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Temporal changes in associations between high temperature and hospitalizations by greenspace: analysis in the Medicare population in 40 U.S. northeast counties

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Abstract

Although research indicates health and well-being benefits of greenspace, little is known regarding how greenspace may influence adaptation to health risks from heat, particularly how these risks change over time. Using daily hospitalization rates of Medicare beneficiaries ≥65 years for 2000-2016 in 40 U.S. Northeastern urban counties, we assessed how temperature-related hospitalizations from cardiovascular causes (CVD) and heat stroke (HS) changed over time. We analyzed effect modification of those temporal changes by Enhanced Vegetation Index (EVI), approximating greenspace. We used a two-stage analysis including a generalized additive model and meta-analysis. Results showed that relative risk (RR) (per 1°C increase in lag0-3 temperature) for temperature-HS hospitalization was higher in counties with the lowest quartile EVI (RR=2.7, 95% CI: 2.0, 3.4) compared to counties with the highest quartile EVI (RR=0.40, 95% CI: 0.14, 1.13) in the early part of the study period (2000-2004). RR of HS decreased to 0.88 (95% CI: 0.31, 2.53) in 2013-2016 in counties with the lowest quartile EVI. RR for HS changed over time

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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in counties in the highest quartile EVI, with RRs of 0.4 (95% CI: −0.7, 1.4) in 2000-2004 and 2.4 (95% CI: 1.6, 3.2) in 2013-2016. Findings suggest that adaptation to heat-health associations vary by greenness. Greenspace may help lower risks from heat but such health risks warrant continuous local efforts such as heat-health plans.

Keywords

Adaptation; climate change; greenspace; heat; hospitalization; temperature

1. Introduction

Climate change has increased exposure to extreme heat (Smith et al., 2014), with the last five years as the warmest on record (NOAA, 2020). Global temperature is expected to increase by 1.5 °C between 2030 and 2052 if greenhouse gas (GHG) emissions of the past decade continue (Tong and Ebi, 2019). Under this scenario, extreme heat events are expected to occur in 47 U.S. states and lead to a four- to twenty-fold increase in the population exposed to extreme heat events by the late 21th century (Dahl et al., 2019). Some communities and populations may have little capability to cope with expected record-breaking heat events and thereby will suffer disproportionately.

Climate change poses direct and indirect threats to health, including through impacts of high temperature and heat waves. Heat stroke (HS) is a direct health outcome exacerbated by thermoregulation failure due to exposure to extremely high temperature and it, which can lead to a mortality rate near 80% (Li et al., 2017). Positive associations between heat exposure and increased heat stoke have been reported in several studies (J.F. Bobb et al., 2014; Wang et al., 2016). Excess cardiovascular deaths associated with high temperature are also a major health burden of climate change (Song et al., 2017). In addition to deaths, significant increases in cardiovascular hospitalizations during warm seasons were reported (Phung et al., 2016). While relatively fewer studies focused on hospitalization compared with mortality for cardiovascular diseases (CVDs) (Campbell et al., 2018), evidence for the associations between temperature and cardiovascular hospitalizations has been inconsistent. Several studies of heat-related hospitalizations have shown increased admissions for CVDs in the U.S. (J.F. Bobb et al., 2014; Li et al., 2019; Lin et al., 2009; Schwartz et al., 2004), Europe (Kovats et al., 2004), Asian countries (L. Cui et al., 2019; Son et al., 2014), and Australia (Turner et al., 2012). Some other studies did not observe associations between high temperature and increased risk of hospitalizations for CVDs in the U.S. (Gronlund et al., 2014a) and Europe (Michelozzi et al., 2009; Monteiro et al., 2013; Urban et al., 2014; Wichmann et al., 2011). Examining hospitalization risks from temperature aids our understanding of the burden from heat on the health care system. Further, analyzing heat effects on hospitalizations could provide timely evidence for monitoring of population health (Cheng et al., 2016). Given the inconsistent findings among studies on the effects of high temperature on hospitalization, further research is needed to provide evidence on the temperature-hospitalization associations and what factors may function as effect modifications on those associations. Associations between heat and health appear to change over time (Jennifer F. Bobb et al., 2014). Studies in countries such as France, Italy, South

Korea, and the U.S. reported significant temporal shifts in the heat-mortality association, mostly finding decreasing risk (i.e., adaptation) (Barreca et al., 2016; A. Fouillet et al., 2008; Schifano et al., 2012; Vicedo-Cabrera et al., 2018). Temporal changes in heat's impacts on health can relate to changes in economy, population characteristics, temperature distribution, and behavior (Hondula et al., 2015). Some epidemiological studies suggested that increased prevalence of air conditioning over time contributed to adaptation to heat (Barreca et al., 2016). However, little is known regarding which environmental factors that may explain or contribute to adaptation to heat.

Greenspace is a potential environmental factor that could modify the association between temperature and risk of hospitalizations. Interest in greenspace as a nature-based solution is growing, and many studies noted health benefits of greenspace (e.g., reduced risks of mortality, obesity, mental disorders, adverse birth outcomes) in urban populations (Dadvand et al., 2015; Kim and Kim, 2017; Laurent et al., 2019; Vienneau et al., 2017). Growing evidence indicates benefits of greenspace in relation to air pollution and heat, as well as direct health benefits (Fong et al., 2018). Greenspaces in urban settings can help mitigate heat through tree-shaded spaces (Park et al., 2017).

Normalized difference vegetation index (NDVI) is a primary metric of the amount of vegetation (i.e., greenspace) used in research including studies to examine the benefits of greenspace. Some recent studies used enhanced vegetation index (EVI), an advanced version of NDVI with adjustments for errors over variable atmospheric and ground conditions below vegetation (Matsushita et al., 2007). Studies have suggested that increased greenness measured by NDVI or EVI is negatively associated with land surface temperature, ambient temperature, and urban heat island effect (Y. Cui et al., 2019; Stephen et al., 2014). Decreased temperature-related mortality in regions with higher NDVI or EVI levels have been reported as well (Burkart et al., 2016; Madrigano et al., 2013; Son et al., 2016). However, little is known regarding greenspace's effect on adaption of heat-related hospitalization risks over time (Choi et al., 2012). Scientific evidence is needed on whether urban greenspace impacts temporal trends in how heat impacts health.

We hypothesized that areas with higher levels of greenspace have lower association between high temperature and risk of hospitalizations, and that the influence of greenspace on the heat-health relationship changes over time. We analyzed temporal changes in temperature-related hospitalization risks (CVD and HS), including effect modification by local amount of greenspace, in 40 urban U.S. counties. This study can aid decision makers in planning urban greenspace to address heat-related health risks in the present day and under a changing climate.

2. Materials and Methods

2.1. Data

We focused on 40 urban U.S. counties in the Northeast (Connecticut, Pennsylvania, New Hampshire, New Jersey, New York, and Massachusetts) with populations > 200,000 based on the 2010 Census. Daily county-level rates of hospitalizations for the warm season (June–September) for the years 2000-2016 were obtained for persons ≥ 65 years from billing claims of Medicare enrollees (fee-for-service beneficiaries). We used International Classification of Diseases, Ninth Revision (ICD-9) primary discharge codes: all CVD [390-398, 401-405, 410-414, 415-417, 420-429 and HS [992.0]. Hospitalization counts were stratified by age (65 – 74, ≥75 years) for each county and day.

We obtained 4×4km gridded projections of average daily temperature and dew point temperature from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) AN81D dataset (Daly et al., 2008). We used PRISM data of the next day to match health data of a given day, since PRISM used noon in Coordinated Universal Time of the previous day as the start of a day, corresponding to 8am the previous day in Eastern Standard Time (Weinberger et al., 2019). We calculated county-specific daily averages of meteorological values as the population-weighted average of census tract values (Weinberger et al., 2019).

We included a variable for fine particulate matter ($PM_{2.5}$) as a potential confounder. We utilized daily 1×1km gridded $PM_{2.5}$ concentrations estimated with a hybrid model using convolutional neural network technique to incorporate data from multiple sources and the detailed methods were described elsewhere (Di et al., 2016). We calculated census tract-level daily $PM_{2.5}$ as the average of all grid cells within the census tract and estimated county-level $PM_{2.5}$ using population-weighted averaging. First, we calculated a $PM_{2.5}$ concentration for each census tract as the average of $PM_{2.5}$ among all grid cells within that census tract. A grid cell's pollution level was included if any portion of that grid cell was within the census tract. Next, we calculated $PM_{2.5}$ levels for each county (i.e., the county-specific population-weighted average $PM_{2.5}$) as the weighted average of census tract $PM_{2.5}$ concentrations where the weights were proportional to the population size of the census tract (U.S. 2010 Census). This method gives higher weight to parts of the county with high population and lower weight to those with lower population, thereby creating a "population-weighted" average. We calculated the county-specific population-weighted average $PM_{2.5}$ as the weighted average of census tract $PM_{2.5}$ concentrations within the county with weights equal to census tract population sizes.

We estimated greenspace with EVI, which is calculated as the difference between near-infrared radiation and visible radiation divided by near-infrared radiation plus visible radiation. EVI ranges from −1 to +1 with higher values indicating denser vegetation and −1 indicating waterbody features (NASA, 2018). We excluded negative values indicating water bodies. We obtained a 16-day composite image 250-m resolution EVI data from Moderate Resolution Imaging Spectroradiometer (MODIS) product MOD13Q1. We estimated county-specific EVI using population-weighting (Heo and Bell, 2019). First, the average EVI for every census tract in each county was calculated using the EVI pixel values (without negative values indicating waterbodies) within and surrounding the census tract boundary for January 1, 2000 to December 31, 2016. Then, we calculated the population-weighted average EVI for each county for each time of observation (16-day composite of the MODIS imagery data) through the study period as: $EVI_{i,t}\sum_{1}^{i}\left(EVI_{ci,t} \times POP_c\right)/POP_i$, where $EVI_{i,t}$ is the EVI of county i for time t, $EVI_{ci,t}$ is the EVI value of census tract c of county i at time t, POP_c is the population of census tract c (2010), and POP_i is the population of county i.

We explored seasonal and yearly trends of EVI; EVI showed strong seasonality with higher vegetation in the warm seasons, but annual mean of EVI was constant over the 17 years in all study counties (Supplementary Figure S1). Therefore, we used the average of 16-day composite EVI over the study period to representative local vegetation level of each county.

2.2. Models for temporal variation in temperature-hospitalization associations

A two-stage statistical model (Bell et al., 2012) was used to quantify impacts of short-term exposure to high temperature on hospitalization risk for each county, and then to estimate overall risk across counties. In the first stage, we used a generalized additive model (GAM) with Poisson distribution to estimate associations between lag0-3 days temperature (e.g., lag0 for the same day as hospitalization; lag0-3 for same day and the 3 previous days) and hospitalization for each county. Applying a 4-day lag period is similar to the lag structures used in previous studies (Cheng et al., 2016; Guo et al., 2011b; Wang et al., 2014; Yang et al., 2012) and allows comparisons of research findings. Natural cubic splines were applied for weather variables as they are less sensitive to outliers and more able to capture the true curve (Goldberg et al., 2011). We quantified Relative Risks (RR) of hospitalization as the linear changes in hospitalization per 1°C increase in daily mean temperature above a specified threshold (i.e., 95th percentile) of daily mean temperature in each time period and county. RRs for the entire period (i.e., not accounting for temporal change in association) were calculated by:

$$\ln\left(E\left[\mu_t^c\right]\right) = \beta_0^c + \alpha^c DOW_T + ns(time_t, 2) + ns\left(D_t^c, 3\right) + \alpha_1^c A_t + A_t ns(time_t, 1) + \beta_{PM}^c PM_t^c + pop_t^c + \beta_1^c T1_t^c + \beta_2^c T2_t^c$$

where $E[\mu_t^c]$ = expected cause-specific hospitalization count for county c on day t; β_0^c = model intercept; α^c= vector of regression coefficients for day-of-the-week for county c; DOW_t = categorical variable for day-of-the-week on day t; $ns(time_t, 2)$ = natural cubic spline of time with degrees of freedom (df) (3 df/season for CVD, 2 df/season for HS); $ns\left(D_t^c, 3\right)$ = natural cubic spline of dew point temperature for county c on day t with df=3; A_t = indicator for those ≥75 years; $A_t ns(time, 1)$ = natural cubic spline of time with df=1 for those ≥75 years; PM_t^c = $PM_{2.5}$ = $PM_{2.5}$ in county c on day t; pop_t^c = offset term of the number of total beneficiaries of Medicare in county c on day t; $T1_t^c$ = continuous variable of daily mean temperature of county c for day t and lag0-3 when daily mean temperature < county-specific threshold^c, and 0 otherwise; and $T2_t^c$ = continuous variable of daily mean temperature of county c on day t and lag0-3 when daily mean temperature > county-specific threshold^c, and 0 otherwise. Associations between heat and hospitalization were estimated by β_2 (equation 1). County-specific thresholds were set to the 95th percentile of daily mean temperature for that county.

Next, we assessed temporal changes in RRs by year and in separate time periods for each county. For yearly changes in RRs, we applied an interaction term between temperature $\left(T2_t^c\right)$ and an indicator term of each year. Separately, we estimated temporal changes in RRs by generating a separate estimate by time periods using stratified GAMs for 4 separate periods (2000-2004, 2005-2008, 2009-2012, and 2013-2016). The use of two approaches (interaction term and stratification by 4-year periods) allows us examine robustness of effects and presenting findings in multiple ways, thereby aiding comparison to other studies.

We combined county-specific estimated RR for each of time period using random-effects meta-analysis with restricted maximum likelihood (REML) estimation method as:

$$R_c = \mu + u_c + e_c, u_c \sim N\left(0, \tau^2\right), e_c \sim N(0, V_c)$$

where R_c = log RR in county c, μ = log of the average true temperature-hospitalization association, u_c = variability in the parameter from county c around its mean (μ), e_c = sampling error for county c, T^2 = residual heterogeneity among true estimates across all counties, and V_c = sampling variance-covariance matrix.

2.3. Effect modification by greenspace

We estimated whether the temporal pattern in associations between temperature and hospital admissions differs by level of greenspace. Using equation 2, we pooled county-specific RRs separately by EVI quantile: first quartile (Q1) (counties with EVI <0.23); Q2 (0.23 ≤ EVI <0.27); Q3 (0.27 ≤ EVI <0.3); Q4 (EVI ≤0.3). Statistical software package R 3.4.0 and R ‘mgcv’, ‘splines’, and ‘metafor’ packages were used.

2.4. Sensitivity analysis

We conducted several sensitivity analyses. First, we used a different metric of greenspace instead of EVI to test the robustness of how greenspace may modify risk estimates of hospitalizations associated with high temperature. We used population-weighted percent tree canopy cover for each county using the 30-m resolution 2016 Tree Canopy Cover Dataset from the U.S. Forest Service (USFS) in assessing effect modification by greenspace. Second, we conducted analysis using different df for in the models to adjust for seasonal and long-term trends. While the main analysis used 2 df/season for HS and 3 df/season for CVD, sensitivity analysis applied 3, 4, and 5 df/season. Third, we controlled for daily mean ozone concentration (ppm) in the models for CVD hospitalizations in addition to the adjustment of $PM_{2.5.}$ Fourth, we considered different percentile distributions for the comparison of temperatures to estimate risks. Whereas the main analysis presents results for a 1°C increase in temperature above the 95th percentile, we also calculated RR comparing the relative risk daily hospitalization at the 99th percentile of the daily mean temperature distribution for the study period to the 90 th percentile in each county. As different studies use a range of approaches to present numerical estimates from the non-linear temperature-health association, the sensitivity analysis comparing risk at the 99th to 90th percentile of temperature aids comparison of findings to other work.

3. Results

3.1. Descriptive statistics

Table 1 provides descriptive statistics of temperature, EVI, and cause-specific hospitalizations. Over the 17 years, EVI level was relatively constant.

Temperature distributions of study counties grouped by county-level EVI for 2000-2007 and 2008-2016 are shown in Supplementary Figure S2. The Q4 group showed the lowest temperature ranges (mean of 21.1°C in 2000-2016), meaning that on average the areas with the highest greenness has the lowest temperatures.

The sum across the 40 counties for hospitalizations from HS and CVD and daily mean temperature for each month and date for the study period (2000-2016) are shown in Figure 1. HS hospitalizations were higher on days with higher daily mean temperature. Relatively fewer CVD hospitaliztions were observed on July 4, which is a public holiday.

3.2. Temporal changes in temperature-hospitalization relationships

High temperature was positively associated with HS but showed no associations with CVD. RRs for a 1 °C increase in lag0-3 daily temperature for the entire period (2000-2016) were 1.000 (95% CI: 0.998, 1.001) for CVD and 2.285 (95% CI: 2.143, 2.428) for HS. Estimates of RRs by year for CVD and HS did not consistently show consistent values of risk of CVD or HS hospitalization from high temperature across the years of the study period (Figure 2).

We also estimated how these risks change over time by dividing the study period into four 4-year periods. The RRs for 1 °C increase in lag0-3 daily temperature for the 4 separate periods indicated a consistently decreasing pattern for risk of HS over time (e.g., 2.019 in 2000-2004 to 1.212 in 2013-2016) (Table 2). The temporal change in the CVD risks was not significant despite a slight decrease in the RRs over time.

3.3. Effect modification by greenness

Pooled risks of hospitalization for 4 separate periods (2000-2004, 2005-2008, 2009-2012, 2013-2016) and EVI categories showed that log RRs of high temperature and HS tended to decrease over time in counties with the lowest EVI (Q1) and increased in counties with the highest EVI (Q4) (Figure 3, Supplementary Table S1). The RRs in 2013-2016 were significantly lower than the RR in 2000-2004 (ratio of RRs = 0.614, p-value = 0.080) at a significance level of 0.1. The RR (0.397, 95% CI: 0.139, 1.134) was lowest in the highest EVI group (Q4) at earlier time period (i.e., 2000-2004); the lowest EVI group (Q1) showed the highest risk for the same period (2.707, 95% CI: 1.367, 5.362). For the estimated association between high temperature and CVD, the central estimates tended to increase slightly over time in the Q4 EVI quantile group in 2005-2008 but RRs were lower than 1 in later time periods.

The sensitivity analysis using tree canopy cover instead of EVI showed similar results for HS: an increasing pattern in Q1 group and a decreasing pattern in Q4 group (Supplementary Figure S3). The correlation between EVI and tree canopy cover was 0.8. The sensitivity analysis using different df for the temporal trend of hospitalizations showed robust results for the RRs of CVD and HS hospitalizations (Supplementary Figure S4, Table S2). Controlling for daily mean ozone concentration did not meaningfully change RRs of CVD hospitalizations (Supplementary Table S3). Lastly, we estimated the RR of hospitalization at the 99th percentile of daily mean temperature distribution compared to the 90th percentile for each county (Supplementary Table S4). RRs for CVD showed negative associations between high temperature and CVD hospitalizations across the 4 separate study time periods and the

EVI quantiles. The temporal changes in the temperature-hospitalization associations for HS over time in the EVI groups were robust: high temperature-related HS risks in the early time period (2000-2004) in the lowest EVI group (Q1) and high temperature-related HS risks in later period (2013-2016) in the highest EVI group (Q4).

4. Discussion

The health effects of heat appear to change over time, potentially due to changing temperature range, characteristics of heat waves (e.g., duration), and physical acclimatization to heat (Jennifer F. Bobb et al., 2014). Temporal changes in heat-hospitalization relationships imply the importance of a long study period to investigate adaptation. Greenspace may contribute to reduced temperature and improved general health and well-being on a long-term basis, which could contribute to changes in health risks of temperature over time. In this study, we found that the temporal patterns of the association between high temperature and HS hospitalizations may be partially attributable to county-specific greenness, as measured by EVI. In general, results suggest a decline in temperature-hospitalization associations over time for counties with lower EVI. During 2005-2016, counties with high greenness (in the highest quartile of EVI) showed a slightly increasing pattern for risks, although the results are not significantly different. The mechanisms through which greenspace modifies temperature-health associations and contributes to changes over time for these risks is unclear, although several plausible pathways have been proposed. One potential reason for higher risks during earlier periods could be that the areas with lower greenness might have higher exposure to heat and causing higher heat-related hospitalization risks, followed by the population adapting to heat over time, resulting in lower associations in recent years. Higher temperature in areas with less greenspace could be related to urban characteristics such larger impervious areas, high population density, and high energy consumption. Further, interventions to reduce short-term heat exposure and resulting health impacts also may have played a role (Jennifer F. Bobb et al., 2014). The impacts of high risk of HS hospitalization from high temperature might have led to implementation of preventive measures in some areas that meaningfully lowered those risks over time. A survey conducted in 2007-2008 for 285 U.S. communities found that various local health preventive actions implemented across the U.S. included broadcasting heat exposure symptoms and health guidelines, operating information phone lines, designating public cooling shelters, extending operation hours of community centers with air conditioning, increasing outreach efforts to vulnerable populations such as the elderly and the homeless, paving with cool materials, and installing vegetated roofs (i.e., green roofs) (O’Neill et al., 2010). Preventive measures including cooling centers and heat wave alert systems were implemented in some of our study counties (Supplementary Table S5). Further research is required to verify the direct effectiveness of these local preventive actions for diminishing the impacts of high temperature on adverse health impacts such as hospitalizations, including how the effectiveness of such policies vary by greenspace. We also note that counties with the highest temperatures, which are also the counties with overall low EVI in this study, would be vulnerable to more frequent record-breaking extreme heat events in the future under climate change (Perkins, 2015), which would lead to higher risks of heat-related health outcomes. As overall temperatures increase and heat waves become more frequent, intense, and longer in duration under climate change, populations may experience increased risks despite acclimatization. Further research is needed to better understand the various pathways through which greenness modifies the heat-health relationship and how greenness contributes to changes in this association over time, as well as the complex systems of temperature, greenness, and health under a changing climate.

On the other hand, the risk of HS hospitalization associated with high temperature did not decrease in the counties with higher greenness as measured by EVI. This may be associated with potential changes in demographics and environment in these regions over time. While we only focused on urban regions, counties with higher EVI can be considered as suburban areas in comparison with urban counties with lower EVI. Urbanization and land-use changes (e.g., increased impervious area) (Zhang et al., 2013) in recent decades in suburban areas may result in increases in population and congestion in greenspace (e.g., high population per park area if the population size grow and less greenspace is available). These changes in environment and population combined with the increased ambient temperature (e.g., urban heat island) (Zhang et al., 2013) might hinder the benefits of adaptation to heat-hospitalization associations in populations in these areas. Adaptation to heat-health associations over time may be another contributor for the absence of decreasing patterns for the HS hospitalization risks associated with high temperature. To the best of our knowledge, these potential factors have not been fully examined to date, so they should be further examined to better understand the reasons for the absence of adaptation to heat-hospitalization associations over time in regions with high levels of greenspace.

We found that both higher measures of greenness considered (EVI and percent tree canopy cover) tended to have decreasing associations between temperature and HS hospitalization over time (Figure 3, Supplementary Figure S3). EVI considers healthiness of vegetation such as trees, shrub, and grass but the tree canopy cover merely considers leaves, branches, and stems of woody plants. While short vegetation such as grass and shrubs can effectively cool surface temperature as do tress in urban areas (Armson et al., 2012), short vegetation does not provide much shade. Thus, health benefits through cooled ambient temperature and reduced heat exposure may be more comprehensively captured by EVI, but pathways of reducing hospitalization effects of high temperature could vary by type of greenspace and thereby the metric used to estimate greenspace. Nonetheless, both EVI and tree canopy cover showed a potential role of greenspace for adaptation to heat-related hospitalization risks. Further research is needed to differentiate the influence of different forms of greenspace, including various types of vegetation.

Changes over time for heat-related health impacts may relate to various other factors that have changed over time. Impacts from heat may be modified by air conditioning (Barreca et al., 2016; Jennifer F. Bobb et al., 2014), and interventions such as early warning systems. Changes in demographics, land use, built environment, and behavior may also lead to spatiotemporal differences in the health effects of high temperature, which are also related to latitude and temperature range. To maximize the health benefits of greenspace for reducing impacts of high temperature on hospitalization in the future, greenspace efforts should be combined with thoughtful urban planning approaches that consider the range of benefits from urban green space. Further, to better understand the benefits of greenspace in relation to impacts of heat, epidemiological studies should develop and apply methods to examine exposure to various features of urban greenspace instead of overall vegetation levels for a given city (e.g., green building, green roof, shelter systems, water architecture, roadside trees).

Research findings for the temperature-hospitalization associations for CVD have been less conclusive than for some other health endpoints (Dang et al., 2019; Iñiguez et al., 2021). According to a systematic review (Phung et al., 2016), negative associations between heat and CVD hospital admissions were reported by some studies in Copenhagen, Denmark (Wichmann et al., 2011); Chiang Mai, Thailand (Pudpong and Hajat, 2011); and some urban regions in the U.S. (Green et al., 2010; Gronlund et al., 2014b), although the overall association was positive. On the other hand, significant temperature-hospitalization associations were found in studies conducted in several cities in the United States (Gronlund et al., 2014a; Koken et al., 2003; Lin et al., 2009; Schwartz et al., 2004). While the CVD hospitalization effects of ambient temperature have been less consistent among studies, studies have consistently found positive associations between heat waves (i.e., prolonged heat exposure) and CVD hospitalization (Phung et al., 2016) indicating the cardiovascular effects of heat. Further, studies of the present day consistently identified the Northeast U.S. as having the highest heat-related mortality and hospital admissions (Curriero et al., 2002; Wang et al., 2016). In our study, higher temperature was associated with lower risk of cardiovascular hospitalizations. As CVDs are the main cause of heat-related mortality (Linares and Díaz, 2007), the relationship between higher temperature and lower cardiovascular hospitalizations could relate to high temperature causing people with cardiovascular diseases to die before reaching hospitals (e.g., out-of-hospital cardiovascular deaths) (Pudpong and Hajat, 2011). Given the contrasting pattern of temperature between mortality and hospitalization among different populations and geographical regions, further investigations of temperature's effects on hospitalizations are needed to better understand the mechanisms by which temperature triggers fatal or non-fatal health outcomes including for various vulnerable populations.

We examined the changes in heat-hospitalization relationships using two approaches (by each year and by 4-year time periods). Various approaches can be applied to examine temporal changes in temperature-health relationships. Several studies compared 2 or more time periods with the equivalent number of years (Barreca et al., 2016; Heo et al., 2016; Kim et al., 2019; Schifano et al., 2012), while some other studies examined how risk changes by each year (Guo et al., 2012). Studies also compared the health effects among different specific heat wave episodes to examine adaptation (A Fouillet et al., 2008; Kyselý and Plavcová, 2012). A variety of modeling decisions and parameter settings are needed to examine changes in the exposure-response relationships. Several studies applied a constant linear relationship above a fixed temperature threshold, often selecting the minimum mortality temperature or minimum risk temperature, forcing a V-shaped relationship curve (Guo et al., 2011a). Others applied nonlinear relationships using smooth curves for the exposure-response relationships and quantified effects of temperature changes by comparing the risk at certain percentiles (e.g., 99^{th} vs. 90^{th} percentile) of the city's temperature range (Anderson and Bell, 2009). To ensure the comparability of the models and results, we focused on U.S. urban counties in the northeast area that would likely have similar climate as in some previous studies performed in the U.S. (O'Neill et al., 2003). To ease interpretation, we used relative thresholds and V-shaped relationship functions using two temperature variables. However, a V-shaped relationship function may not fully capture the relationship for regions that show no minimum risk temperature (Anderson and Bell, 2009). We also estimated effects by comparing risks at the 99th and 90th percentiles of the county's daily mean temperature distribution. The results of RRs of hospitalizations of CVD and HS from this analysis were robust compared with our main analysis.

Further, a lag structure can be modeled with short lags (e.g., lag0-3) or a longer lag (e.g., lag0-21) (Yang et al., 2012). We chose a 4-day lag period (i.e., lag0–3) as the main exposure variable in our model. Sensitivity analysis applying a 21-day lag period for CVD hospitalization showed similar results with the main analysis. Long lag periods were not applied to HS hospitalization since prior studies suggested that the impact of short-term exposure to high temperature was acute and lasted for a short period of lag days (e.g., 3-5 days) (Cheng et al., 2016; Guo et al., 2011b; Wang et al., 2014; Yang et al., 2012). Results from the sensitivity analysis using different degrees of freedom for time to control for long-term and seasonal changes in CVD hospitalizations showed that the RRs for CVD hospitalization associated with a 1°C increase in lag0-3 temperature above the county-specific threshold temperature (95th percentile) did not differ based on different degrees of freedoms. In addition to the exposure-response relationships between temperature and health, lag structure and threshold temperature may also change over time (Heo et al., 2016). Future studies could investigate model to fit functions for the temporal changes in all these aspects, but the model fitting would become complicated with excessive parameters and difficult interpretation. We focused on the changes in the temperature-hospitalization associations over time assuming consistent lag structure over time.

This study has a few limitations. Temperature cooling effect may differ by vegetation types (e.g., tree, grass, shrub, etc.) (Park et al., 2017) and future analysis should consider the variance of vegetation composition among the study regions. We could not consider potential effect modifiers such as air conditioning prevalence due to lack of available data for our study counties. Effect modification by socioeconomic status or changes in other population characteristics warrant investigation. Our geographical coverage focused on the northeast area of the U.S. and is not globally representative, particularly for areas in developing countries or regions with different species of vegetation (e.g., tropical forest). Future studies with more or different geographic regions are required to assess the benefits of greenspace for adaption to heat-related risks for a range of locations.

There are several strengths of this study. We applied a long study period of 17 years, while most previous studies applied study periods of 5 years or less (Phung et al., 2016; Ye et al., 2012). We examined effect modification by greenspace using different greenness metrics (i.e., EVI and tree canopy cover) although we did not consider the changes in tree canopy cover over time. We used high-resolution modeled temperature data, and a population weighing method was applied in calculating county-specific representative meteorological values.

5. Conclusions

We investigated how the association between temperature and risk of hospitalization changes in the U.S. Medicare population over time and whether these temporal trends are modified by amount of greenspace. We estimated statistically significant positive risks of HS hospitalization from heat in 2000-2016. The risks of HS hospitalization from temperature tended to decrease over time in counties with the lowest EVI levels, while the risks increased in counties with the highest EVI levels. The increased risks of temperature-related HS hospitalizations over time in counties with the highest EVI levels implied a potential increasing relationship between heat exposure and hospitalization. This may relate to a variety of factors such as a non-linear relationship between temperature and health in combination with the increased temperature and less efforts in these regions to adapt to high temperature. Even though decreased risks of temperature-related HS hospitalization in recent years (2013-2016) were found in the counties with the lowest EVI, it is assumed that high temperature would continue to contribute to a heat-related health burden under climate change. Findings imply the importance of combining greenspace-based adaptation plans and local heat-health plans. Continuous investigation of the long-term temporal changes in the heat-related hospitalization risks are needed to monitor population's ability to cope with the health burdens from high temperature and climate change.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Data statement

The research data is confidential.

Abbreviation

CI	Confidence interval
CVD	Cardiovascular disease
EVI	Enhanced vegetation index
HS	Heat stroke

NDVI	Normalized difference vegetation index
RR	Relative risk

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Highlights

- Trends in heat-hospitalization associations over time were compared by greenness.
- Hospitalizations from heat stroke and cardiovascular diseases were examined.
- Higher overall risks of heat stroke were found in regions with less greenspace.
- Risks for heat stroke decreased over time in regions with less greenspace.
- Adaptation to heat-hospitalization associations differed by amount of greenspace.

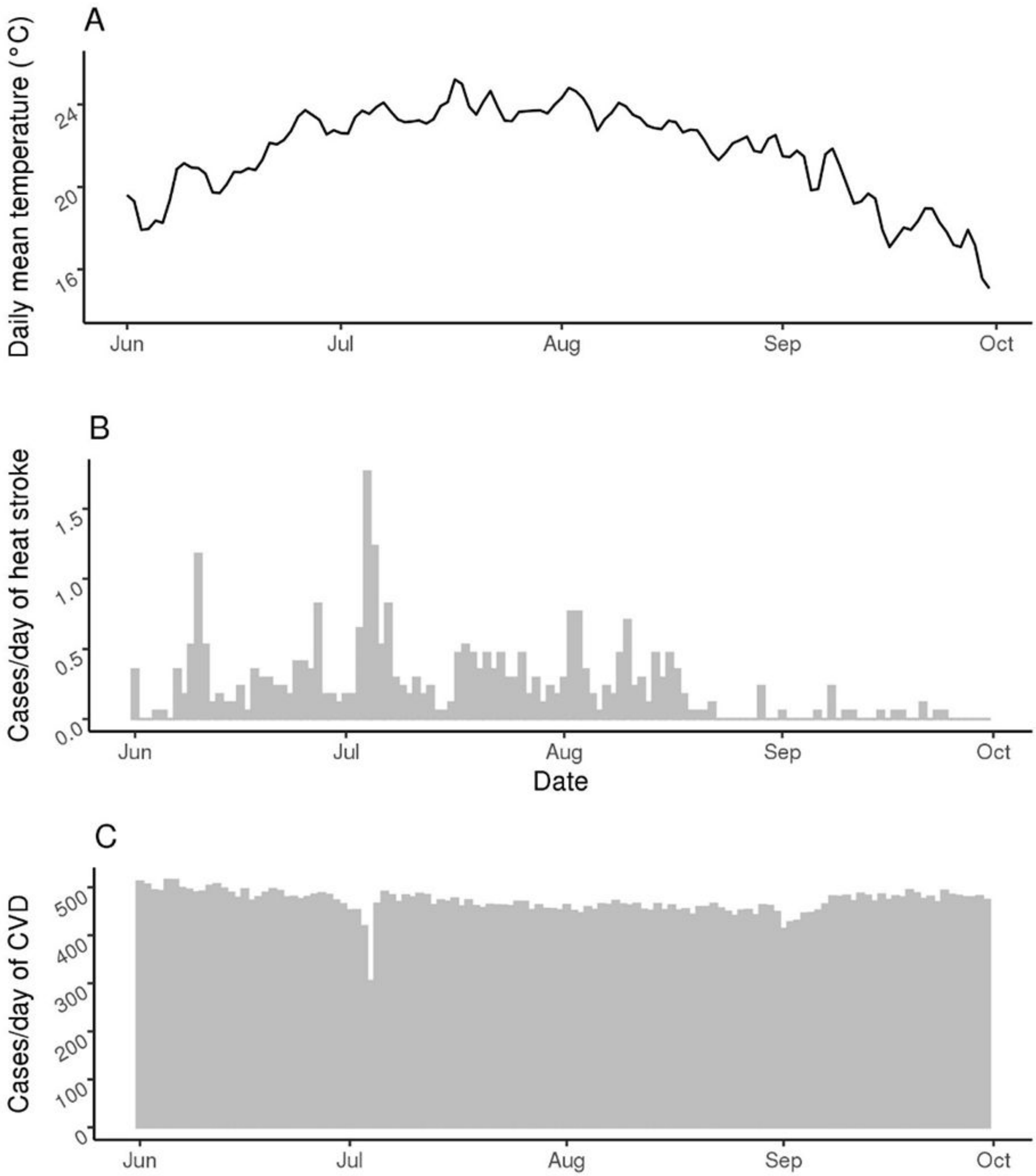

Figure 1.

Daily mean temperature and average hospitalizations for each month and day for 2000-2016. Values for a given day (e.g., June 1) are based on the average of values of that day in each year of the study period. CVD: all cardiovascular disease. A: Daily mean temperature averaged across 40 counties, B: Heat stroke hospitalizations/day summed across 40 counties, C: CVD hospitalizations/day summed across 40 counties.

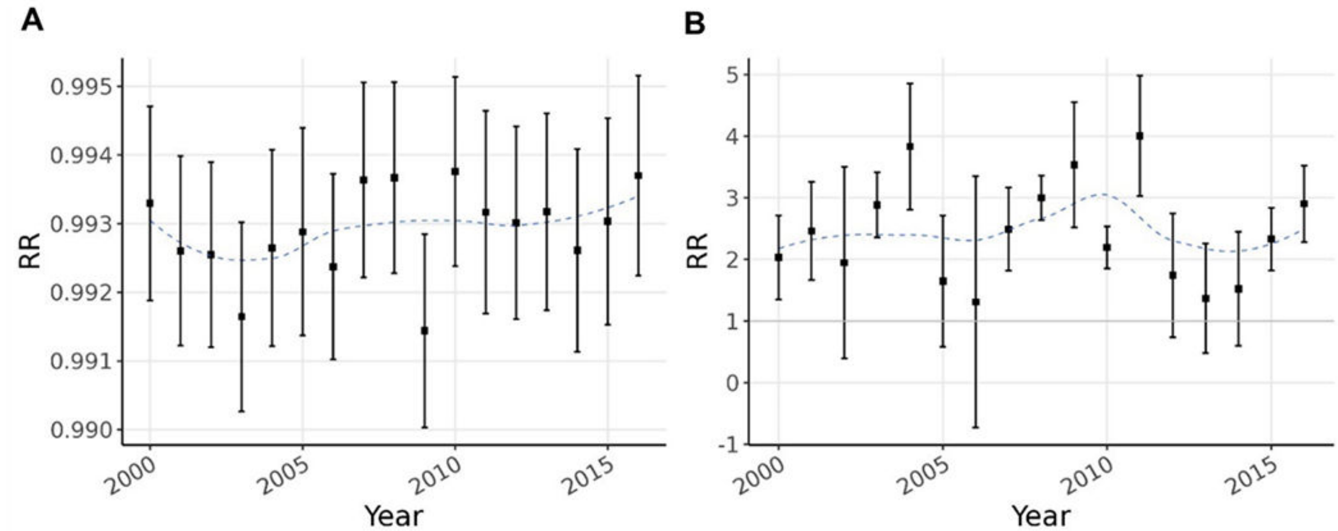

Figure 2.

Relative risks of hospitalization associated with a 1°C increase in lag0-3 temperature above the county-specific threshold temperature (95th percentile) by year. A: all cardiovascular disease. B: heat stroke. Dots indicate central estimates; vertical lines indicate 95% intervals; dotted lines are Loess curves.

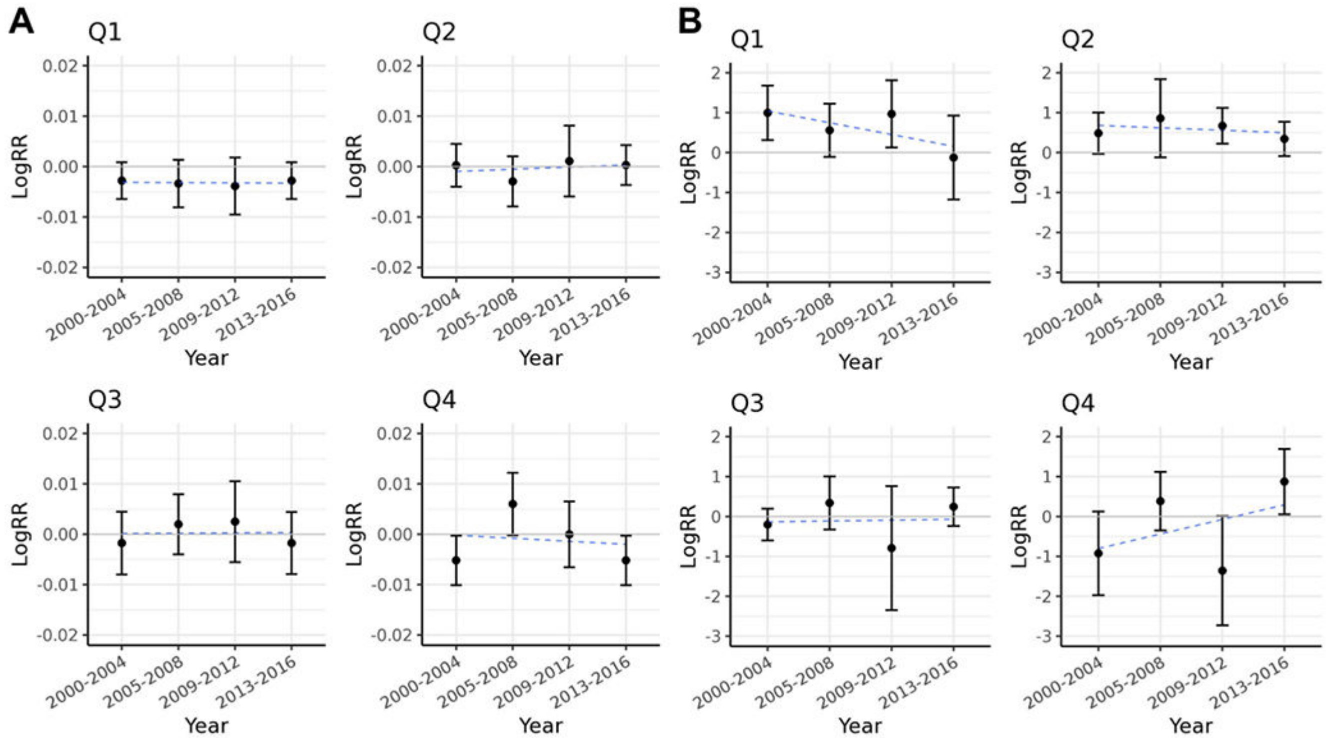

Figure 3.

Log relative risks (LogRRs) of daily hospitalization rate associated with a 1°C increase in lag0-3 daily mean temperature above the county-specific threshold temperature (95th percentile) in 4 separate time periods, by EVI strata. A: all cardiovascular disease, B: heat stroke. The threshold was defined as the 95th percentile of temperature in each county. Q1: EVI < 0.23, Q2: 0.23 ≤ EVI < 0.27, Q3: 0.27 ≤ EVI < 0.3, Q4: EVI ≥ 0.3.

Table 1.

Descriptive statistics of temperature, air pollution, and cause-specific hospitalization in the 40 study counties in the warm season for 2000–2016, and in separate time periods (2000–2007 and 2008–2016).

Variable	2000–2016			2000–2007			2008–2016		
	Mean (SD)[b]	25th to 75th percentiles	Minimum to maximum	Mean (SD)	25th to 75th percentiles	Minimum to maximum	Mean (SD)	25th to 75th percentiles	Minimum to maximum
Daily mean temperature (°C)[a]	21.7 (3.9)	19.1 to 21.7	4.4 to 34.2	21.4 (3.9)	18.9 to 24.3	4.4 to 33.3	21.8 (3.9)	19.3 to 24.6	7.2 to 34.2
Daily mean dew point temperature (°C)	15.0 (4.1)	12.2 to 18.3	−1.7 to 24.7	15.1 (4.1)	12.3 to 18.4	−1.7 to 24.2	15.0 (4.0)	12.2 to 18.2	−0.8 to 24.7
Daily mean $PM_{2.5}$(μg/m^3)	12.0 (8.0)	6.5 to 15.2	0.8 to 118.8	14.7 (9.6)	7.6 to 19.2	1.3 to 118.8	9.6 (5.4)	5.8 to 12.0	0.8 to 47.1
EVI	0.25 (0.07)	0.23 to 0.30	0.03 to 0.35	0.25 (0.07)	0.23 to 0.30	0.03 to 0.35	0.25 (0.07)	0.23 to 0.30	0.03 to 0.35
Average warm season (June-Sep.) number of hospitalizations in each county									
All cardiovascular causes	1431 (746)	896 to 1746	395 to 4213	1690 (802.5)	1094 to 2146	613 to 4213	1201 (607)	754 to 1475	395 to 3703
Heat stroke	0.7 (1.2)	0.0 to 1.0	0.0 to 9.0	0.8 (1.3)	0.0 to 1.0	0.0 to 9.0	0.6 (0.9)	0.0 to 1.0	0.0 to 6.0

[a]The mean of daily mean temperature is the average daily mean temperature across all 40 counties.

[b]The min and max represent the lowest and highest values, respectively, for a given county across all 40 counties. Temperature distributions of study counties grouped by county-level EVI for 2000–2007 and 2008–2016 are shown in Supplementary Fig. S2. The Q4 group showed the lowest temperature ranges (mean of 21.1 °C in 2000–2016), meaning that on average the areas with the highest greenness has the lowest temperatures.

Table 2.

Relative risks of daily hospitalization rate associated with a 1°C increase in lag0-3 temperature above the county-specific threshold temperature (95th percentile) in 4 separate time periods.

Time period	CVD		HS	
	RR	**95% CI**	**RR**	**95% CI**
2000-2004	1.000	0.998, 1.002	2.019	1.863, 2.174
2005-2008	1.000	0.997, 1.003	1.907	1.727, 2.087
2009-2012	1.000	0.997, 1.003	1.755	1.632, 1.878
2013-2016	0.998	0.995, 1.002	1.212	0.879, 1.545

CVD: all cardiovascular disease; HS: heat stroke.