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Extreme heat and hospital admissions in older adults

A small-area analysis in the Greater Boston metropolitan area

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Abstract: Extreme heat (EH) is a leading cause of weather-related fatalities in the United States. In Massachusetts, average temperatures have increased by 1.9 °C since the 20th century, higher than the global average increase of 1.1 °C. EH disproportionately impacts communities, exacerbating social inequities. This study examined the risks of heat-related hospitalizations in each small area of the Greater Boston Metropolitan Area using Medicare data (2000–2016). EH events included daily heat index (HI), days with an HI above the 90th percentile, and heat waves (≥2 consecutive EH days). We applied a case-crossover design to estimate area-specific associations between EH and hospitalizations and assessed effect modifications by an individual (age ≥85, sex, Medicaid dual eligibility) and ZIP-code characteristics (green space, poverty, educational attainment, and household income). Results were pooled using random effects meta-analysis. Area-specific analysis revealed higher hospitalization risks in Boston compared with surrounding areas. Pooled results indicated heat-related hospitalizations increased by 9.0% (95% CI = 5.7, 12.3) per 10 °C rise in HI, 14.4% (95% CI = 8.8, 20.3) on EH days, and 17.9% (95% CI = 11.1, 25.1) during heat waves. Risks were more pronounced in Boston, and some indications of elevated risk among males and residents in low-income, low-education areas. These findings underscore that heat-related health risks may be different across the level of geographic units and suggest the need for targeted public health strategies to mitigate the impacts of EH.

Introduction

In recent years, heat-related deaths and illnesses have increased, becoming one of the major public health issues associated with climate change.[1,2] According to the Centers for Disease Control and Prevention, heat-related deaths, one of the deadliest weather-related health outcomes in the United States, about 1220 people are killed by extreme heat (EH) annually.[3] Studies have reported a significant increase in heat-related emergency department visits[4] and hospital admissions[5–7] during periods of increased temperature, which led to approximately $1 billion in added healthcare costs each summer.[8] In addition, a growing body of literature shows that those most vulnerable to EH are the elderly, children, and people with mental health or preexisting chronic diseases.[3] Research has found that exposure to high temperatures can increase the risk of respiratory,[5,9] cardiovascular,[9,10] mental health,[11] and renal[5] cause-specific morbidity or mortality in addition to heat stroke or heat exhaustion.[7,12]

Along with the intensity and duration of EH events, there are multiple risk factors for heat illness, including individual (e.g., age, body mass index, and existing preconditions), social (socioeconomic status, poverty, and racism exposure), and environmental (e.g., neighborhood environment, household condition, and built environment) characteristics. These risk-modifying factors could vary across different climatic or geographical regions, but overall, growing research agrees that socially and environmentally marginalized communities bear a higher burden of heat-related illness from EH, exacerbating existing health disparities.[13–15] While some heat-related illnesses can be anticipated and mitigated through targeted public health

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What this study adds:
This study reveals geographic and demographic differences in heat-related health risks, highlighting the varying vulnerabilities across populations and regions. Using small-area analysis, it uncovers localized trends that broader studies often miss, providing valuable insights into specific areas most affected by extreme heat. These findings underscore the importance of tailored public health strategies to address the unique needs of vulnerable communities and reduce the health impacts of extreme heat.

interventions, significant challenges remain in accurately identifying at-risk populations and implementing timely, effective measures—especially as climate change continues to intensify the frequency and severity of EH events.[16]

Health effects from EH may be particularly acute in urban versus rural areas. For example, in Boston, Massachusetts, USA, the city reported in 2022 that Boston experienced more hot days (days exceeding 90 °F or 32.22 °C) during the last decade (2010–2020) than any decade in the previous 50 years.[17] Compared with less urban areas, cities, including Boston, especially face challenges related to EH due to several factors, including the high concentration of buildings, roads, and concrete surfaces, which creates an urban heat island effect, increasing summer temperatures. Furthermore, the 2022 report by the City of Boston highlighted that the heat island effect in Boston is closely associated with racial health inequity.

Epidemiological studies of EH have been typically conducted at the county[4,6,7,18] or metropolitan statistical area (MSA) level.[19,20] However, MSAs and counties are relatively large geographical units that do not permit assessing heterogeneity in effects among diverse populations with different sociodemographic or socioeconomic characteristics and environmental conditions. Few epidemiologic studies have been conducted at the small-area level to identify localized trends or risk factors in certain communities. The recent article by Hansen et al[21] showed that heat events and hospital admissions vary greatly within large urban areas, highlighting the need for more localized studies. Similarly, Williams et al[22] showed differences in heat-related mortality across census tracts in Boston, and Wellenius et al[23] showed that heat-related health risks can vary in 15 sites near weather stations. These results suggest that it is important for adaptation strategies to consider small-area disparities in EH risk; however, these analyses have been limited by geography or have not fully considered social factors that contribute to heat vulnerability, and a better understanding of which populations are at higher risk would be valuable to inform EH adaptation strategies.

In this article, we used the Medicare Fee-for-service (FFS) inpatient claims data to examine the association between risk of heat index (HI) (apparent temperature that combines temperature and humidity), EH (days on which the HI exceeds the 90th percentile of the HI), and heat waves (EH days lasting more than 2 days) on hospitalization with heat-illness-related diagnosis in older adults. The aim of this study is to examine these associations at a smaller-area level, by focusing on the city of Boston and each city or town within the Greater Boston Metropolitan Area (GBMA), which is known to be a diverse area. We focused on small areas (such as cities, towns, or neighborhoods) rather than zip codes, as these provide more meaningful insights. These geographic units are more relevant to local governance and community identity, making them better suited for understanding public health trends and tailoring strategies. We also investigate potential effect modification of individual- and area-level characteristics. Identifying the vulnerable groups within a smaller area can significantly improve intervention strategies to prevent heat-related illnesses that align with regional characteristics and local demographics.

Methods

Study area and periods

Our study area includes the city of Boston and 38 surrounding cities and towns within the GBMA, Massachusetts. We excluded the towns of Dover, Lincoln, and Nahant due to insufficient hospitalization data (less than 100 cases, defined below, during the study period from 2000 to 2016). The city of Boston consists of 15 neighborhoods with diverse demographics and temperature variations. The average study area size was 40.9 km² (standard deviation [SD] 30.2 km²), with a median of 33.6 km² for areas in GBMA and 16.2 km² (SD 9.6 km²), with a median of 16.4 km² for areas in Boston. Thus, our analysis focused on 53 areas (38 cities and towns, 15 neighborhoods) in and around Boston (Figure 1A). We analyze the

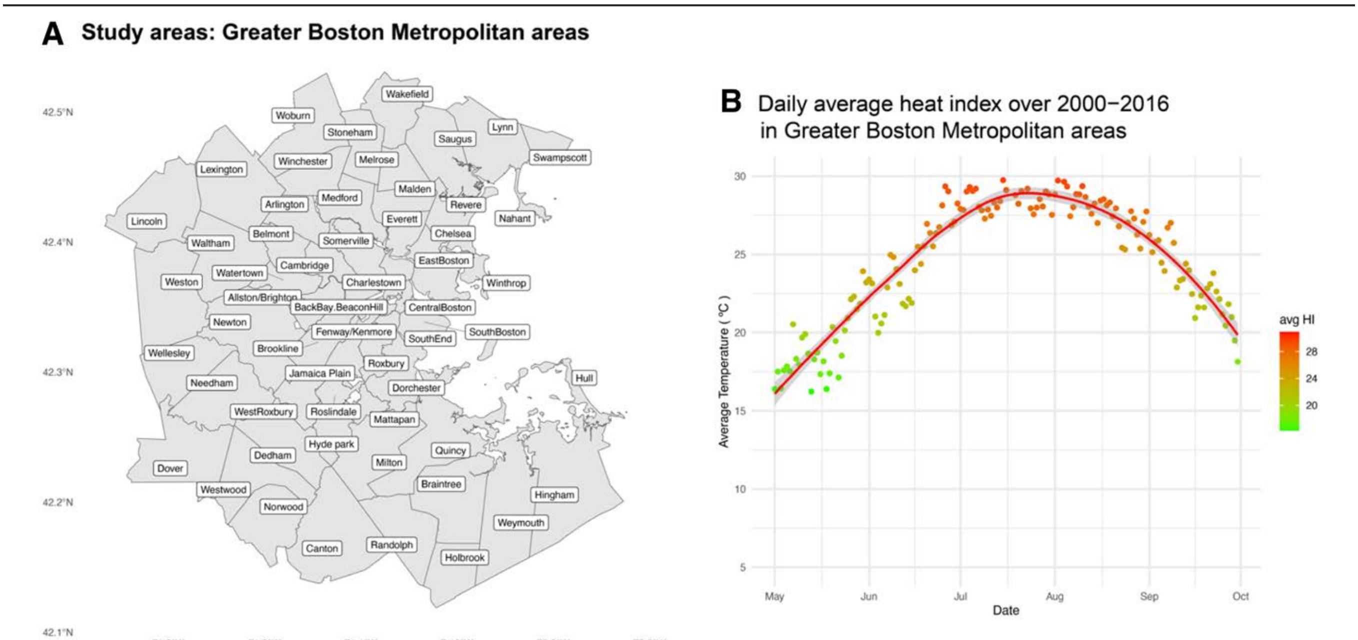

Figure 1. Study area and Daily Average Heat Index in Greater Boston Metropolitan areas, 2010–2016. A, The map shows the study areas within the Greater Boston Metropolitan areas, MA. We included towns and cities surrounded by Boston. Boston is divided into smaller neighborhood areas, each of which is delineated according to the neighborhood boundaries as defined by the city. (Source: https://owd.boston.gov/wp-content/uploads/2015/07/Neighborhood-Boundaries-and-Zip-Codes.pdf). B, The figure represents the daily average heat index from 2000 to 2016 across our study areas. The heat index, calculated using temperature and humidity, is color-coded with green representing lower values and red indicating higher values. The figure highlights that the average daily heat index peaks in July and August.

5-month period between May and September, the hottest season in Massachusetts (Figure 1B).

Health outcome

We extracted the hospitalizations of individuals 65 years and older who enrolled in Medicare FFS and resided within the study area between May 1st and September 31st during the years 2000–2016 from US Centers for Medicare and Medicaid Services MedPAR Part A inpatient billing records and Medicare Beneficiary Summary File with enrollment records. Each claim included information on admission date, primary and secondary diagnosis code, age, sex, dual eligibility for Medicaid, race (non-Hispanic white, non-Hispanic Black, and others), and residential zip code at the time of hospitalization (therefore, zip code was the spatial unit of our analysis).

Hospitalizations with heat-related illness were identified based on the International Classification of Disease, Ninth Revision, Clinical Modification (ICD-9-CM) or Tenth Revision, Clinical Modification (ICD-10-CM) codes on primary and secondary diagnosis codes, including heat-related illness (ICD-9-CM: 992.0-992.9; ICD-10-CM: T67.3-67.5), exposure to excessive natural heat (ICD-9-CM: E900; ICD-10-CM: X30), and dehydration (ICD-9-CM: 276.51; ICD-10-CM: E86.0). We excluded readmission records, retaining only the first hospitalization if multiple hospitalizations occurred within a 30-day period.

Heat exposure assessment

In our study, we used three definitions of heat: HI, EH, and heat waves. The HI represents continuous exposure, while EH and heat waves are treated as binary variables. To calculate the HI for ZIP Code Tabulation Areas (ZCTAs), we used population-weighted daily maximum temperature and average dew point data derived from the 800 m PRISM data (approximately 900 × 700 m at 40N latitude), developed by the climate group at Oregon State University.[24] and gridded population estimates of individuals aged 65 and older using WorldPop population estimates.[25–27] These data were then averaged to ZCTAs and used to calculate the daily HI using the daily maximum temperature and average dew point using the R package *weathermetrics* (v.1.2.2).[28,29] Additionally, we defined extremely hot days as those with a daily HI at or greater than the 90th percentile of HI based on the HI distribution during the entire study period. We also defined a heat wave as those days when extremely hot days lasted 2 or more consecutive days. Heat data were then matched to health outcome data using a ZIP code to ZCTA crosswalk.

Covariates and modifiers

For the effect modifiers, we obtained zip code-level demographic information, including median household income, the percentage of the Black population, the percentage of the population without a high school degree, and the percentage below the poverty level (poverty rate), from the US Census and American Community Survey.[30] As not all years were available from the US. Census data (2000, 2009–2016), temporal interpolation using a moving average algorithm within each zip code was performed for missing years, as described previously.[31]

In addition, we included the spatially weighted summer average of the Normalized Difference Vegetation Index (NDVI) at the zip code level, which is estimated from satellite imagery. NDVI is an indicator of greenness, with a value close to one indicating areas densely covered by live vegetation and values close to zero indicating less vegetation. More detailed information about NDVI estimation can be found in a previous study.[32]

Finally, for use in sensitivity analyses, we utilized the following covariates, the daily mean concentrations of particulate matter less than 2.5 micrometers in diameter ($PM_{2.5}$), NO_2, and 8-hour daily maximum ozone on a high-resolution 1 km^2 grid from previously validated models, as air pollution levels may potentially influence health outcomes. Briefly, pollution exposure data was estimated using an ensemble model intergrading multiple machine learning algorithms with various sources of predictor variables and chemical transport models. Technical details of the exposure prediction models have been previously published.[33–35]

Statistical analysis

To estimate the association between daily HI, EH, and heat waves and hospital admissions with heat-related diagnoses, we follow the two steps: (1) conducted a time-stratified case-crossover design for each small area, and (2) area-specific outcomes were pooled across areas using a random effect meta-analysis. In the first step, to examine the association between heat and hospitalization in each area, we used the case-crossover design, efficient for studying the effects of transient, short-term exposures on the risk of acute events.[36] In this design, cases (hospitalizations) serve as their own controls on days other than the case day, within the same month, year, and day of the week as the case day. Therefore, time-invariant individual characteristics, measurable or unmeasurable, are not confounders.[36,37] In addition, it helps control for seasonal patterns and avoid some subtle selection bias issues, resulting in proper conditional logistic likelihood.[38] For each outcome of interest, we used a conditional logistic regression model with a strata variable for each person. We examined potential nonlinearity in the exposure–response relationship using a natural spline with 3 degrees of freedom as in the previous study (Supplementary Figure 1; https://links.lww.com/EE/A346).[15] The exposure–response relationship is approximately linear, with hospitalization risk increasing as the HI rises. We observed a steeper slope at higher temperatures, particularly above 30°C, which aligns closely with our predefined threshold for EH days (90th percentile of the HI). Therefore, based on existing literature[39–41] and model interpretability, in our main analysis, we assumed a linear relationship between continuous heat exposure and hospitalizations and used EH exposure to capture the effect of extreme temperatures. In the second stage of analysis, the area-specific results were combined using a random effect meta-analysis.[42] We used the restricted maximum likelihood procedure of the meta package in R.[43] From the meta-analysis, we assessed the between-area heterogeneity using the I^2 statistics, which measure the percentage of total variability in effect sizes attributable to heterogeneity.

As exposure to EH might disproportionately and systemically affect marginalized groups; we further assess effect modification by the individual (sex, age above 85, dual eligibility for Medicaid) and area-level characteristics (median household income, % of Black population, % without high school degree, % poverty, and greenness) by adding interaction terms between each heat exposure and each potential effect modifier. For area-level characteristics, we estimated the effects at high and low values using the 75th and 25th percentiles as cut points within each city. We tested each effect modifier one at a time. Although race and/or ethnicity have been identified as effect modifiers for the risk of heat-related illness in our previous studies,[5,13,15,44] we were unable to test for effect modification by race and/or ethnicity because the majority of our data were non-Hispanic white (approximately 90%; Table 1).

As a sensitivity analysis, we included air pollutants ($PM_{2.5}$, NO_2, and ozone levels) in the model. In addition, we then assessed potential effect modification by air pollutants through an interaction term between heat exposure and pollutant levels. We estimated the impacts at high and low pollutant levels, using the 75th and 25th percentiles of pollutant concentrations within each city as cut points, to assess each air pollutant as

Table 1.

Characteristics of Medicare fee-for-service patients 65 years and older hospitalized with heat-related diagnoses, temperature, and area-level characteristics in Boston and areas near Greater Boston Metropolitan Areas in Massachusetts, US, May–September, 2010–2016

	Total[a]	Boston[b]	Areas around Boston[c]
Heat hospitalizations (n)	27,582	5053	22,529
Patient characteristics (%)			
Male	38%	39%	38%
Non-Hispanic Black race	6%	22%	3%
Non-Hispanic White race	90%	68%	95%
Other races	4%	10%	2%
Dual eligible	21%	39%	17%
Age under 85	57%	61%	56%
Daily exposure			
Heat Index (°C), mean (SD)	25 (6.2)	25 (6.2)	25 (6.2)
Extremely hot days	11%	12%	10%
Heat wave 2 days	6%	7%	6%
Daily other pollutants			
Ozone, mean (SD)	40 (11)	38 (12)	41 (11)
NO_2, mean (SD)	20 (9.2)	24 (9.7)	19 (8.8)
$PM_{2.5}$, mean (SD)	9.4 (5.8)	9.8 (6.1)	9.3 (5.7)
Area-level characteristics			
Average greenness, NDVI (0-1), mean (SD)	0.46 (0.13)	0.35 (0.13)	0.49 (0.12)
Average percent of residents (>65) below poverty level (% poverty), mean (SD)	11% (0.070)	20% (0.083)	9.3% (0.049)
Average percent of residents of black race (% Black), mean (SD)	9.5% (0.14)	25% (0.25)	6.1% (0.067)
Average percent of residents (>65) without a high school degree (% No HS), mean (SD)	20% (0.11)	31% (0.11)	17% (0.094)
Average median value of household income ($), mean (SD)	76,000 (28000)	57,000 (19000)	80,000 (28000)

[a]Hospitalizations among Medicare beneficiaries residing in the study area: the Greater Boston Metropolitan Area, Massachusetts.

[b]Hospitalizations among Boston residents only.

[c]Hospitalizations among residents outside of Boston but within the study area.

NDVI indicates Normalized Difference Vegetation Index.

an individual effect modifier. Effect modification analyses by air pollutants were performed on the full dataset instead of limited to the Boston area, given the limited power and sample size in that region.

All the outcomes were reported in percent change in risk. Since hospitalization events were rare, the estimated odds ratios (ORs) were assumed to approximate risk ratios, and the percent change in risk was calculated as (OR – 1) * 100%. No adjustments for multiple testing were applied for the analysis.

Results

Summary statistics

There were 27,827 FFS hospitalizations due to heat illness among Medicare beneficiaries age 65 or older (n = 23,808) residing in the GBMA, who were hospitalized with a heat-related diagnosis during the study period. The majority of our cohort was non-Hispanic White (90% of total hospitalization), female (62%), aged between 65 and 85 years old at study entry (57%), and not eligible for Medicaid (79%) (Table 1). The average HI peaks during July and August (Figure 1). During the study period, the average daily HI was 25 °C, and 6% of days were classified as heat waves lasting at least 2 consecutive days. Daily heat exposure variables were similar across Boston and areas around Boston (Supplementary Figure 2; https://links.lww.com/EE/A346).

We also examined the distribution of the area-level characteristics by Boston neighborhood and surrounding areas in GBMA (Supplement Figures 3 and 4; https://links.lww.com/EE/A346). We found that, compared with surrounding areas, Boston neighborhoods had higher poverty rates, a higher percentage of Black residents, a higher percentage of individuals without high school degrees, and a lower median value of household income. However, variations of area-level characteristics across the GBMA or Boston were small.

Main outcome

We first examined the association between heat exposure and the risk of hospitalization with heat-related diagnosis at the area level. We observed spatial variability in the percent change in risk of hospitalizations due to heat exposures across the small areas (Figure 2). Overall, areas in Boston are likely to have higher increases in risk compared with other areas. In addition, we found that the increase in risk was greater in the southern part of the GBMA compared with the northern areas. When focusing only on areas in Boston, we found the South End neighborhood showed the highest increase in risk of hospitalization due to EH.

We first examined the association between heat exposure and the risk of hospitalization with heat-related diagnosis at the area level. Table 2 presents the combined random effect estimated percentage change in risk of hospitalization associated with each type of heat exposure assessment: (1) continuous HI (°C), (2) binary indicator for EH days, and (3) binary indicator for a heat wave, lasting at least two consecutive EH days. We found that for each 10 °C increase in the HI, there was about a 9.0% (95% confidence interval [CI] = 5.7, 12.3%) increase in the risk of hospitalization with heat-related diagnosis among the study population. When we compared the EH day versus no-heat day, the risk of hospitalization increased by about 14.41% (95% CI = 8.8, 20.3%). The risk increased to 17.9 % (95 CI = 11.1, 25.1%) when comparing the heat wave versus no-heat wave days.

Overall, we found a stronger association between EH and risk of hospitalization in the Boston neighborhood areas compared to when looking at all areas in GBMA (Table 2). With each 10 °C increase in the HI, there was an 18.15% (95% CI = 11.5, 25.2%) increase in the risk of hospitalization with heat-related diagnosis among the study population. The risk of hospitalization increased by 21.5% (95% CI = 10.0, 34.1%) during the EH day compared with the no-heat day and 33.0% (95% CI = 17.4, 50.7%) when comparing the heat wave 2 days versus no-heat wave days.

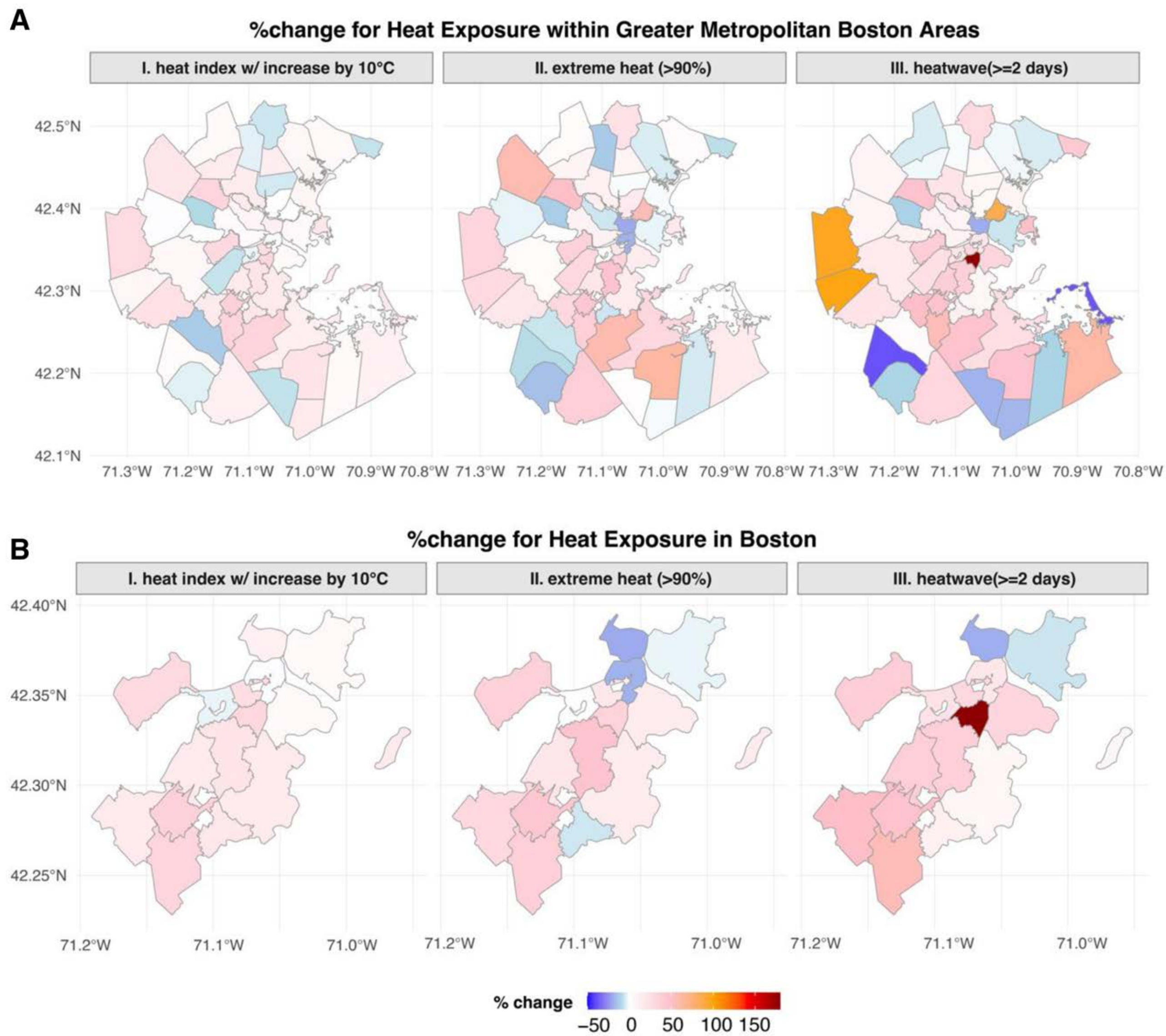

Figure 2. Percent changes in hospitalization with heat-related diagnoses by different heat exposure assessments in each city near Greater Boston Metropolitan Areas, Massachusetts, 2000–2016. Figures represent the percent changes in hospitalizations with heat-related diagnoses by different heat exposure assessments: (I) heat index, (II) extremely hot (EH) days vs. non-EH days, and (III) heatwaves (EH days at least 2 days consecutively) vs. non-heatwaves. A, The results for the areas within Greater Boston Metropolitan Areas (GBMAs). B, The results for the areas in Boston areas.

Table 2.

Percent change in risk of admissions with heat-related diagnoses associated with a 10 °C increase in temperature, and extreme heat and heatwave days during summer months (May–September) in and around Boston areas

	(1) Greater Boston Metropolitan areas		(2) Areas in city of Boston	
	% (95% CI)	I^2	% (95% CI)	I^2
N	27,582		5053	
10 °C increase in Heat index	9.0 (5.7, 12.3)	18.2%	18.2 (11.5, 25.2)	0.0%
Extreme heat day	14.4 (8.8, 20.3)	12.5%	21.5 (10.0, 34.1)	0.0%
Two-day heatwave	17.9 (11.1, 25.1)	0.0%	33.0 (17.4, 50.7)	0.0%

When looking at the heterogeneity (I^2), we found low heterogeneity in areas in GBMA (18–20%). When we only looked at the small areas in Boston, there were no variabilities in the effect of heat.

Effect modification by individual- and area-level characteristics

We found effect modification for median household income (Figure 3A). Individuals residing in areas with lower (<25th percentile) median household income experienced about a 30.3% (95% CI = 15.9, 46.4%) increase in risk of hospitalizations with heat-illness-related diagnosis during an EH day, compared with a 12.98% (95% CI = 6.9%, 19.5%) increase in hospitalization risk in individuals living in areas with higher (>75th percentile) median household income. Similar results were observed for heat waves. We also observed variation in the association by sex, with higher effects among males, and by area-level educational attainment with a stronger association in areas with a higher percentage of the population with less than a high school degree. We observed little evidence of effect modification for the other potential effect modifiers we examined. However, individuals in areas with lower median household income appeared to have a higher risk of hospitalization. While the interaction was not statistically significant,

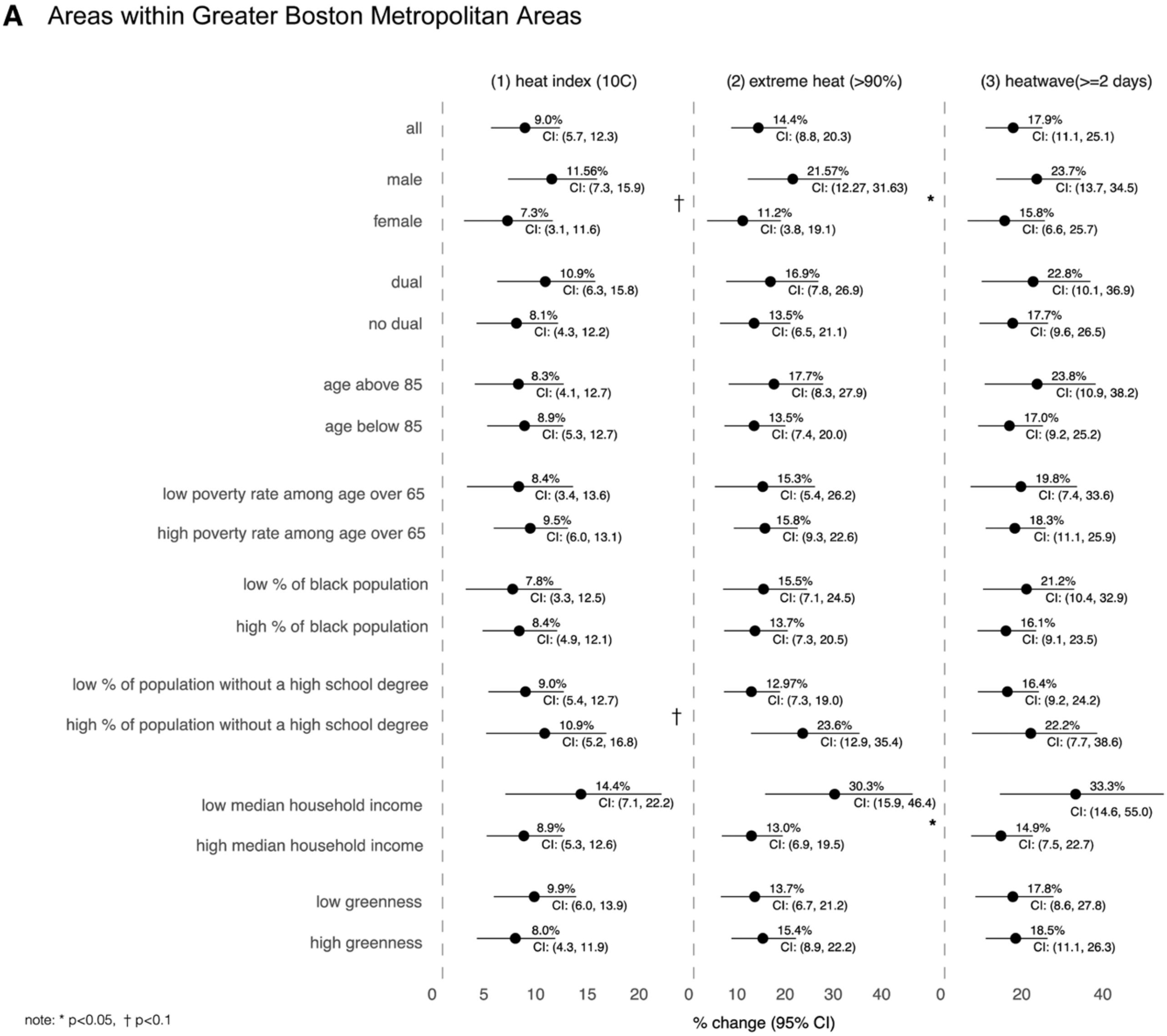

Figure 3. Combined % changes in hospitalization with 95% CIs related to heat-related illness. Percent changes in hospitalization and 95% confidence intervals for heat-related causes among individuals aged 65 years and older for effects of three different extreme heat exposure assessments; (1) heat index increased by 10 °C, (2) extremely hot days (heat index >90th percentile) vs. non-EH days (heat index <90th percentile), and (3) heat wave consecutively 2 days vs. nonheat wave. Individual-level characteristics and area-level characteristics were used for the effect modifier. Area level characteristics 75th percentile (high) or 25th percentile (low) of the characteristic (ZIP-code level) within areas, holding the other characteristics at the study-wide median values. A, Areas within Greater Boston Metropolitan Areas. B, Areas in Boston.

the differences by income level were consistent and notable in magnitude across heat exposure metrics, warranting cautious interpretation.

When the analysis was restricted to Boston neighborhoods only (Figure 3B), we found a difference in the association between heat waves and hospitalization among individuals aged 85 and older compared with those younger than 85. The group aged 85 and older experienced a 62.8% increase in hospitalizations (95% CI = 33.2, 99.0%), while the group under 85 saw a 22.2% increase (95% CI = 4.6, 42.8%) during heat wave days. Interestingly, we did not observe a similar effect modification by age when using continuous HI, suggesting that the increased vulnerability among the oldest adults may be most pronounced during EH events. Unlike the GBMA area, we did not observe a clear pattern of effect modification by the area-level percentage of individuals without a high school degree within Boston neighborhoods.

Sensitivity analysis

Further controlling models by 8-hour ozone, $PM_{2.5}$, and NO_2 did not substantially change the overall results. We also explored potential effect modification analysis by air pollutant levels. Broadly, we observed stronger heat-related hospitalization risks in areas with higher concentrations of $PM_{2.5}$ and ozone when using a continuous HI. Detailed results are provided in Supplementary Section A and Figure 5; https://links.lww.com/EE/A346.

Discussion

This study investigates the effect of HI and EH on hospital admissions with a heat-related diagnosis using the small-area level to better understand its variabilities and localized trends. We focused on the GBMA, which consists of 15 neighborhoods in Boston and 38 neighborhoods surrounding Boston, for a total

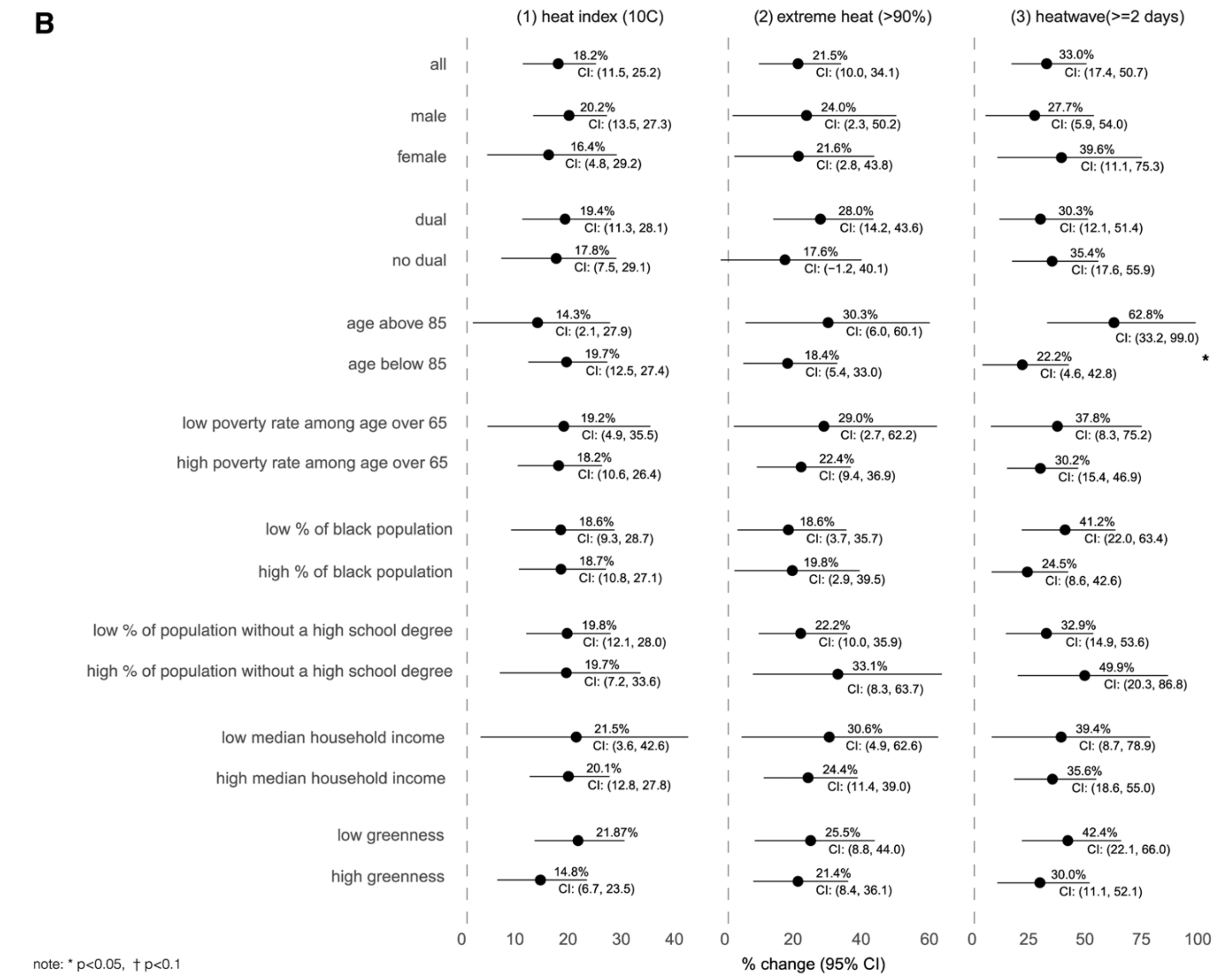

Figure 3. Continued

of 53 smaller neighborhoods. We found that certain neighborhoods in Boston and the southern parts of areas surrounding Boston were likely to have an increased percent change in hospitalization risk among the elderly. Moreover, the pooled effect suggests that the risk was greater in Boston neighborhoods compared with the surrounding areas.

EH is a major global weather concern due to climate change, with the potential for a greater impact on health outcomes. Although limited, there have recently been some studies that used a small-scale geographic level to understand the effects of heat on mortality and morbidity. These studies suggest that the spatial variation in the impact of EH is related to population structure, urbanization, socio-demographics, and geographic characteristics.[21,45,46] Therefore, using a small-area-level approach could help better identify disparities in the health risks posed by EH. Our area-level results provide evidence that the impact of EH varies in its effect on hospitalizations across small areas in the GBMA. Even within the city of Boston, we were able to capture substantial variability. For example, admission due to heat illness increases up to 30% when there is a 10°C increase in HI, up to 50% on EH days compared with non-EH days, and up to 200% during heat waves. This variability indicates that the local factors and vulnerabilities to the EH might be correlated.

Currently, the Massachusetts Emergency Management Agency issues heat advisory when daytime heat indices are 100 °F (37.8 °C)–104 °F (40 °C) for two or more hours. However, our study used the HI thresholds at 30 °C for EH days for all areas and still observed large increases in hospitalization in certain areas, suggesting a lower threshold to issue a heat advisory may benefit those areas. Our findings are consistent with the study by Wellenius et al[23], who also indicate that moderately hot days with a HI below the thresholds for issuing heat advisory were still associated with substantial excess morbidity and mortality.

Our pooled effect of EH on hospitalizations was positive, aligning with previous studies; however, the effect size in our study was smaller. This difference is likely due to the geographic scale used, as county-level analyses often yield relatively larger effect sizes. Isaksen et al[6] found a 242% (rate ratio [RR] = 3.4; 95% CI = 2.3, 5.1) surge in county-level heat-related illness hospitalization among the elderly on EH days compared with a nonheat day. Similarly, Hopp et al[47] also reported a 215% rise in county-level heat stroke-related hospitalizations (RR = 22.5; 95% CI = 14.9, 34.2). Knowlton et al[48] found a more than 10-fold increase in heat-related hospitalization during a heat wave compared with a reference period (RR = 14.2; 95% CI = 9.6, 22.1).[29] In a meta-analysis of 15 studies focusing on the elderly, direct heat illness or dehydration-related morbidity (including office visits, hospitalization, and emergency department visits) increased by 25% (RR = 1.3; 95% CI = 1.2, 1.3).[12] While our results are directionally consistent with these previous studies, our smaller mean effect estimates (13% increase in risk during a heat wave) are likely to reflect our use of a lower threshold to define heat days (90th percentile vs. 99th for most studies[22]) and using granular geographic units of analysis. Here, we improve on these previous studies by showing effects at a lower threshold, which is important for interventions since effects may be much larger in 99th percentile heat days but those are much rarer.

Our effect modification results showed some heterogeneity but suggest that the impact of EH on hospitalizations might be stronger among individuals living in areas with lower median household income and a high percentage of individuals without a high school degree during extremely hot days in the GBMA. While the analysis for extremely hot days showed a stronger association among males in the GBMA, this pattern was not consistently observed across other exposures or in Boston areas. Consistent with other studies, we observed that the effects were stronger for men compared with women.[12,49,50] While it is not yet clear why men are more susceptible to EH, researchers assume that men may engage in more physical exertion outdoors than women, although studies on physical activity levels by gender have yielded mixed results.[51–53] Low socioeconomic status, typically assessed through several factors like income and educational attainment, is closely linked to environmental exposure inequality. As a result, many studies on EH have investigated the impact of socioeconomic status on the association between EH and hospitalizations, but the findings from these studies are inconsistent.[5,12,15,54–56] Lower education attainment, which often relates to income disparities, cognitive deficits, and health literacy, has been linked to an increased risk of mortality or morbidity during EH events in prior studies.[57] However, some studies found no relation or protective effect between education level and heat-related admissions.[15] Our findings also found that individuals residing in economically disadvantaged areas (areas with low median household income and with a higher percentage of the population without a high school degree) are likely to have an elevated risk of hospitalizations with a heat-related diagnosis, which is consistent with previous studies.[50,56] This might be due to a heat island effect, higher exposure to poor environments, and limited access to cooling systems.[7,58]

However, when we examined areas only within Boston, we did not find any effects modified by individual or area-level characteristics. This may be due to the less variation in these characteristics across the areas within Boston (Supplement Figure 3; https://links.lww.com/EE/A346). Moreover, due to limitations in medical records regarding information on education or income, our study, like many other studies, relied on community or neighborhood education levels as proxies. Therefore, further research at the individual level is required. Moreover, unlike previous studies, our study sample mainly consists of a non-Hispanic White population. For example, 90% of heat-related hospitalizations on EH days in the GBMA and 68% of hospitalizations in Boston were made by non-Hispanic Whites. We did not assess whether the observed differences across subgroups reflect true differences in susceptibility to EH or are influenced by other factors such as hospital-seeking behavior, access to care, or differential diagnosis patterns. This limitation applies to all effect modification analyses, as any systematic differences in healthcare utilization or diagnosis by the examined modifiers could bias the interpretation of effect modification.[59] Further research is needed to explore these possibilities. Recent studies also have identified a protective association between green space and heat-related mortality and hospitalizations.[60,61]

In addition, we conducted effect modification analyses to assess whether the relationship between heat and hospitalizations varied by ambient air pollution levels as a sensitivity analysis. These analyses suggest that the risk of heat-related hospitalizations was greater in areas with higher concentrations of $PM_{2.5}$, NO_2, and ozone—with the most consistent results observed for NO_2. These findings suggest a possible synergistic effect between heat and air pollution on health outcomes. However, further studies are needed to fully understand this interaction. Details are presented in Supplementary Section A; https://links.lww.com/EE/A346.

Our study has several strengths. Small area analysis informs that in certain regions, the impact of EH could be substantially greater compared with the pooled effect. Even a city might be too large to adequately analyze the impact of EH and its neighborhood characteristics. Therefore, our results suggest the importance of acquiring more localized data for effective EH prevention strategies. Another advantage of our study is its utilization of temperature variables at a more granular level using the gridded climate dataset compared with previous studies. This refined exposure assessment can capture temperature variations across small areas, helping to distinguish the local climate effect, which may influence heat exposure and vulnerability.

This study has several limitations. Since our study focuses on individuals aged 65 and older due to the use of Medicare data, the impact of EH may only be generalizable to the elderly population. Due to the limited availability of data, we used the mean dew point instead of the minimum dew point, which may lead to a slight overestimation of the maximum HI. Next, due to the small sample size and correlations between effect modifiers (Supplement Table 1; https://links.lww.com/EE/A346), we evaluated one modifier at a time. However, there could be synergies or combined effects between these effect modifiers that might affect the association between EH and health outcomes. In addition, we only have NDVI as a measure of green space which does not differentiate between types of greenspaces and does not reflect how individuals experience the environment, although several studies have shown the protective effect of greenspace using NDVI and several health outcomes. The limitations of the administrative database prevented us from obtaining detailed socioeconomic characteristics of individuals, which might affect their vulnerability to EH. While area-level characteristics can serve as proxies for individuals' SES and are widely used in epidemiology studies, there may still be a gap in accurately capturing the individuals' SES, although previous studies found similar results with and without adjusting for individual-level risk factors.[62] In addition, we were not able to explore whether green space, air conditioning, and lack of access to cooling systems could attenuate the heat-related risks found in the more deprived areas, given that the GBMA is a relatively green area with only a few areas with less than 30% areas with green space. Lastly, the use of small areas resulted in a relatively small sample size for this study, which may introduce uncertainty to the findings and may limit the study's power in smaller population areas.

Conclusions

In the GBMA area, we found an increased risk of hospitalization with heat-illness-related diagnoses due to HI, EH, and heat waves. We observed differences by areas in these associations suggesting that small-area analysis could give better ideas on how to prepare for EH and can help identify the areas that might benefit from a lower threshold to issue a heat advisory. While we observed some heterogeneity in the association between EH and hospitalizations, our effect modification analyses did not identify consistent or clear patterns across subgroups. This inconsistency suggests that commonly used modifiers may not fully capture the complexity of heat vulnerability. Nevertheless, the observed variation highlights the importance of identifying vulnerable populations at the local level, which can enhance intervention strategies to prevent heat-related illnesses. Moreover, these findings can inform area-specific preparedness plans—whether at the city, town, or neighborhood level—to mitigate the health impacts of EH, particularly for the most at-risk populations.

Conflicts of interest statement

The authors declare that they have no conflicts of interest with regard to the content of this report.

References

1. Reese P. Heat-Related Deaths Are Up, and Not Just Because It's Getting Hotter. KFF Health News. 8 September 2023. Available at: https://kff-healthnews.org/news/article/heat-related-deaths-increase-temperature-drug-use/. Accessed 4 April 2024.
2. Climate change and public health: The effects of global warming on the risk of allergies and autoimmune diseases: EMBO reports: Vol 24, No 4. Available at: https://www.embopress.org/doi/abs/10.15252/embr.202356821. Accessed 10 December 2023.
3. CDC. Extreme Heat and Your Health. Extreme Heat. 21 June 2024. Available at: https://www.cdc.gov/extreme-heat/about/index.html. Accessed 8 November 2024.
4. Bobb JF, Obermeyer Z, Wang Y, Dominici F. Cause-specific risk of hospital admission related to extreme heat in older adults. *JAMA*. 2014;312:2659–2667.
5. Gronlund CJ, Zanobetti A, Wellenius GA, Schwartz JD, O'Neill MS. Vulnerability to renal, heat and respiratory hospitalizations during extreme heat among U.S. elderly. *Clim Change*. 2016;136:631–645.
6. Jagai JS, Grossman E, Navon L, Sambanis A, Dorevitch S. Hospitalizations for heat-stress illness varies between rural and urban areas: an analysis of Illinois data, 1987–2014. *Environ Health*. 2017;16:38.
7. Isaksen TB, Yost MG, Hom EK, Ren Y, Lyons H, Fenske RA. Increased hospital admissions associated with extreme-heat exposure in King County, Washington, 1990-2010. *Rev Environ Health*. 2015;30:51–64.
8. The Health Care Costs of Extreme Heat. Center for American Progress. 27 June 2023. Available at: https://www.americanprogress.org/article/the-health-care-costs-of-extreme-heat/. Accessed 12 April 2024.
9. Braga ALF, Zanobetti A, Schwartz J. The effect of weather on respiratory and cardiovascular deaths in 12 U.S. cities. *Environ Health Perspect*. 2002;110:859–863.
10. Alahmad B, Khraishah H, Royé D, et al. Associations between extreme temperatures and cardiovascular cause-specific mortality: results from 27 countries. *Circulation*. 2023;147:35–46.
11. Nori-Sarma A, Sun S, Sun Y, et al. Association between ambient heat and risk of emergency department visits for mental health among US adults, 2010 to 2019. *JAMA Psychiatry*. 2022;79:341–349.
12. Faurie C, Varghese BM, Liu J, Bi P. Association between high temperature and heatwaves with heat-related illnesses: a systematic review and meta-analysis. *Sci Total Environ*. 2022;852:158332.
13. Hsu A, Sheriff G, Chakraborty T, Manya D. Disproportionate exposure to urban heat island intensity across major US cities. *Nat Commun*. 2021;12:2721.
14. EPA. Climate Change and Social Vulnerability in the United States: A Focus on Six Impacts. U.S. Environmental Protection Agency; 2021. Available at: https://www.epa.gov/cira/social-vulnerability-report. Accessed 8 November 2024.
15. Gronlund CJ. Racial and socioeconomic disparities in heat-related health effects and their mechanisms: a review. *Curr Epidemiol Rep*. 2014;1:165–173.
16. Ebi KL, Capon A, Berry P, et al. Hot weather and heat extremes: health risks. *Lancet (London, England)*. 2021;398:698–708.
17. City of Boston. Heat Resilience Solutions for Boston. 2022. Available at: https://www.boston.gov/departments/climate-resilience/heat-resilience-solutions-boston. Accessed 27 September 2024.
18. Weinberger KR, Wu X, Sun S, et al. Heat warnings, mortality, and hospital admissions among older adults in the United States. *Environ Int*. 2021;157:106834.
19. Thomas N, Ebelt ST, Newman AJ, et al. Time-series analysis of daily ambient temperature and emergency department visits in five US cities with a comparison of exposure metrics derived from 1-km meteorology products. *Environ Health*. 2021;20:55.
20. Guo C, Ge E, Yu M, et al. Impact of heat on emergency hospital admissions related to kidney diseases in Texas: uncovering racial disparities. *Sci Total Environ*. 2024;909:168377.
21. Hansen K, Schwartzman A, Schwarz L, Teyton A, Basu R, Benmarhnia T. The spatial distribution of heat related hospitalizations and classification of the most dangerous heat events in California at a small-scale level. *Environ Res*. 2024;261:119667.
22. Williams AA, Allen JG, Catalano PJ, Spengler JD. The role of individual and small-area social and environmental factors on heat vulnerability to mortality within and outside of the home in Boston, MA. *Climate (Basel, Switzerland)*. 2020;8:29.
23. Wellenius GA, Eliot MN, Bush KF, et al. Heat-related morbidity and mortality in New England: evidence for local policy. *Environ Res*. 2017;156:845–853.
24. Daly C, Halbleib M, Smith JI, et al. Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *Int J Climatol*. 2008;28:2031–2064.
25. WorldPop (www.worldpop.org - School of Geography and Environmental Science, University of Southampton; Department of Geography and Geosciences, University of Louisville; Departement de Geographie, Universite de Namur) and Center for International Earth Science Information Network (CIESIN). doi: 10.5258/SOTON/WP00646
26. Nieves JJ, Sorichetta A, Linard C, et al. Annually modelling built-settlements between remotely-sensed observations using relative changes in subnational populations and lights at night. *Comput Environ Urban Syst*. 2020;80:101444.
27. Pezzulo C, Hornby GM, Sorichetta A, et al. Sub-national mapping of population pyramids and dependency ratios in Africa and Asia. *Sci Data*. 2017;4:170089.
28. Anderson GB, Bell ML, Peng RD. Methods to calculate the heat index as an exposure metric in environmental health research. *Environ Health Perspect*. 2013;121:1111–1119.
29. Heat Index Calculation. Available at: https://www.wpc.ncep.noaa.gov/html/heatindex.shtml. Accessed 25 March 2024.
30. Klompmaker JO, Hart JE, James P, et al. Air pollution and cardiovascular disease hospitalization – Are associations modified by greenness, temperature and humidity? *Environ Int*. 2021;156:106715.
31. Di Q, Wang Y, Zanobetti A, et al. Air pollution and mortality in the Medicare population. *N Engl J Med*. 2017;376:2513–2522.
32. Klompmaker JO, Laden F, James P, et al. Long-term exposure to summer specific humidity and cardiovascular disease hospitalizations in the US Medicare population. *Environ Int*. 2023;179:108182.
33. Di Q, Amini H, Shi L, et al. An ensemble-based model of PM2.5 concentration across the contiguous United States with high spatiotemporal resolution. *Environ Int*. 2019;130:104909.
34. Requia WJ, Di Q, Silvern R, et al. An ensemble learning approach for estimating high spatiotemporal resolution of ground-level ozone in the contiguous United States. *Environ Sci Technol*. 2020;54:11037–11047.
35. Di Q, Amini H, Shi L, et al. Assessing NO2 concentration and model uncertainty with high spatiotemporal resolution across the contiguous United States using ensemble model averaging. *Environ Sci Technol*. 2020;54:1372–1384.
36. Maclure M. The case-crossover design: a method for studying transient effects on the risk of acute events. *Am J Epidemiol*. 1991;133:144–153.
37. Mostofsky E, Coull BA, Mittleman MA. Analysis of observational self-matched data to examine acute triggers of outcome events with abrupt onset. *Epidemiology*. 2018;29:804–816.
38. Levy D, Lumley T, Sheppard L, Kaufman J, Checkoway H. Referent selection in case-crossover analyses of acute health effects of air pollution. *Epidemiology*. 2001;12:186–192.
39. Phung D, Thai PK, Guo Y, Morawska L, Rutherford S, Chu C. Ambient temperature and risk of cardiovascular hospitalization: an updated systematic review and meta-analysis. *Sci Total Environ*. 2016;550:1084–1102.
40. Xu R, Zhao Q, Coelho MSZS, et al. The association between heat exposure and hospitalization for undernutrition in Brazil during 2000–2015: a nationwide case-crossover study. *PLoS Med*. 2019;16:e1002950.
41. Basu R, Pearson D, Malig B, Broadwin R, Green R. The effect of high ambient temperature on emergency room visits. *Epidemiology*. 2012;23:813–820.
42. Zanobetti A, Schwartz J. The effect of particulate air pollution on emergency admissions for myocardial infarction: a multicity case-crossover analysis. *Environ Health Perspect*. 2005;113:978–982.
43. Balduzzi S, Rücker G, Schwarzer G. How to perform a meta-analysis with R: a practical tutorial. *Evid Based Ment Health*. 2019;22:153–160.
44. Renteria R, Grineski S, Collins T, Flores A, Trego S. Social disparities in neighborhood heat in the Northeast United States. *Environ Res*. 2022;203:111805.
45. Hattis D, Ogneva-Himmelberger Y, Ratick S. The spatial variability of heat-related mortality in Massachusetts. *Appl Geogr*. 2012;33:45–52.

46. Sheridan SC, Allen MJ. Temporal trends in human vulnerability to excessive heat. *Environ Res Lett*. 2018;13:043001.
47. Hopp S, Dominici F, Bobb JF. Medical diagnoses of heat wave-related hospital admissions in older adults. *Prev Med*. 2018;110:81–85.
48. Knowlton K, Rotkin-Ellman M, King G, et al. The 2006 California Heat Wave: Impacts on Hospitalizations and Emergency Department Visits. *Environ Health Perspect*. 2009;117:61–67.
49. Gifford RM, Todisco T, Stacey M, et al. Risk of heat illness in men and women: a systematic review and meta-analysis. *Environ Res*. 2019;171:24–35.
50. Schmeltz MT, Petkova EP, Gamble JL. Economic burden of hospitalizations for heat-related illnesses in the United States, 2001–2010. *Int J Environ Res Public Health*. 2016;13:894.
51. Amagasa S, Fukushima N, Kikuchi H, Takamiya T, Oka K, Inoue S. Light and sporadic physical activity overlooked by current guidelines makes older women more active than older men. *Int J Behav Nutr Phys Act*. 2017;14:59.
52. Lee YS. Gender differences in physical activity and walking among older adults. *J Women Aging*. 2005;17:55–70.
53. Chen M, Chen S, Wu Y, et al. Are men dominant? Evidence of differences between physical activity and quality of life among older adults in China. *Front Public Health*. 2023;11:1210374. doi: 10.3389/fpubh.2023.1210374.
54. Zhang Y, Nitschke M, Bi P. Risk factors for direct heat-related hospitalization during the 2009 Adelaide heatwave: a case crossover study. *Sci Total Environ*. 2013;442:1–5.
55. Zanobetti A, O'Neill MS, Gronlund CJ, Schwartz JD. Susceptibility to mortality in weather extremes: effect modification by personal and small-area characteristics. *Epidemiology*. 2013;24:809–819.
56. Jung J, Uejio CK, Kintziger KW, et al. Heat illness data strengthens vulnerability maps. *BMC Public Health*. 2021;21:1999.
57. O'Neill MS, Zanobetti A, Schwartz J. Modifiers of the temperature and mortality association in seven US cities. *Am J Epidemiol*. 2003;157:1074–1082.
58. Harlan SL, Brazel AJ, Prashad L, Stefanov WL, Larsen L. Neighborhood microclimates and vulnerability to heat stress. *Soc Sci Med (1982)*. 2006;63:2847–2863.
59. Wan YI, Robbins AJ, Apea VJ, et al. Ethnicity and acute hospital admissions: multi-center analysis of routine hospital data. *eClinicalMedicine*. 2021;39:101077.
60. Choi HM, Lee W, Roye D, et al. Effect modification of greenness on the association between heat and mortality: a multi-city multi-country study. *eBioMedicine*. 2022;84:104251.
61. Heo S, Chen C, Kim H, et al. Temporal changes in associations between high temperature and hospitalizations by greenspace: analysis in the Medicare population in 40 U.S. northeast counties. *Environ Int*. 2021;156:106737.
62. Makar M, Antonelli J, Di Q, Cutler D, Schwartz J, Dominici F. Estimating the causal effect of fine particulate matter levels on death and hospitalization: are levels below the safety standards harmful? *Epidemiology*. 2017;28:627–634.