census region (Midwest, Northeast, South and West). There is a positive relationship between percent Hispanic and summer temperature at the residential and network scales across all regions except the Midwest, where no relationship exists. The negative relationship between percent White and summer temperature appears in the South and Northeast, but not in the West and Midwest. Black composition exhibits contrasting regional results. Percent Black is positively associated with summer temperature in the Northeast, negatively associated in the West, and shows no association in the Midwest and South.

Conclusion

The results indicate that levels of heat exposure in the residential neighborhood extends to the neighborhoods that residents travel to for daily routines. Mean summer temperature in the residential neighborhood is 86.7 degrees. In comparison, mean summer temperature in the network of neighborhoods based on mobility flows is slightly lower at 85.8.

We also find that documented racial/ethnic disparities in heat exposure at the residential scale extend to the network scale. Neighborhoods with a greater White composition are exposed to lower temperatures while neighborhoods with a greater presence of Hispanic residents experience higher temperatures. This heat disparity also applies to the neighborhoods that White and Hispanic neighborhoods are connected to based on where their residents travel to for school, work and leisure. We also find socioeconomic disparities in heat exposure, but only at the network scale: socioeconomic disadvantage is positively associated with higher temperatures at the network scale, but shows no association at the residential level.

Figures

Figure 1: Regression-adjusted estimates and 95% confidence intervals of mean summer temperature exposure (in degrees Fahrenheit) in residential neighborhoods (Residential), adjacent neighborhoods (adjacent), and the nonadjacent neighborhoods that residents visit (network)

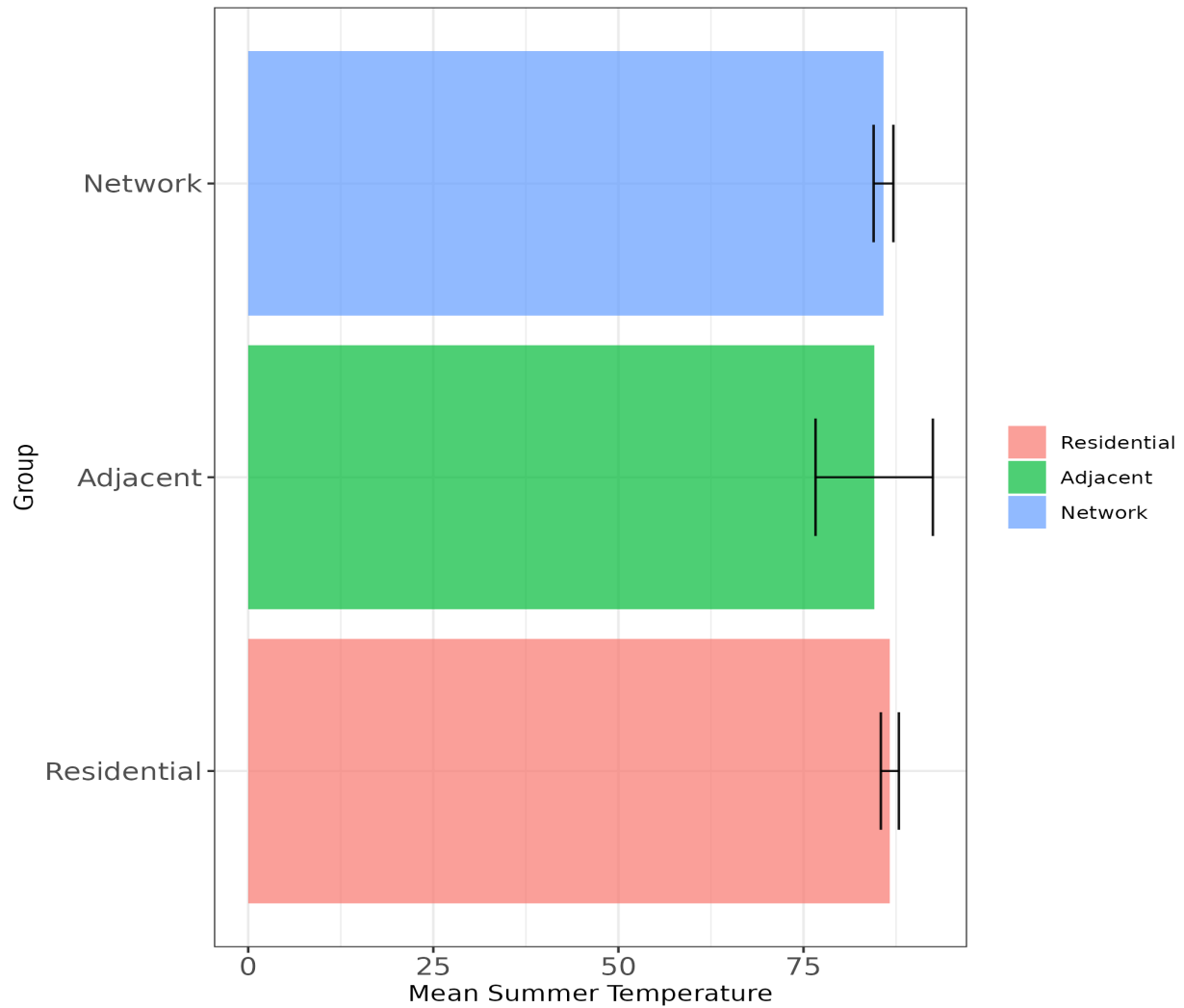


Figure 2: Regression-adjusted estimates and 95% confidence intervals of mean summer temperature exposure (in degrees Fahrenheit) in residential neighborhoods (Residential) and the nonadjacent neighborhoods that residents visit (network) by percent racial/ethnic composition.

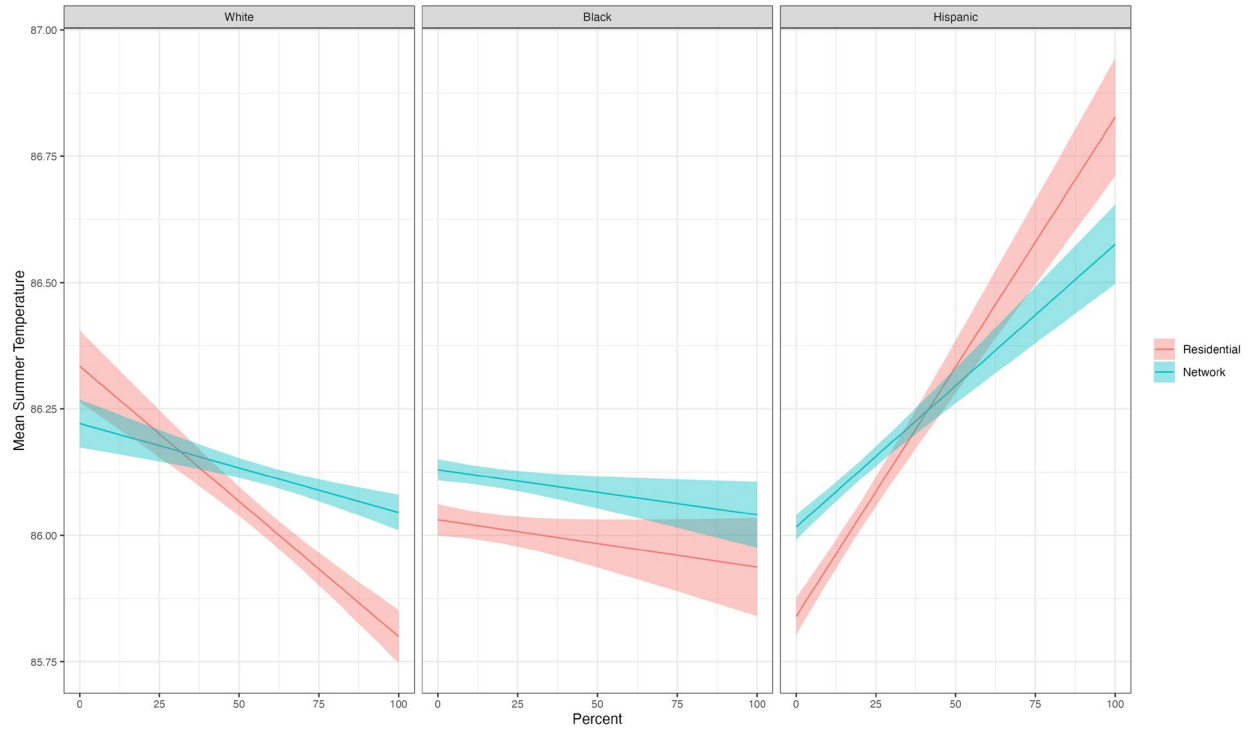


Figure 3: Regression-adjusted estimates and 95% confidence intervals of mean summer temperature exposure (in degrees Fahrenheit) in residential neighborhoods (Residential) and the nonadjacent neighborhoods that residents visit (network) by socioeconomic disadvantage.

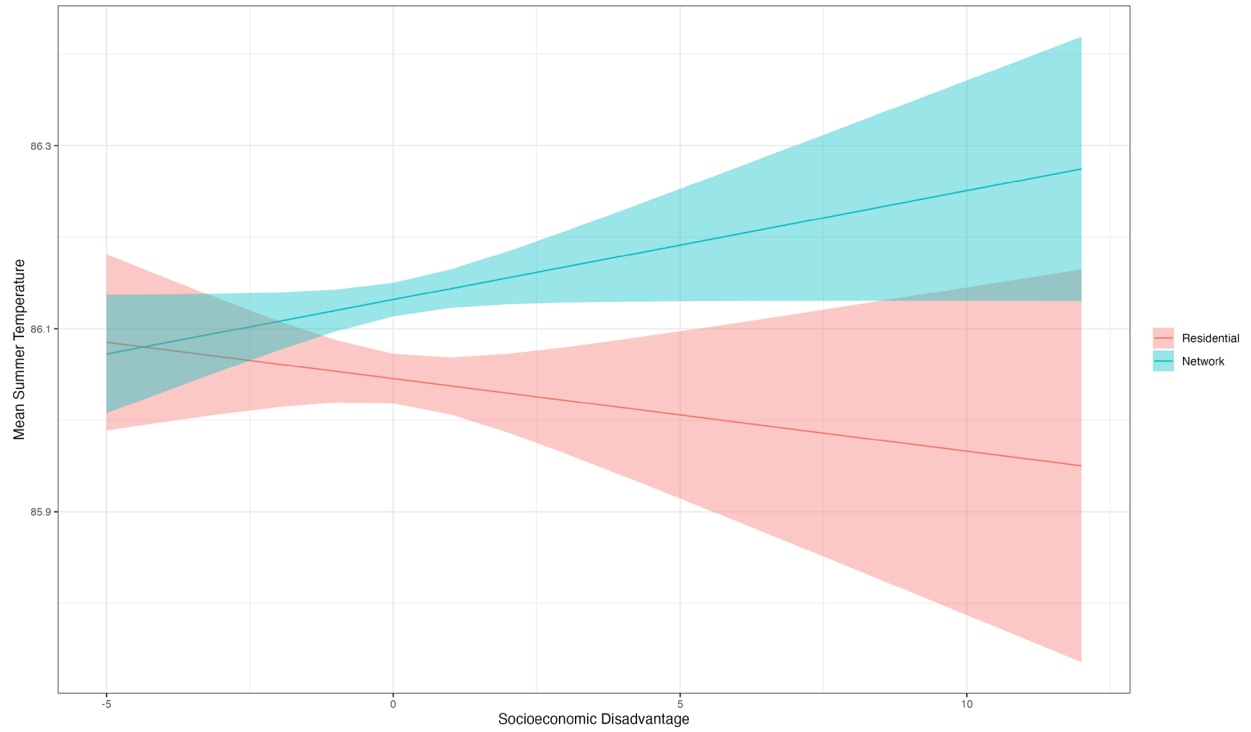


Figure 4: Regression-adjusted estimates and 95% confidence intervals of mean summer temperature exposure (in degrees Fahrenheit) in residential neighborhoods (Residential) and the nonadjacent neighborhoods that residents visit (network) by racial/ethnic composition and poverty status.

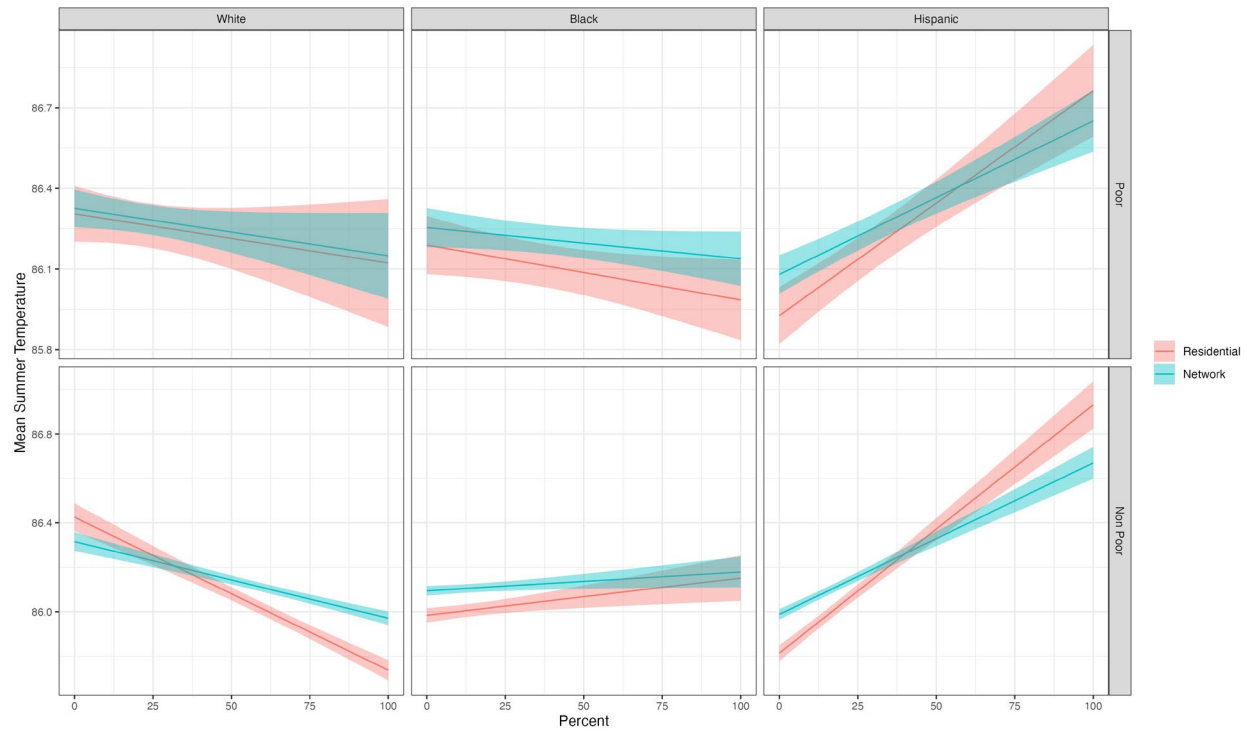
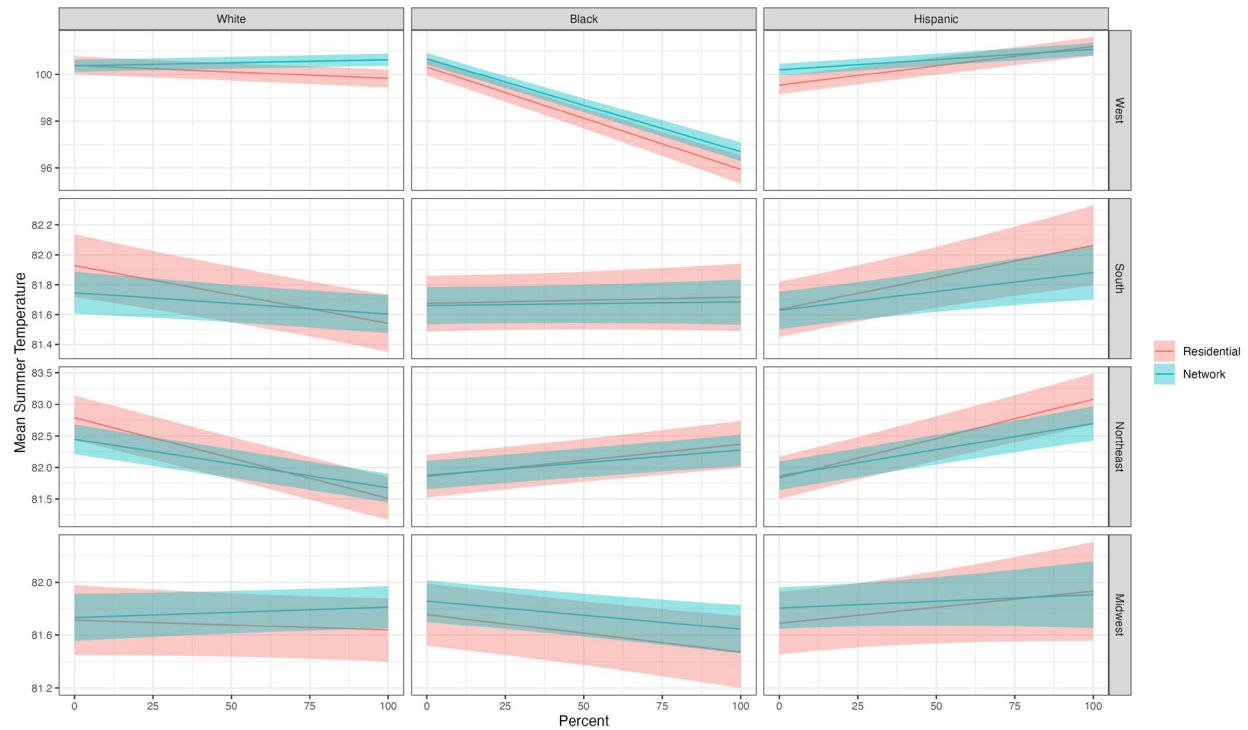


Figure 5: Regression-adjusted estimates and 95% confidence intervals of mean summer temperature exposure (in degrees Fahrenheit) in residential neighborhoods (Residential) and the nonadjacent neighborhoods that residents visit (network) by racial/ethnic composition and Census region.



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