Heat and Mortality in a Semi-Arid City: A Multi-Scalar Analysis

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Introduction

We examined the temperature-mortality relationship in for summers in Denver from 1990-2019 using generalized additive models at the city, tract, and block group scales. We evaluated multiple temperature metrics, model structures, and temporal lags to assess their performance. Specifically, our goal is to:

- Assess how temperature metrics and model selection influence estimates of heat-related mortality risk in a semi-arid urban context.
- Examine the presence and magnitude of a heat wave effect persisting beyond daily temperature exposure.
- Characterize spatial and temporal variation in mortality risk across intra-urban contexts.
- Evaluate how spatial resolution shapes the interpretation of temperature–mortality relationships.

These objectives guide a multi-scalar analysis designed to advance scientific understanding and inform public health planning about urban heat risk in semi-arid settings. We hypothesize that multi-day temperature averages capture mortality risk better than daily lags; that there will be a detectable heat wave effect on mortality risk; and that fine-scale intra-city variability complicates interpretation. We observe that the census tract is a more appropriate spatial unit for intra-city analysis, given the high level of variability at the census block group scale.

Literature Overview

- The impacts of extreme heat are temporally and spatially relative (Anderson & Bell, 2009; Kalkstein & Davis, 1989; Sheridan et al., 2021). Net warming across the globe has set the conditions for increased heat variability, and consequently, risk of extreme temperatures (Hansen et al., 2012).
- Increased risk demands focused attention from researchers on the relationships between heat and mortality within a broad range of local contexts (Kinney, 2018).
- Linear and non-linear modelling have been used in previous analyses to examine the influence of temperature on daily mortality (Braga et al., 2001; Curriero et al., 2002; Metzger et al., 2010).
- There is a nonlinear relationship between temperature and mortality with a "U" or "V shaped exposure-response relationship (Li et al., 2013; Wang et al., 2025).
- The health impacts of heat can be modelled as the effects of daily, averaged, or lagged temperatures (Anderson & Bell, 2009; Sheridan et al., 2021).
- Some studies investigate the additional "heat wave effect" by accounting for the additional risk of consecutive days of heat (Hajat et al., 2006). The evidence for a heat wave effect on mortality is mixed and often contradictory; studies have identified added effects (Anderson & Bell, 2009; Chen et al., 2015; Hajat et al., 2006), no added heat wave effects (Barnett et al., 2012; Gasparrini & Armstrong, 2011), or varying heat wave effects for different countries (Guo et al., 2017).

Methodology

Using Temperature Data (PRISM Climate Group, 2024) and all-cause geolocated mortality data (CDPHE) we:

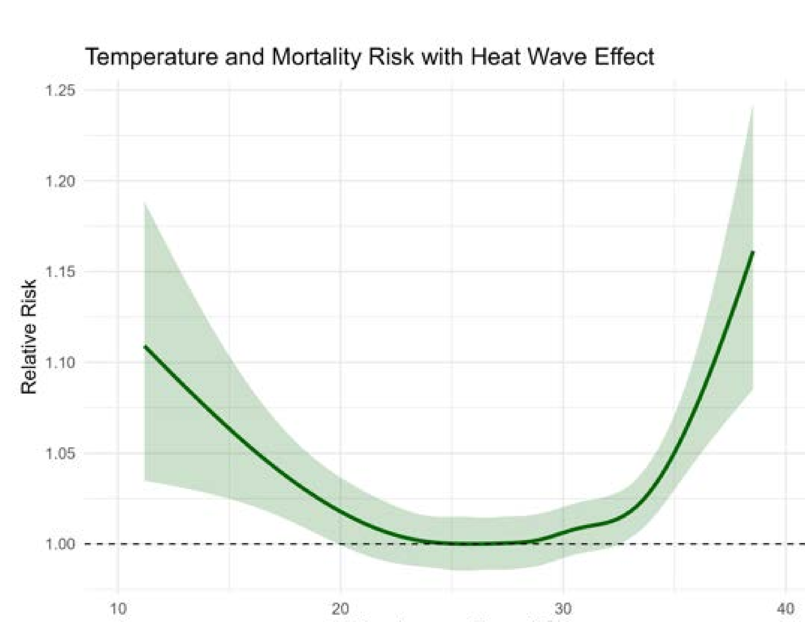
- Constructed quasi-Poisson generalized linear models and generalized additive models
- Compared temperature metrics (Tmin/mean/max, AT) and lags (0 to 5 day)
- Examined the spatial relationship at the tract (n=171) and block group (n=517) scale using a spatial fixed effect
- Tested for a heat wave effect [heatwave = 3+ days 95 percentile maximum temperature (34.4ºC)]
- Conducted a decadal analysis to identify temporal patterns (1990-99, 2000-09, 2010-19)

Generalized Additive Model for intra-city analysis:

$$\log(\mu_i) = \beta_0 + f_1(T)\cdot I(j) + \sum_{j=1}^{J}\alpha_j + f_2(year_i) + \beta_1 \cdot heatwave$$

Results

- City models exhibited the expected U-shaped mortality curve, finer-scale analyses highlighted substantial heterogeneity in heat-related risk.
- Maximum surface air temperature (Tmax) had the strongest and most consistent association with mortality.
- A 5-day rolling average of Tmax best captured the delayed and cumulative impacts of heat, revealing a small but detectable heat wave effect.
- The best model to represent the mortality-temperature relationship is a generalized additive model with a cubic spline for year and a fixed spatial effect
- Census tract–level models outperformed those at the census block group level, which suffered from high variability and sparse mortality counts, limiting interpretability.
- Predictive mortality maps revealed spatial patterns that diverge from conventional socioeconomic vulnerability metrics, emphasizing the need for more localized and multidimensional approaches to risk assessment
- 2000-2009 had the highest rates of predicted mortality



Intra-City Analysis

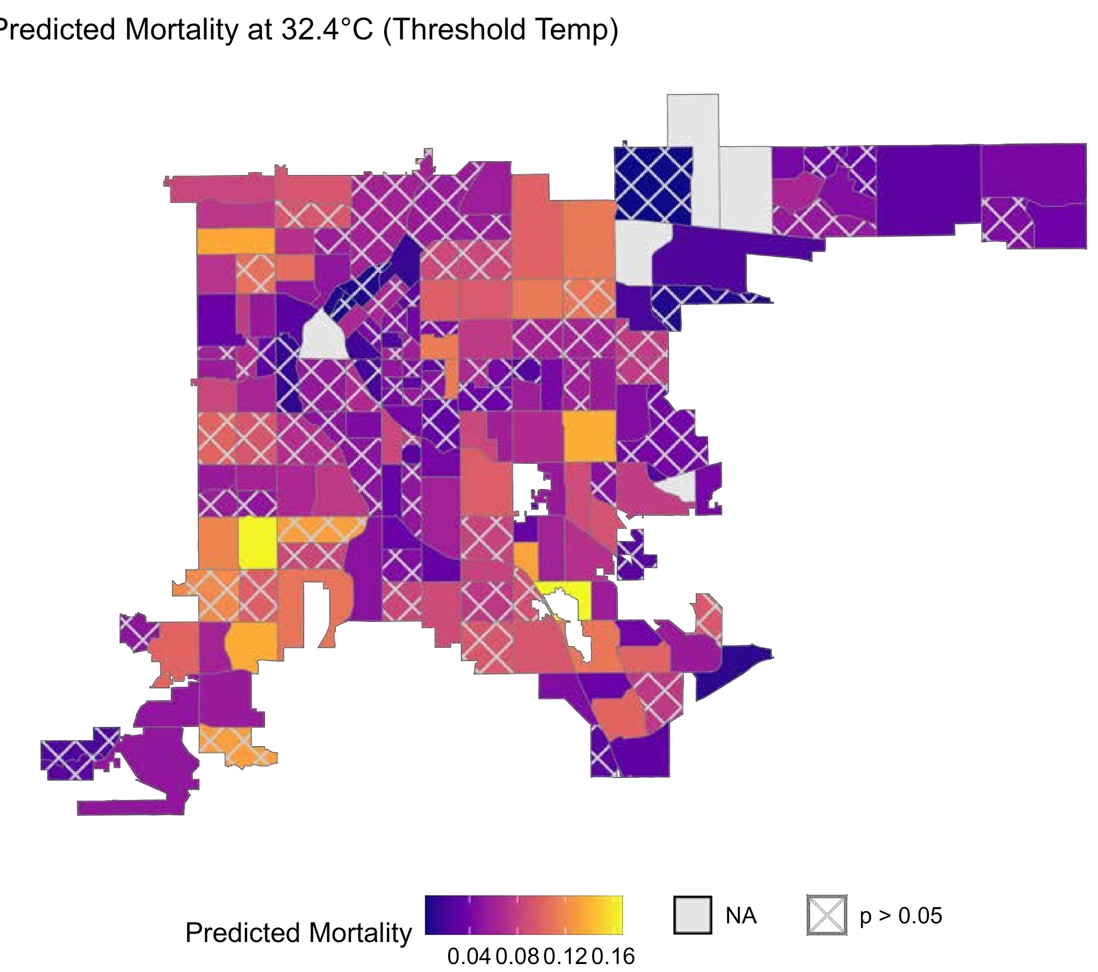


Figure 2: Predicted mortality by census tract at the threshold temperature (32.4° C) for Denver. Hatching indicates tracts with statistically insignificant temperature–mortality associations.

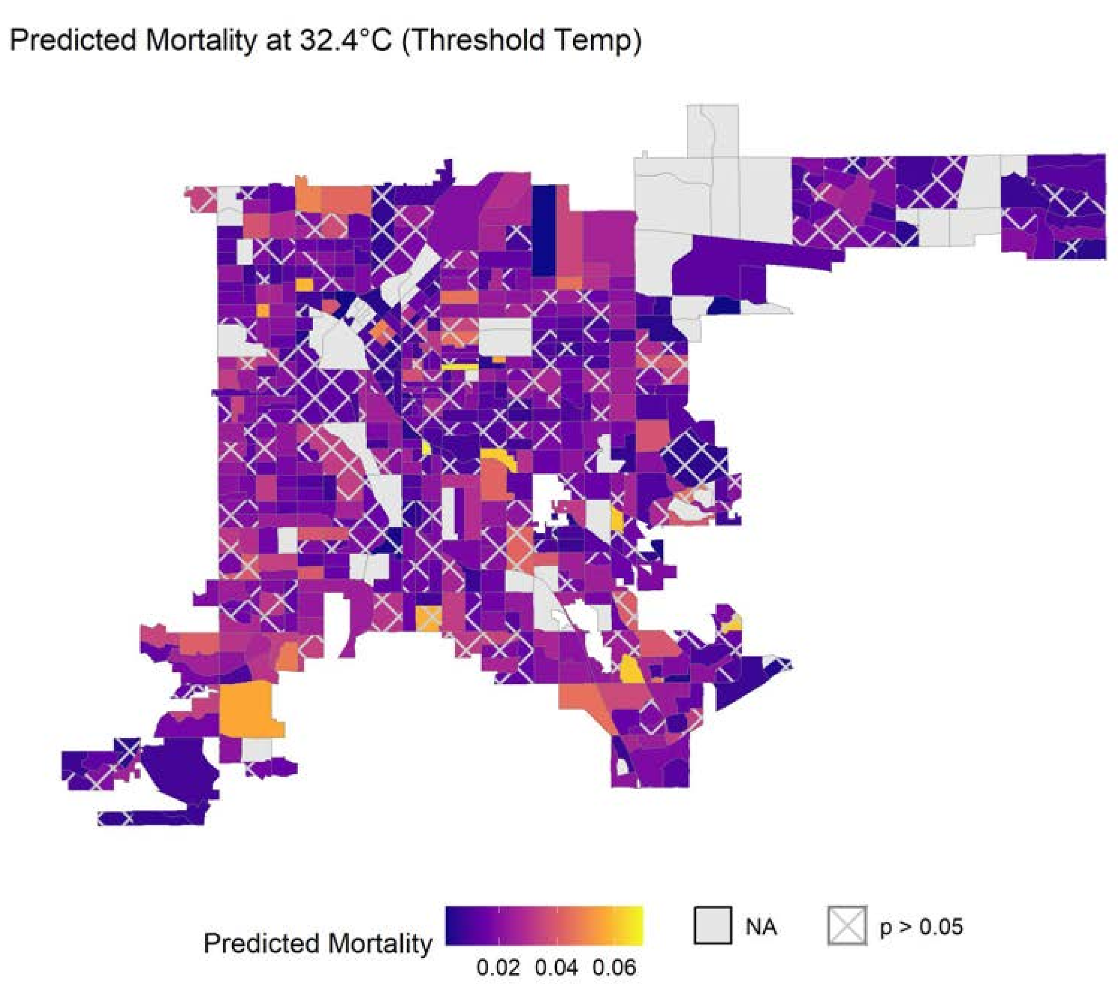


Figure 3: Predicted mortality by census block group at the threshold temperature (32.4° C).

- The finding that multi-day temperature averages outperform single-day lags highlights the importance of accounting for the cumulative effects of heat on mortality.
- The small, but present, heat wave effect further supports the finding.
- We observed no consistent patterns in the shape or slope of the temperature-mortality curves across quartiles. The lack of discernible patterns is notable, though not unexpected, given the complex and heterogeneous nature of heat-related mortality. The absence of consistent differences in curve shape across census tracts or block groups suggests that the relationship between temperature and mortality is not uniformly distributed across the city. This implies that other local factors (population vulnerability, infrastructure) may drive heat-related mortality and highlights the challenges of generalizing temperature–mortality relationships, even among areas with similarly high predicted impacts.
- The higher risk tracts span a variety of social-environmental conditions, including socioeconomic status, tree cover, and age of housing stock. The higher-risk areas do not overlap with low socioeconomic areas within Denver

Census Tract Model Outputs

Model	Pseudo R^2	Deviance Explained	EDF	Percent of Tracts p<0.05	Heatwave p-value
30 year, lag 0	0.02	0.05	1.32	7.60	NA
30 year, lag 0 + HW	0.02	0.05	1.32	7.60	0.83
30 year, Tmax5	0.08	0.10	3.16	55.60	NA
30 year, Tmax5 + HW	0.08	0.10	3.17	56.10	**0.02**
1990s, Tmax5 + HW	0.11	0.15	3.08	57.30	0.11
2000s, Tmax5 + HW	0.09	0.12	2.97	55.00	0.49
2010s, Tmax5 + HW	0.09	0.11	3.06	59.10	**0.04**

Table 1: GAM Outputs for Census Tracts

Decadal Analysis

Temporal analysis yields interesting, and unexpected results. Comparing the predicted mortality outputs between 1990-1999, 2000-2009, and 2010-2019, we identified distinct decadal patterns that are hidden within the 30-year analysis. Most notably, 2000-2009 had the highest predicted mortality. Comparing 1990-1999 to 2000-2009 many tracts, particularly in the southern and eastern parts of the city, experienced substantial increases in heat-related mortality risk, however some tracts experienced decreases. In contrast, the 2000s to 2010s period several tracts experiencing declines in predicted risk, with notable declines in some northern and eastern tracts. The cumulative changes from the 1990s to the 2010s reflect the net effects of both decades, with most areas showing an overall increase, though some northern and central tracts exhibit reductions or minimal change. These spatial disparities underscore the importance of examining heat-related mortality trends at fine spatial scales to identify vulnerable neighborhoods and inform targeted public health interventions.

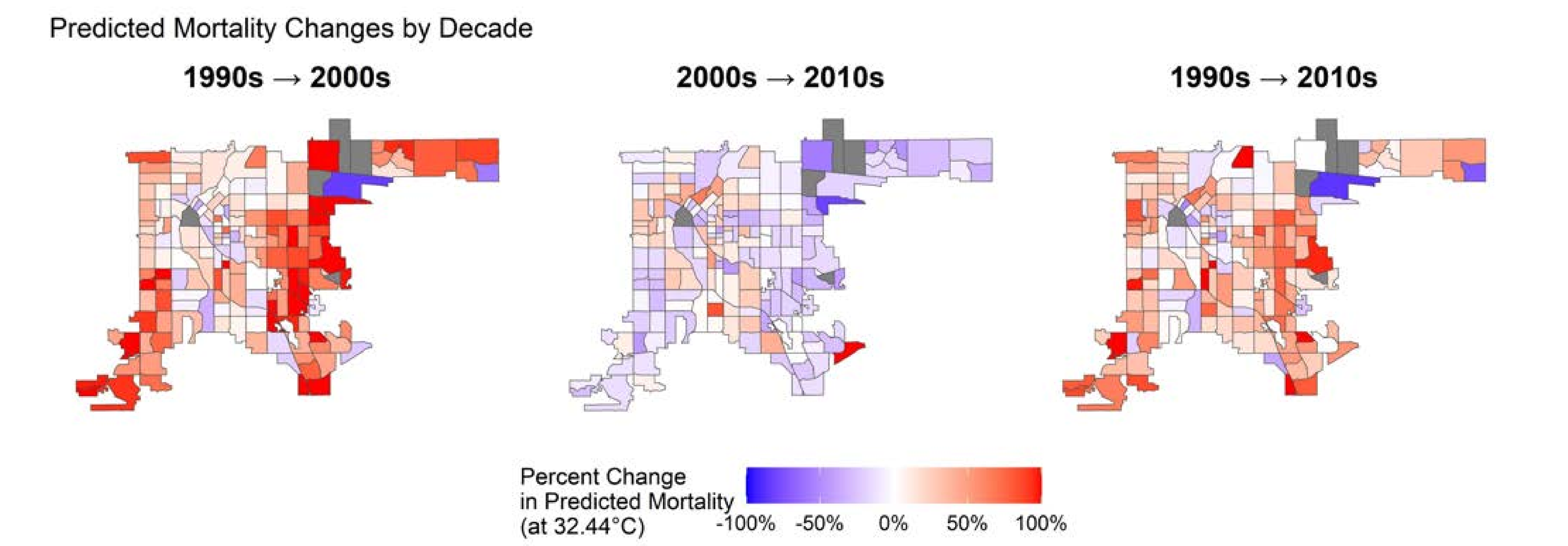


Figure 4: Percent change in predicted heat-related mortality at 32.44° C across census tracts in Denver, Colorado. Percent change was calculated as difference in predicted mortality between the later decade and the earlier decade

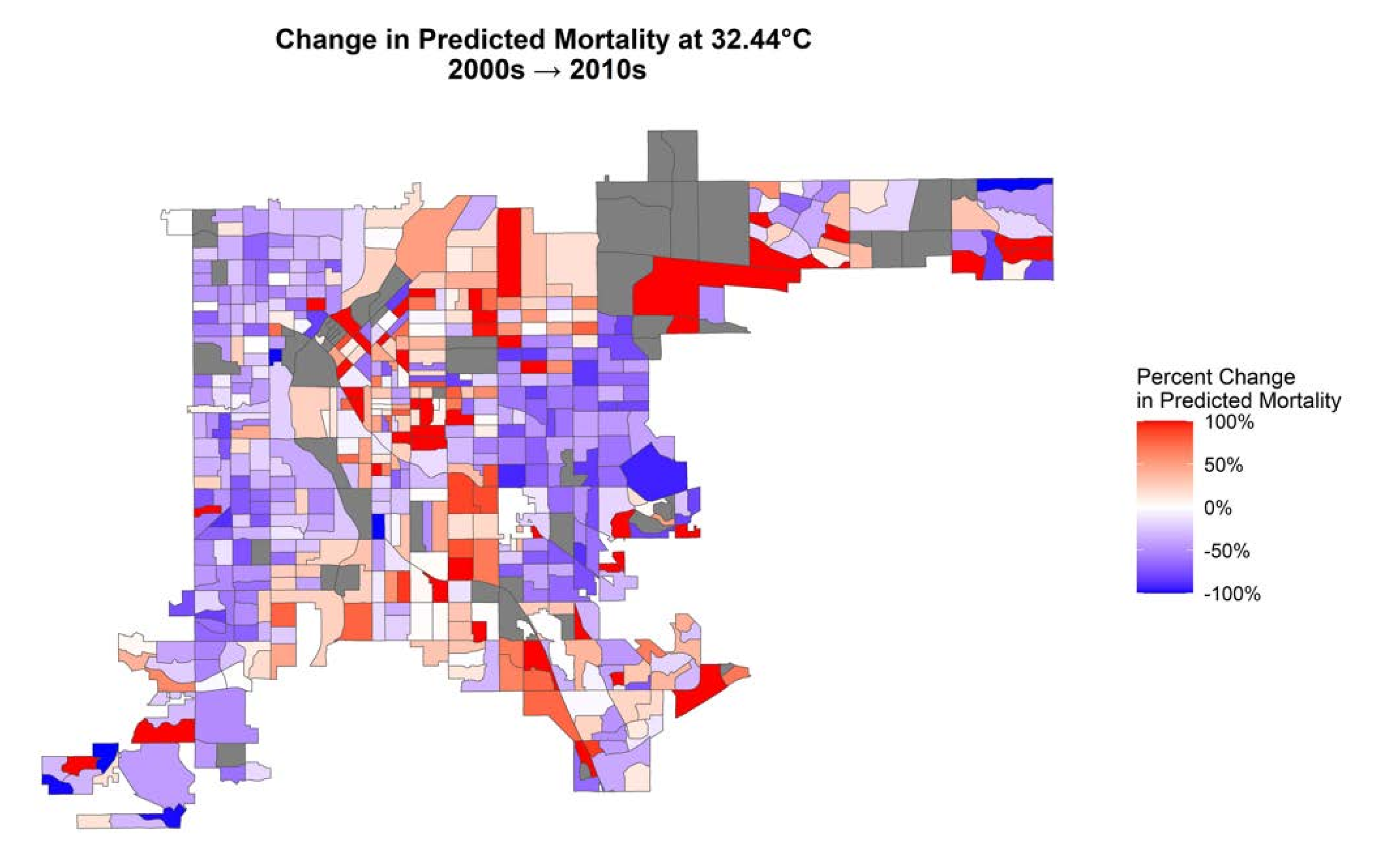


Figure 5: Percent change in predicted heat-related mortality at 32.44° C across census block groups in Denver, Colorado. Percent change was calculated as difference in predicted mortality between the later decade and the earlier decade..

Conclusion

This study underscores the value and complexity of examining heat-related mortality at multiple spatial scales within a single urban environment.

- Citywide analyses produced the expected U-shaped temperature–mortality curve, finer-scale analyses revealed substantial challenges and no discernible patterns.
- At the census block group level, sparse mortality counts and relatively few extreme heat days resulted in wide confidence intervals and obscured clear patterns. These limitations suggest that the CBG scale may be too granular to reliably detect consistent heat–mortality associations.
- Models at the census tract level provided more stable and interpretable results, consistently outperforming those at the CBG scale, suggesting that census tracts may strike a better balance between spatial resolution and data reliability for intra-urban climate-health research.
- Generalized additive models using 5-day rolling averages of temperature and mortality better capture the impacts of heat than single-day lag models. This approach not only revealed spatial heterogeneity in heat risk but also identified a modest yet consistent "heat wave effect" on mortality—evidence that prolonged exposure to high temperatures carries distinct public health risks.
- Predictive mortality maps revealed patterns that diverged from traditional indicators of social vulnerability, highlighting the importance of moving beyond broad socioeconomic proxies. Effective adaptation strategies will require more localized, data-driven approaches that account for neighborhood-level variation in exposure, sensitivity, and adaptive capacity.

From a policy perspective, these findings support the design of hyper-local heat mitigation and public health interventions, such as targeted cooling infrastructure, real-time heat alerts, and neighborhood-specific outreach during extreme heat events. Investing in data systems and modeling capacity at the census tract level could enhance cities' ability to identify emerging risks and deploy resources where they are most needed.

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