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Variation in estimates of heat-related mortality reduction due to tree cover in U.S. cities

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ABSTRACT

Heat-related mortality is one of the leading causes of weather-related deaths in the United States. With changing climates and an aging population, effective adaptive strategies to address public health and environmental justice issues associated with extreme heat will be increasingly important. One effective adaptive strategy for reducing heat-related mortality is increasing tree cover. Designing such a strategy requires decision-support tools that provide spatial and temporal information about impacts. We apply such a tool to estimate spatially and temporally explicit reductions in temperature and mortality associated with a 10% increase in tree cover in 10 U.S. cities with varying climatic, demographic, and land cover conditions. Two heat metrics were applied to represent tree impacts on moderately and extremely hot days (relative to historical conditions). Increasing tree cover by 10% reduced estimated heat-related mortality in cities significantly, with total impacts generally greatest in the most populated cities. Mortality reductions vary widely across cities, ranging from approximately 50 fewer deaths in Salt Lake City to about 3800 fewer deaths in New York City. This variation is due to differences in demographics, land cover, and local climatic conditions. In terms of per capita estimated impacts, hotter and drier cities experience higher percentage reductions in mortality due to increased tree cover across the season. Phoenix potentially benefits the most from increased tree cover, with an estimated 22% reduction in mortality from baseline levels. In cooler cities such as Minneapolis, trees can reduce mortality significantly on days that are extremely hot relative to historical conditions and therefore help mitigate impacts during heat wave conditions. Recent studies project highest increases in heat-related mortality in the cooler cities, so our findings have important implications for adaptation planning. Our estimated spatial and temporal distributions of mortality reductions for each city provide crucial information needed for promoting environmental justice and equity. More broadly, the methods and model can be applied by both urban planners and the public health community for designing targeted, effective policies to reduce heat-related mortality. Additionally, land use managers can use this information to optimize tree plantings. Public stakeholders can also use these impact estimates for advocacy.

1. Introduction

The health effects of extreme summer temperatures can lead to physician visits, hospitalizations, emergency room visits, and death. In the United States, heat-related mortality is a continuing public health concern (Vaidyanathan et al., 2020) and is one of the leading causes of weather-related deaths (CDC, 2020; Davis et al., 2003). Studies have estimated between 1300 and 12,000 heat-related deaths annually in the United States (Kalkstein et al., 2011; Shindell et al., 2020; Weinberger et al., 2020), with more during a heat wave year. For example, a heat wave in July 1995 resulted in approximately 700 deaths in Chicago alone (Kaiser et al., 2007). Under climate change scenarios, the number of premature heat-related deaths is projected to increase by the thousands in the United States with similar trends seen around the world (Gasparrini et al., 2017; USGCRP, 2016). Further challenges for the public health community and policy makers arise because people with

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specific demographic and socioeconomic characteristics are more sensitive to extreme heat. For example, adults above the age of 65 may be impacted more (Gamble et al., 2016). Timing of heat events also matters; higher temperatures during early summer result in greater health impacts than later in the summer because people have not adapted to warmer temperatures (Anderson and Bell, 2011; Baccini et al., 2008; Luber and McGeehin, 2008). Uncertainties associated with climate projections add another layer of complexity.

Adaptation actions, preparedness, and societal responses can reduce the number of deaths. The health implications of extreme temperature change over time and vary across locations (USGCRP, 2016), so developing effective adaptation strategies needs a thorough understanding of not just total impacts, but where the impacts are, when they occur, and who might be impacted. Variation in health impacts have important policy implications, especially in the light of spatial differences in projections of heat-related mortality under future conditions (Schwartz et al., 2015; Shindell et al., 2020).

Decision-support tools can provide valuable information needed for designing effective and targeted adaptation strategies. Increasing urban tree cover is one adaptation action that can substantially reduce heat-related mortality. Recent studies demonstrate the temperature and mortality benefits of tree cover and provide estimates of these impacts (e.g., Santamouris et al., 2020; Venter et al., 2020; Burkart et al., 2016; Graham et al., 2016). For example, Donovan et al. (2013) shows that loss of trees to the emerald ash borer increased mortality related to cardiovascular and lower-respiratory-tract illness. McDonald et al. (2020) estimated that across 97 U.S. cities, urban tree canopy reduced summer daily mean air temperatures by approximately 1.0 °C, associated with reduced mortality and energy usage. Kondo et al. (2020) estimate reductions of 298–618 deaths annually by increasing Philadelphia's tree cover from 20% overall to about 30%.

While existing studies identify important trends, they focus on estimating mortality reductions due to green space without directly modeling temperature changes, or they model temperature change using statistical relationships rather than process-based modeling. A direct link between tree cover, temperature, and mortality is needed to better understand the processes involved and develop adaptation strategies under different climate scenarios. Further, existing studies do not account for acclimatization or distinguish between mortality benefits due to reductions in temperature throughout the season, versus on extremely hot days. Estimated epidemiological relationships show that mortality responses to extremely hot days are much higher than those for more moderate temperatures and what is considered a hot day varies across cities (e.g., Medina-Ramón and Schwartz, 2007). Moreover, patterns of seasonal temperature projections and the frequency of extremely hot days under climate scenarios vary across cities and may have different policy implications.

To address these gaps, Sinha et al. (2021) provided a method to establish a direct link between tree cover, air temperature, and mortality. The method involves using local environmental, demographic, and health data to estimate changes in air temperatures due to changes in tree cover and the associated impact on premature human mortality throughout the season and on extremely hot days. Yang et al.'s (2013) process-based air temperature model is used to explicitly simulate how changes in tree cover affect temperature and this provides more adaptability than statistical models. Sinha et al. (2021) demonstrated the method in Baltimore, Maryland to show that increasing current tree cover by 10% could reduce annual mortality by 181–416 deaths. The economic value of these avoided deaths is large, ranging from $1.5 billion to $3.4 billion in the latter study. This study in Baltimore provided a method that can be applied to other cities and also provided a foundation for expanding the i-Tree suite of tools. to include a heat-related mortality component that can inform adaptation decision-making.[1]

It is yet to be determined whether Sinha et al.'s (2021) estimates for Baltimore can be extrapolated to other cities with different environmental and demographic conditions. The aim of this current study is to apply the method and tool developed in Sinha et al. (2021) to quantify the impacts of tree cover on air temperature and mortality in 10 cities in the United States (Section 2.1). These cities are located across different climate regions and also vary widely in terms of other characteristics such as land cover and demographics (Section 2.2). This paper explores whether mortality impacts due to tree cover changes are different across cities and what factors drive these differences (Section 3.2.1). Spatial and temporal variations in impacts of tree cover within cities are also analyzed (Section 3.2.2). Sensitivity of mortality reductions to a heat metric that allows for acclimatization is assessed, and impacts for extremely hot days versus for conditions throughout the season are compared (Section 3.3). We summarize implications of our findings for decision making in hot cities as well as cooler cities (Section 4) and identify further research needs (Section 5).

2. Methods

2.1. Assessing urban tree benefits

We follow a four-step process typically applied in i-Tree to assess and value the benefits from trees: 1) quantify forest structure, 2) model the functions associated with that forest structure, 3) estimate the impacts that humans experience from those forest functions, and 4) apply economic valuation to those impacts. We tailored these steps for assessing heat-related mortality impacts and associated economic values due to tree cover change in 10 cities (see Section 2.2, Study areas) across the country following methods developed in Sinha et al. (2021). Census Block Groups are used as the spatial unit for implementing each of the four steps and results are presented both at the Census Block Group and city levels.

In the first step, local structural variables relating to tree and other surface cover and meteorology were obtained for each city. Baseline tree cover and impervious cover percentages for each Census Block Group were derived from 2011 National Land Cover Database (NLCD) 30-m resolution tree cover and impervious cover maps (MRLC, 2015). Modeled canopy variables for each city included leaf-on Julian Day, leaf-off Julian Day, leaf area index (LAI), and percent evergreen canopy. Data for these canopy variables were derived from the i-Tree Eco location database, based on local frost dates for leaf phenology and either field or satellite data for LAI (i-Tree Database, 2020). Local hourly meteorological data were obtained from the National Centers for Environmental Information's (NCEI) Integrated Surface Database and preprocessed by a utility for i-Tree Eco weather preprocessing (Hirabayashi and Endreny, 2016). Percent evergreen data were based on local field data or satellite data (Nowak et al., 2014).

In the second step, we estimated the impact of current and alternative tree cover scenarios on air temperature using the i-Tree Cool Air model (Yang et al., 2013). An underlying assumption in the i-Tree Cool Air simulation tool is that the mesoscale climate above the boundary layer is uniform across the simulated area and can be estimated by solving the energy and water balance with meteorological variables

[1] i-Tree provides a framework for assessing various ecosystem services and associated benefits due to changes in tree cover, such as effects on building energy use, stormwater runoff volume and pollution reduction, carbon sequestration, and improvements in public health due to air pollution reduction (Nowak et al., 2008, 2013a, 2013b, 2014, 2017).

from a reference weather station. Variations in temperatures within cities are primarily driven by differences in land cover variables. Tree cover and impervious cover were the land cover variables of focus in this study, following the methods of other air temperature measurement (Ziter et al., 2019; Shandas et al., 2019) and modeling (McDonald et al., 2020; Voelkel and Shandas, 2017) studies that identified these variables as the primary land cover drivers of air temperature differences within cities.[2] Following the methods described by Sinha et al. (2021), i-Tree Cool Air model parameters (i.e., land cover albedo and emissivity) were kept consistent among cities to isolate the effects of alternative tree cover scenarios and three scenarios were considered: 1) increasing the existing tree cover by an absolute 10% of each Census Block Group's area, 2) removing all existing tree cover in each Census Block Group, and 3) removing 10% of each Census Block Group's area from existing tree cover.[3] We focus on impacts due to the absolute 10% increase in tree cover throughout this paper. Simulating a standard alternative tree cover scenario enabled us to better compare tree cover impacts across cities. The 10% change in tree cover is consistent with the range of differences between existing canopy and canopy goals among select cities in the eastern United States (Safavi, 2012) and is also used by other studies (e.g., Kondo et al., 2020).

In the third step, we applied relationships between heat metrics and mortality from Medina-Ramón and Schwartz (2007) to translate changes in temperature to changes in human mortality. There is considerable debate about what is extreme heat and a variety of definitions and measures have been used in the epidemiological literature (Sarofim et al., 2016; Smith et al., 2013). Further, mortality impacts of temperature have been documented not just for heat extremes, such as during heatwaves, but also for temperatures that are moderately hot (Gasparrini et al., 2015; Lee et al., 2014). We selected the Medina-Ramón and Schwartz (2007) relationships because they are applicable to a wide range of climatic conditions and include two different heat metrics that represent moderately hot days and extreme heat.

The first metric has a piecewise linear functional form where mortality varies linearly with daily minimum air temperature (T) and is truncated at 17 °C (i.e., it assumes that with minimum temperatures that are less than or equal to 17 °C, the heat exposures causing mortality impacts are zero). Under this definition, heat impacts people in the same way across cities and these impacts occur throughout the summer season.

The second heat metric represents extremely hot days. The functional form is binary, implying that reductions in heat metrics will only be seen if the increase in tree cover causes T to drop from above the historical 99th percentile threshold to below the threshold. The thresholds are city-specific and capture the notion that what is extreme is relative to the typical local conditions. For example, a 30 °C air temperature will impact people in Phoenix, Arizona differently than people in Chicago, Illinois. In Phoenix, days with a daily minimum temperature of 30 °C will not be considered as an extremely hot day because 30 °C is lower than the historical 99th percentile of 32 °C (in our data) and local people are used to such temperatures. However, this is not the case in Chicago where a daily minimum temperature of 30 °C is much higher than the historical 99th percentile of 23 °C. This adaptation phenomenon is evidenced in the epidemiological literature, which shows that people can adapt at least partly to the temperature they are used to due to infrastructure and physiological acclimatization (Medina-Ramón et al., 2006; Sarofim et al., 2016). We focus on the months of May through September because the Medina-Ramón and Schwartz (2007) study relationships were estimated for this period.

Changes in the heat metric (*HEAT*) were obtained by taking the difference in the heat metric under the alternative scenario and the baseline tree cover–impervious cover conditions as follows:

$$\Delta HEAT = HEAT_{Alt} - HEAT_{Base} \tag{1}$$

For the binary heat metric, indicator variables were used to calculate whether the threshold was exceeded under the baseline and alternative scenarios. We estimated the changes in mortality (Δy) due to change in each *HEAT* by applying a health impact function (Voorhees et al., 2011) as follows:

$$\Delta y = y_0 * \left(e^{\beta \Delta HEAT} - 1\right) * P \tag{2}$$

where y_0 is the baseline health incidence rate for mortality for each age group; P is the exposed population for each age group; and β, which represents the relationship between the change in *HEAT* and mortality, was derived from Medina-Ramón and Schwartz (2007) and is summarized in Table S3.1. County-level baseline incidence rates for cause-specific mortality were obtained for each age group from BenMAP-CE (CDC, 2015; Sacks et al., 2018). Population for 5-year age groups at the Census Block Group level was obtained from the 2010 decennial census.[4] To obtain the total changes in mortality, we added the mortality impacts across all age groups relevant for the study. We also estimated lower and upper bounds for health impacts $\{\Delta y_{UB}, \Delta y_{LB}\}$ using the confidence interval $\{\beta_{UB}, \beta_{LB}\}$ to represent the uncertainty in β estimates.

The last step involved monetizing changes in premature mortality using evidence from economic valuation literature on the Value of a Statistical Life (V). Following U.S. EPA (2018),[5] we applied a value of $8.22 million for V. This value was multiplied by the computed change in mortality (Δy) to obtain the monetary benefit of the change in mortality (B):

$$B = \Delta y * V \tag{3}$$

2.2. Study areas

Ten cities were selected to represent a range of climatic conditions across the United States (Table 1). The selected cities represented zones of heating and cooling standards across the contiguous United States in the International Energy Conservation Code map of climate zones (IECC, 2012) (Figure S3.1). They represent different climate regions and moisture regimes, based on i-Tree Eco Climate Zones (McPherson and Simpson, 1999) (Table S3.2). City selections avoided locations that are significantly affected by meteorological drivers not represented in the i-Tree Cool Air model's processes. For example, instead of simulating San Diego and its Santa Ana winds, Los Angeles was selected to represent Region 3B. Far northern colder cities were also avoided because the minimum temperature in such cities is typically lower than 17 °C,[6] along with cities that have a marine climate (e.g., Seattle, Portland, San Francisco) as the Medina-Ramón and Schwartz (2007) are not applicable for these cities.

The cities vary widely in terms of different city characteristics such as climate, land cover, city size, demographics and baseline health

[2] The i-Tree Cool Air model predictions of land cover effects on air temperature and humidity were initially validated at nine weather stations from August 20 to 29, 2010 for Syracuse, New York (Yang et al., 2013).

[3] We provide aggregate results for the loss of all tree cover in Supplementary Material 1. Impacts of reducing current tree cover for Baltimore by 10% are analyzed further by Sinha et al. (2021). Results for that latter scenario are available upon request.

[4] We follow Sinha et al. (2021) in applying the incidence rates to the populations in different age groups.

[5] The value that is used by EPA in benefits analysis is $7.4 million in 2006 dollars (U.S. EPA, 2018). We adjusted to 2011 dollars using the Consumer Price Index Inflation Calculator from the U.S. Bureau of Labor Statistics (n.d.).

[6] For example, in Fargo, North Dakota, the minimum temperature for the monthly normals (averaged over 1981–2010) is typically 7–9 °C in May and September, 13–14 °C in June and August, and 15 °C during the hottest month of July (U.S. Climate Data, 2021).

Table 1
City characteristics.

City	Climate			Land Cover (%)		City Size[a]		Age	Health
	Daily minimum temperature[b]	Daily average temperature[b]	Daily average dewpoint temperature[b]	Median tree cover	Median impervious cover	Number of Block Groups	Population	Persons 65 years and over, percent	Mortality rate (weighted[c])
Phoenix	26.3	32.8	5.2	0	52	974	1,471,559	8.5%	0.48%
Miami	25.3	28.3	22.3	21	58	315	410,097	16.1%	0.81%
Houston	24.0	28.5	20.7	39	55	1736	3,275,911	8.2%	0.54%
Atlanta	18.9	24.8	17.5	62	35	322	441,475	9.9%	0.69%
New York City	18.8	22.2	14.5	10	82	6481	8,175,133	12.1%	0.61%
Albuquerque	16.8	23.8	1.8	19	43	419	635,133	12.1%	0.68%
Chicago	16.8	21.0	13.9	7	67	2206	2,734,226	10.4%	0.65%
Los Angeles	16.1	19.7	13.1	8	63	2513	3,797,846	10.5%	0.55%
Minneapolis	15.8	20.5	12.4	27	50	378	382,583	8.0%	0.46%
Salt Lake City	14.4	20.6	6.3	21	47	168	235,876	9.2%	0.55%

[a] For three cities, some Census Block Groups lie partly outside the boundary. We include the population and land area of the full Census Block Group in our study.
[b] Averaged over May–September.
[c] Baseline mortality for all causes, weighted by population in each age group.

conditions (Table 1, Table S3.2). The average temperature is highest in Phoenix and Houston and lowest in Los Angeles and Minneapolis. The average minimum temperatures had a different ranking among cities with Phoenix and Miami being the warmest, and Salt Lake City and Minneapolis being the coolest. Dewpoint temperature also differs in ranking, indicating which cities tend to be more humid. While the heat metrics in Medina-Ramón and Schwartz (2007) do not use dewpoint temperature or relative humidity as an input, humidity is used by the i-Tree Cool Air model to regulate evaporation and the partitioning of energy into air temperature.

Land cover conditions vary widely across the cities (Table 1). Phoenix has the lowest median tree cover followed by Chicago and Los Angeles. Atlanta has the highest tree cover, followed by Houston and Minneapolis. New York City has the highest impervious cover, followed by Chicago and Los Angeles. Atlanta, Albuquerque, and Salt Lake City have the lowest impervious cover.

Population demographics also vary among the cities (Table 1, with additional characteristics such as income provided in Table S3.2). New York City is the largest, and Salt Lake City is the smallest both in terms of number of Census Block Groups and population. Miami has the highest percent of population aged over 65 and Minneapolis has the lowest. The age distribution varies not just across cities (Table S3.3) but also within cities. This is important for two reasons: 1) baseline mortality rates (y_0) vary across age groups with the population over 65 having a much higher mortality rate than younger age groups; and 2) the population over 65 is more vulnerable to extreme heat (Gamble et al., 2016). While we apply age-specific mortality rates in equation (2), unlike Sinha et al. (2021), we do not apply age-specific epidemiological information in this study.

3. Results and discussion

We conducted our analysis across three different dimensions: 1) aggregate impacts were compared across cities and the role that different city characteristics play were examined; 2) spatial patterns of impacts within cities were analyzed to provide information on which populations may be impacted, and 3) impacts across months were examined to inform preparedness efforts (Supplementary Material 1).

3.1. Baseline conditions

3.1.1. Across cities

Existing tree and impervious cover are key drivers of i-Tree Cool Air results. Tree cover estimates are conservative as NLCD is known to underestimate tree cover (Nowak and Greenfield, 2010). We expect the NLCD underestimation of tree cover does not affect the relative impacts of adding tree cover, because tree cover effects are linear for any given amount of impervious cover (Sinha et al., 2021). Tree and impervious cover estimates varied among Census Block Groups (Table 1). Baseline impervious cover is a key driver of the magnitude of temperature impacts caused by changes in tree cover. Of the 10 cities studied, Atlanta had the highest median tree cover across Census Block Groups (62%) and Phoenix had the lowest (0%) (Table 1). New York City had the highest median impervious cover across Census Block Groups (82%) and Atlanta had the lowest (35%).

Temperature trends across the season (Fig. 1) affect the heat metric calculations and consequently, the estimated mortality impacts for cities. For example, Miami's reference weather always had weekly average T's above 20 °C, whereas Los Angeles' reference weather had T's at or below 17 °C for most of the season. Because the piecewise linear heat metric uses a threshold of 17 °C, during periods where baseline T is below 17 °C, there are zero reductions in mortality with reduced temperature due to increased tree cover. Thus, Los Angeles, with its lower T's, will have lower reductions in mortality. Minneapolis also had temperatures below 17 °C for most of the season but had warmer temperatures toward the middle of the season. Broadly speaking, Fig. 1 indicates that hotter cities will tend to experience larger reductions in mortality due to increased tree cover.

3.1.2. Within cities

There is substantial variation of tree cover, impervious cover, and baseline minimum temperatures within each city (Fig. 2[7] and Figures S3.2A through S3.2I). Within cities, higher tree cover tends to be concentrated in the outskirts and higher impervious cover tends to be concentrated downtown (e.g., Houston, Figure S3.2B; Atlanta, Figure S3.2C). There is some variation from that trend, as in southern Los Angeles (Figure S3.2G) where a high percentage of tree cover and impervious cover is observed in the same area.[8]

Temperatures are higher in areas with less tree cover and more impervious cover (Fig. 2, Table S3.4). This is because areas with low tree cover have less shading and evaporative cooling and areas with higher impervious cover have greater heat storage and are warmed to a greater extent during the day as compared with other areas. To summarize,

[7] Boundaries of the 974 Census Block Groups in Phoenix are shown in Fig. 2.
[8] Percent impervious cover and tree cover in each Census Block Group are not mutually exclusive in the NLCD dataset. It is possible that impervious cover and tree cover percentages can sum to values greater than 100% because tree cover can overlap impervious cover.

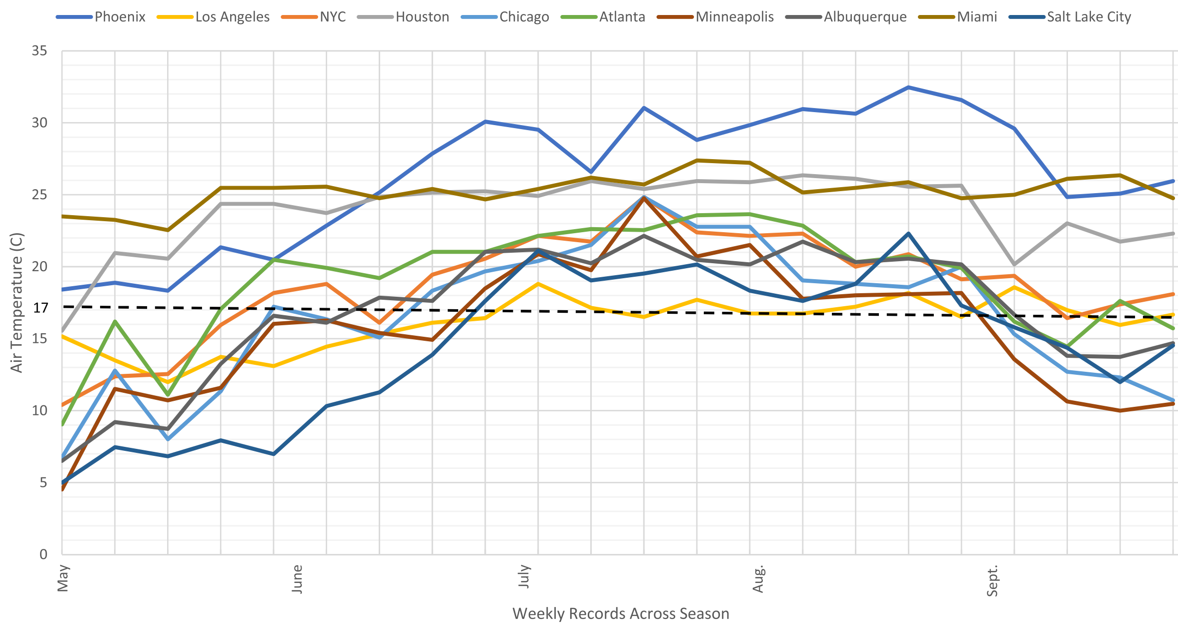

Fig. 1. Daily minimum air temperature (°C) (observed at nearby international airport weather stations over May 1–Sept 30, 2011, averaged by week).

there are three basic patterns observed with land cover: higher impervious cover tends to result in higher air temperatures, lower tree cover tends to result in higher air temperatures, and higher impervious cover tends to coincide with lower tree cover. Further, how the spatial variation in tree and impervious cover within cities aligns with the spatial variation in population age distribution affects mortality outcomes.

3.2. Impacts of increasing tree cover on mortality

3.2.1. Across cities

Tree cover impacts on avoided deaths (estimated using the piecewise linear heat metric) vary substantially across cities (Table 2). The total estimated number of deaths avoided annually when tree cover is increased by 10% is largest in New York City (3834 with a 95% confidence interval of 2188 to 5478) and smallest in Salt Lake City (56 with a 95% confidence interval of 32–80). The mean monetary value of these impacts ranges from $460 million in Salt Lake City to $31.5 billion in New York City.

Hotter cities are expected to have larger mortality impacts due to changes in tree cover (Section 3.1.2). Although this pattern holds for some cities, temperature rankings do not align perfectly with impact rankings (Table 3). For example, Salt Lake City and Minneapolis have the lowest mortality reductions. However, New York City and Phoenix have the highest mortality reductions.

Total impacts are driven by population, mortality rates, and the reductions in heat metrics (equation (2)), and we examine the role of each of these factors in driving the results, starting with demographics. First, larger populations imply higher total health impacts (holding other factors constant), and this explains high impacts for New York City, which has the largest population. Second, cities vary widely in terms of mortality rates (Table 3) due to age distribution, the quality and availability of health care, and other factors. The decrease in per person mortality as a percentage of the baseline mortality is highest in the two hottest cities (Phoenix and Miami). However, not all cities follow this relationship with temperature.

To summarize key takeaways from Table 3, note the following four anomalies in the last column which shows reductions in per person mortality as a percentage of the baseline mortality. First, impacts in Phoenix are an order of magnitude higher than other cities, including Miami, which is very close to Phoenix in terms of *T*. Second, impacts in Houston are lower than in Albuquerque and New York City, although Houston is much hotter than both cities. Third, impacts in Atlanta are lower (although not by much) than cities that are much cooler. Fourth, Salt Lake City, although colder than Minneapolis, has much higher impacts. Reductions in heat metrics, which is the third variable in equation (2), must be driving these four anomalies as is confirmed in Table S3.5.

Differences in each city's distribution of change in *T* (on which this study's heat metric calculations are based) are affected by a variety of factors. Land cover is a significant driver of temperature model results, and this study focuses on changes in temperature and associated heat metrics caused by changes in tree cover specifically. With the same change in tree cover—such as the 10% addition used in this study's alternative case—the extent of temperature change depended on a city's baseline land cover conditions and model parameterization. Census Block Groups with more baseline impervious cover had a greater response to a given increase in tree cover, as apparent from comparing maps of each city's impervious cover with maps of each city's average change in heat metric (Fig. 2 and Figures S3.2A through S3.2I). This sensitivity of tree cover impact on temperature to the amount of baseline impervious cover is driven by increased heat storage associated with higher impervious cover (Grimmond and Oke, 1999; Yang et al., 2013). While variations in impervious cover among cities (Table 1, Table S3.6) may partly explain some of the anomalies, it does not explain all patterns. For example, Atlanta has the lowest median impervious cover, which results in smaller reductions in heat metrics and mortality impacts as compared to cooler cities.

Even if all cities had the same land cover conditions, their simulated temperature change due to a 10% increase in tree cover would vary

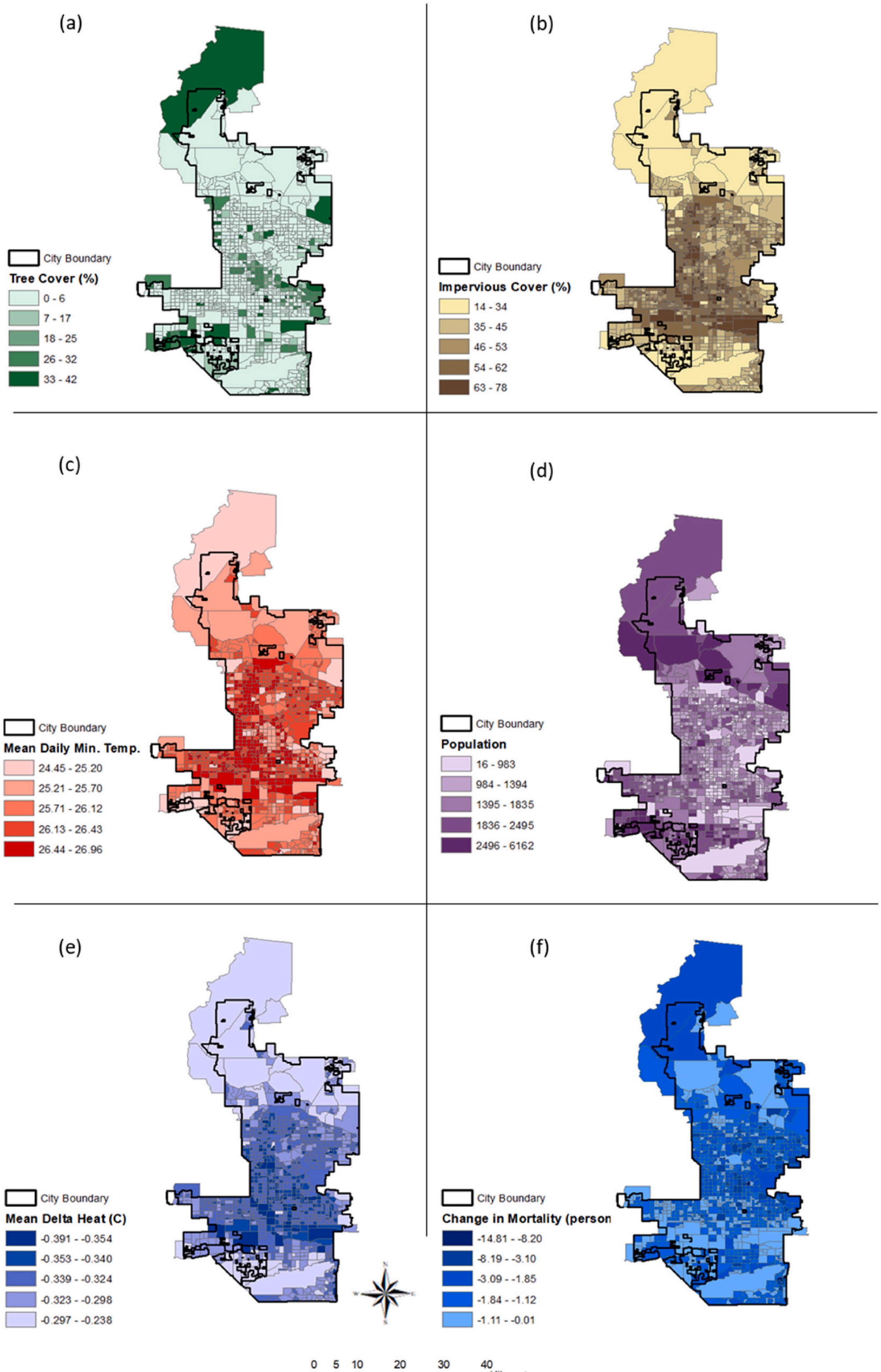

Fig. 2. Baseline conditions within Phoenix for (a) tree cover, (b) impervious cover, (c) daily minimum temperature (°C, averaged over season), and (d) population; and estimated changes under the alternative scenario of a 10% increase in tree cover for (e) piecewise linear heat metric and (f) mortality (changes are averaged across season).

Table 2
Estimated change in mortality[a] and associated monetary benefits under the alternative scenario of increasing tree cover by 10% of Census Block Group area (piecewise linear heat metric).

City	Mortality Change			Economic Value (2011$, billions)		
	LB[b]	Center[b]	UB[b]	LB[b]	Center[b]	UB[b]
Phoenix	(865)	(1514)	(2164)	$(7.11)	$(12.45)	$(17.79)
Miami	(174)	(306)	(437)	$(1.43)	$(2.51)	$(3.59)
Houston	(645)	(1130)	(1615)	$(5.30)	$(9.29)	$(13.28)
Atlanta	(70)	(122)	(174)	$(0.57)	$(1.00)	$(1.43)
New York City	(2188)	(3834)	(5478)	$(17.99)	$(31.51)	$(45.03)
Albuquerque	(195)	(342)	(488)	$(1.60)	$(2.81)	$(4.01)
Chicago	(476)	(835)	(1193)	$(3.92)	$(6.86)	$(9.81)
Los Angeles	(496)	(869)	(1242)	$(4.08)	$(7.15)	$(10.21)
Minneapolis	(33)	(58)	(82)	$(0.27)	$(0.47)	$(0.68)
Salt Lake City	(32)	(56)	(80)	$(0.26)	$(0.46)	$(0.66)

[a] Under the alternative scenarios of increasing tree cover by 10%, mortality is reduced from baseline conditions. Hence the table shows negative values (in parenthesis).

[b] Center uses the estimated Beta coefficient. LB (lower bound) and UB (upper bound) denote estimates using lower and upper bounds of the 95% Confidence Interval for the estimated Beta coefficient.

Table 3
Drivers of differences in impacts on estimated mortality (population characteristics).

City	Daily min. temperature (°C)		Mortality change		Population		Mortality Change/ Person		Baseline mortality rate		Change in Per Person Mortality as a % of Baseline Mortality	
	Mean	Ranking	Mean	Ranking	Mean	Ranking	Mean	Ranking	Mean	Ranking	Mean	Ranking
Phoenix	26.3	1	(1514)	2	1,471,559	5	(0.00103)	1	0.475%	9	(21.7%)	1
Miami	25.3	2	(306)	7	410,097	8	(0.00075)	2	0.806%	1	(9.2%)	2
Houston	24.0	3	(1130)	3	3,275,911	3	(0.00035)	5	0.542%	8	(6.4%)	5
Atlanta	18.9	4	(122)	8	441,475	7	(0.00028)	7	0.689%	2	(4.0%)	9
New York City	18.8	5	(3834)	1	8,175,133	1	(0.00047)	4	0.611%	5	(7.7%)	4
Albuquerque	16.8	6	(342)	6	635,133	6	(0.00054)	3	0.683%	3	(7.9%)	3
Chicago	16.8	7	(835)	5	2,734,226	4	(0.00031)	6	0.648%	4	(4.7%)	6
Los Angeles	16.1	8	(869)	4	3,797,846	2	(0.00023)	9	0.555%	6	(4.1%)	8
Minneapolis	15.8	9	(58)	9	382,583	9	(0.00015)	10	0.460%	10	(3.3%)	10
Salt Lake City	14.4	10	(56)	10	235,876	10	(0.00024)	8	0.548%	7	(4.4%)	7

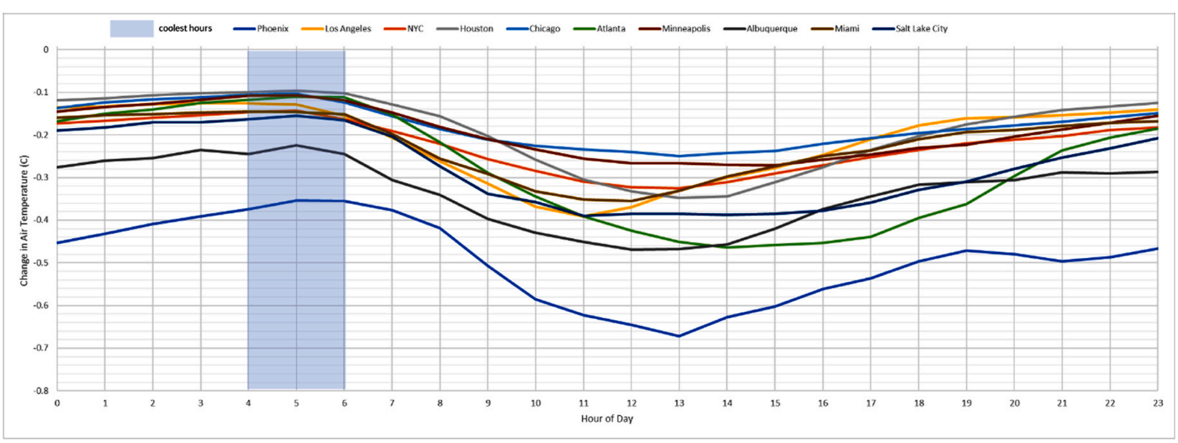

Fig. 3. Average change in air temperature (°C) simulated at each hour for the 10% increase in tree cover scenario from standard land cover conditions (tree cover = 30% and impervious cover = 50% of block group area). Simulated output for an uniform land cover is shown to facilitate comparison across cities.

(Fig. 3,[9] Table S3.7 [10]). For example, given comparable land cover, Phoenix and Albuquerque had the greatest change in *T* due to trees and also the largest range of changes in *T*. These differences in *T* changes are associated with differences in i-Tree Cool Air model inputs between cities, such as meteorological observations and tree canopy parameters (Table 4). The complex relationship among these input variables made it difficult to isolate specific variables as the cause of a difference in results among cities, but correlations and inferences helped clarify the sensitivity of impacts to different conditions.

Meteorological inputs were based on the reference weather station assigned to each city (Table 4, Supplementary Material 4). Meteorological variables—specifically median daily maximum net radiation, daily average dewpoint temperature, and average daytime and nighttime air temperature—tended to be more closely correlated with the median change in temperature (Table 4). Dewpoint temperature appears to play a dominant role in the ranking of cities by mortality impacts per person. In the i-Tree Cool Air model, dewpoint temperature is used to determine vapor pressure gradients and regulate evaporation rates, which impacts the partitioning of energy into air temperature. This use of dewpoint temperature contributes to the ranking of Houston as having lower impacts than Albuquerque and New York City, Atlanta as lower than Chicago, and Salt Lake City as greater than Minneapolis. The significantly greater impact in Phoenix compared with Miami is also explained by their dewpoint temperature: while Phoenix and Miami have similar median *T*'s and distribution of impervious cover, Phoenix has a greater change in *T* compared with Miami, even when assessing the same land cover conditions between the two cities (Table S3.7). The most significant difference between Phoenix and Miami was the much drier meteorological conditions associated with the Phoenix i-Tree Cool Air inputs (Table 4). The lower dewpoint temperatures contribute to increased potential and actual latent heat flux, including by evapotranspiration. For this reason, it is the hotter and drier cities that have the greater estimated impacts due to increasing tree cover, not only the hotter cities.

3.2.2. *Within cities*

The spatial distribution of impacts can also inform decision making. Correlations between mortality reductions and population and correlations between mortality changes and heat metric changes vary widely across cities. The former ranges from 0.17 to 0.72 across cities, while the latter ranges from 0.01 to 0.37. As in Baltimore (Sinha et al., 2021), correlation between mortality impacts and population is greater than the correlation for *ΔHEAT* for all cities indicating that population is a stronger driver of impacts than *ΔHEAT* (Fig. 2, Table S3.8, Figures S3.2A through S3.2I). Mortality changes tend to be the highest where higher population totals coincide with the highest change in heat metrics. However, it is not simply higher counts of people but also the age composition that affects mortality outcomes. A larger number of people in older age groups and the corresponding higher baseline mortality rates result in higher mortality impacts. Distributions of age compositions vary widely across cities (Table S3.3).

[9] Fig. 4 shows the average change in air temperature throughout the day estimated for the standard change in land cover applied to each city. This chart distinguishes trends of when the highest and lowest magnitude changes in air temperature occur throughout the day and highlight how each city compares in its magnitude of impact throughout the day. The smallest magnitudes of average hourly change occur at the coolest hour of the day in all cities, whereas the greater temperature changes occur outside of the daily minimum temperatures, which is the temperature metric used to assess health impacts in this study.

[10] Land cover conditions simulated follow methods described by Sinha et al. (2021). Cities vary in their number of Census Block Groups matching the land cover condition used in Table S3.7, and to that extent, trends shown in Table S3.7 may not represent the most prevalent trends in the entire city.

Table 4
Drivers of differences in impacts on daily minimum temperature (Cool Air model parameters and results).

City	Outputs[a]		Meteorological Inputs[b]								Canopy Inputs			
	Median Daily Min. Air Temp.	Median Change in Delta-*T*[c] for +10% TC	Weather Station (USAF-WBAN)	Daily Min. Air Temp.[d] (°C)	Hourly Air Temp.[d] (°C) (Nighttime, 7pm-6am)	Hourly Air Temp.[d] (°C) (Daytime, 7am-6pm)	Daily Average Dewpoint Temp.[d] (°C)	Daily Max Net Radiation[e] (W/m^2)	Wind Speed[e] (m/s)	Total Precip. (mm)	Leaf-On Day of Year	Leaf-Off Day of Year	Tree LAI	Evergreen %
Phoenix	25.5	(0.35)	722,780–23183	26.3	31.1	34.6	5.2	618.8	3.1	44.2	29	239	3.5	47.4
Miami	25.1	(0.12)	722,020–12839	25.3	26.8	29.7	22.3	849.4	2.7	975.6	0	365	5.75	100
Houston	24.8	(0.10)	722,440–12918	24.0	25.9	31.0	20.7	725.4	3.1	202.4	29	349	2.8	32.6
Atlanta	19.6	(0.10)	722,195–03888	18.9	22.3	27.3	17.5	834.7	1.3	261.6	75	311	5.9	17.7
New York City	19.5	(0.13)	725,030–14732	18.8	20.9	23.6	14.5	820.9	3.6	935.2	97	311	5.6	8.4
Albuquerque	17.7	(0.22)	723,650–23050	16.8	21.2	26.5	1.8	776.9	3.1	45.2	113	297	3.9	16.4
Chicago	17.4	(0.08)	725,340–14819	16.8	19.3	22.7	13.9	668.0	3.6	518.2	113	297	3.8	3.9
Los Angeles	16.1	(0.11)	722,874–93134	16.1	17.3	22.1	13.1	742.0	0.0	12.7	29	239	3.8	52.5
Minneapolis	16.3	(0.10)	726,580–14922	15.8	18.8	22.1	12.4	778.5	3.6	486.9	127	280	3.9	10.6
Salt Lake City	14.8	(0.14)	725,720–24127	14.4	17.9	23.4	6.3	617.4	3.6	196.9	127	280	4.35	44.71
Correlation with Delta-T[c]				(0.43)	(0.61)	(0.63)	0.66	0.68	(0.14)	0.40	0.19	0.46	0.22	(0.17)

[a] Outputs are for the Land Cover Condition of Tree cover = 30% and Impervious Cover = 50% of Block Group Area. Simulated output for an uniform land cover is shown to facilitate comparison across cities.
[b] The primary meteorological input for each city is the reference weather station, and other meteorological inputs listed here are select variables to summarize weather station data.
[c] Delta-*T* refers to the change in Daily Minimum Temperature (not truncated at 17°).
[d] Average across May–September.
[e] Median across May–September.

3.3. Sensitivity analysis

As moderately hot and extremely hot days both affect mortality (Lee et al., 2014), two heat metrics were used. We examined whether the rankings of mortality impacts across cities are sensitive to the choice of these two heat metrics. The piecewise linear metric represents the same threshold across cities, while the binary heat metric includes city-specific thresholds (Medina-Ramón and Schwartz, 2007). The piecewise linear metric focuses on changes throughout the season while the binary metric focuses only on extremely hot days where current minimum daily temperatures exceed city-specific thresholds. The magnitude of β for the binary metric is roughly 10 times the magnitude of the piecewise linear metric (Table S3.1). However, the total number of extremely hot days and the number of days above 17 °C may differ across cities and within cities. The binary heat metric threshold that is unique to each city's climate may be crossed in more or fewer instances than the piecewise linear metric depending on if the selected year was particularly hot or cool relative to historical conditions for each city. Thus, which metric yields higher mortality impacts is an empirical question.

Aggregate mortality impacts and associated economic values using the binary metric vary across cities (Table S3.9). The magnitude of aggregate mortality impacts tended to be higher under the piecewise linear metric than under the binary metric with the exception of Houston and Minneapolis (Table 5). When comparing the change in per person mortality as a percentage of change in baseline mortality across the two metrics, the rankings change dramatically for some cities (e.g., New York City, Minneapolis, Houston).

Cities with higher T's in 2011 are not always the cities with the higher city-specific thresholds (e.g., Albuquerque) (Table 6). Cities with a higher proportion of flips (i.e., proportion of observations for which an increase in 10% of tree cover results in a change from being an extremely hot day to not being one) have higher impacts relative to cities with a lower proportion of flips under the binary heat metric.[11] Under the piecewise linear heat metric, cities that have a higher proportion of observations under 17 °C under baseline conditions have lower impacts because on these days, the mortality impacts are zero. Further, for instances where the temperature flips from above 17 °C to below 17 °C, the mortality impacts are truncated. Houston had the second highest proportion of flips for the binary heat metric among all cities (Table 6), and this resulted in the relative ranking across the cities to increase for Houston, from fifth using the piecewise linear metric to second using the binary metric (Table 5). New York had the highest proportion of records that were above 17 °C under the baseline scenario and was thus ranked relatively high for piecewise linear. However, under the binary heat metric, the proportion of flips in New York City was the lowest and the ranking dropped to tenth. In Minneapolis, the proportion of records under 17 °C under baseline conditions was high relative to other cities (roughly 58%) and therefore the impacts under piecewise linear were relatively small. However, Minneapolis had a large proportion of observations where an extremely hot day flipped to not being an extremely hot day. The combination of these two factors resulted in the impacts for Minneapolis being much higher under the binary metric than the piecewise linear metric and the relative ranking across the cities to increase from tenth to third (Table 5). While tree cover may not reduce mortality as much for cities that are cooler throughout the season, trees can reduce mortality on extremely hot days significantly and help

Table 5
Comparison of estimated mortality changes when applying piecewise linear vs. binary heat metrics.

City	Daily Min. Temp. (°C)	City-Specific Threshold Used for Binary Heat Metric (°C)	Mortality Change				Mortality Change/Person				Change in Per Person Mortality/Baseline Mortality			
			(Piecewise Linear)		(Binary)		(Piecewise Linear)		(Binary)		(Piecewise Linear)		(Binary)	
			Total	Ranking	Total	Ranking	Mean	Ranking	Mean	Ranking	Percentage	Ranking	Percentage	Ranking
Phoenix	26.3	32.1	(1514)	2	(1316)	2	(0.00103)	1	(0.00089)	1	(21.7%)	1	(18.8%)	1
Miami	25.3	27.7	(306)	7	(247)	7	(0.00075)	2	(0.00060)	3	(9.2%)	2	(7.5%)	4
Houston	24.0	26.2	(1130)	3	(2847)	1	(0.00035)	5	(0.00087)	2	(6.4%)	5	(16.0%)	2
Atlanta	18.9	24.4	(122)	8	(76)	9	(0.00028)	7	(0.00017)	9	(4.0%)	9	(2.5%)	9
New York City	18.8	25.6	(3834)	1	(1148)	3	(0.00047)	4	(0.00014)	10	(7.7%)	4	(2.3%)	10
Albuquerque	16.8	21.7	(342)	6	(302)	6	(0.00054)	3	(0.00048)	4	(7.9%)	3	(7.0%)	5
Chicago	16.8	23.2	(835)	5	(555)	5	(0.00031)	6	(0.00020)	7	(4.7%)	6	(3.1%)	8
Los Angeles	16.1	21.2	(869)	4	(727)	4	(0.00023)	9	(0.00019)	8	(4.1%)	8	(3.4%)	7
Minneapolis	15.8	22.0	(58)	9	(181)	8	(0.00015)	10	(0.00047)	5	(3.3%)	10	(10.3%)	3
Salt Lake City	14.4	23.0	(56)	10	(54)	10	(0.00024)	8	(0.00023)	6	(4.4%)	7	(4.2%)	6

[11] We need to consider impacts across all Census Block Groups and all days in the season for each city. The total number of observations are obtained by multiplying the number of Census Block Groups by the total number of days (153) across the season. To account for variations in city size, we consider proportions of flips instead of absolute counts of flips. Table S3.10 shows the distribution of the changes in binary heat metrics. As can be seen, flips occur rarely and the proportion of flips vary widely across cities.

Table 6
Percent of instances above and below thresholds for piecewise linear and binary heat metrics (under baseline and alternative scenarios).

Piecewise Linear

City	Number of Census Block Groups[a]	Number of total records	Threshold (°C)	Percent of times above 17 °C under baseline	Percent of times below 17 °C under baseline	Percent of times above 17 °C under alternative	Percent of times below 17 °C under alternative	Percent of flips above 17 °C to below
Phoenix	974	149,022	17	96.0	4.0	95.8	4.2	0.22
Miami	315	48,195	17	100.0	0.0	100.0	0.0	0.00
Houston	1736	265,608	17	95.2	4.8	94.8	5.2	0.40
Atlanta	322	49,266	17	69.9	30.1	69.2	30.8	0.69
New York City	6481	991,593	17	72.2	27.8	71.5	28.5	0.72
Albuquerque	419	64,107	17	54.8	45.2	53.9	46.1	0.89
Chicago	2206	337,518	17	55.5	44.5	54.6	45.4	0.82
Los Angeles	2513	384,489	17	42.0	58.0	39.4	60.6	2.56
Minneapolis	378	57,834	17	41.7	58.3	40.2	59.8	1.44
Salt Lake City	168	25,704	17	36.2	63.8	34.4	65.6	1.85

Binary

City	Number of Census Block Groups[a]	Number of total records	City-specific threshold (°C)	Percent of times above threshold under baseline	Percent of times below threshold under baseline	Percent of times above threshold under alternative	Percent of times below threshold under alternative	Percent of flips above threshold to below
Phoenix	974	149,022	32.1	7.1	92.9	4.2	95.8	2.81
Miami	315	48,195	27.7	3.2	96.8	2.2	97.8	1.01
Houston	1736	265,608	26.2	13.2	86.8	10.8	89.2	2.40
Atlanta	322	49,266	24.4	1.1	98.9	0.8	99.2	0.37
New York City	6481	991,593	25.6	2.2	97.8	1.9	98.1	0.35
Albuquerque	419	64,107	21.7	7.4	92.6	6.4	93.6	1.06
Chicago	2206	337,518	23.2	9.9	90.1	9.5	90.5	0.43
Los Angeles	2513	384,489	21.2	1.4	98.6	0.9	99.1	0.53
Minneapolis	378	57,834	22	7.8	92.2	6.2	93.8	1.59
Salt Lake City	168	25,704	23	2.8	97.2	2.2	97.8	0.61

[a] Number of total days in the season is 153. Number of Census Block Groups multiplied by 153 is the total number of records for each city.

mitigate impacts during heat wave conditions.

4. Policy implications

Evaluating and designing policies requires estimating the impacts of policy-induced changes on ecological and human systems regardless of whether they are for addressing public health, climate change, environmental justice, or land management issues. In this study, we provide monetary estimates of benefits of increasing tree cover by 10% across 10 U.S. cities. These estimates can be used by urban planners to compare with costs of implementing policies to increase tree cover and design optimal policies. A 10% increase in tree cover is within the broad range of historical city goals (Safavi, 2012). Recognizing the importance of urban forests that provide numerous ecosystem services, cities have historically set targets for increasing tree cover. For example, Philadelphia has a goal of increasing city-wide average tree cover from 20% to 30% by 2025, Washington, DC from 34% to 40% by 2035. In light of pressing climate change concerns, tree cover goals are also included in climate action plans. For example, Phoenix has a goal of achieving 25% tree & shade canopy in pedestrian areas by 2030 prioritizing communities most vulnerable to heat (City of Phoenix, 2021). Our estimates can help inform such goal-setting and implementation by cities in an optimal manner.

This study provides estimates for when and where impacts occur within cities. Public health literature indicates that heat events early in the season can pose higher risks because people have not had a chance to acclimatize to warmer temperatures yet. However, the timing of mortality reductions due to increased tree cover varies across cities and the greatest reductions do not typically happen early in the season (Supplementary Material 1). For cooler cities, impacts are greatest during the hottest months. This pattern does not always hold for the hotter cities—humidity plays a role here as well. Further, there is wide variation in where mortality reductions occur within cities and this spatial variation can be informative for addressing environmental justice issues. Impacts are highest where high reductions in heat metrics coincide with larger populations, especially populations with higher baseline mortality (e.g., over 65).

In addition to providing estimated mortality benefits of increasing tree cover by 10%, we examined whether increasing tree cover by the same amount results in similar mortality impacts across the different types of cities. This analysis can inform two policy questions. First, can the results from a specific city be extrapolated to other locations in an accurate and credible manner? Policy analysts must often rely on benefits transfers to assess impacts of policies due to lack of time and resources to conduct new studies for the context at hand (Smith et al., 2002). We find that the heat-related mortality reductions due to the same increase in tree cover vary widely across cities. Population is a primary driver of the estimated total impacts. Other drivers include population age composition and associated baseline mortality rates. Meteorological factors, specifically air and dewpoint temperature trends, also play a dominant role. Differences in these drivers create varying results across the landscape (within and across cities) and through time. Extrapolating results from one city to another will therefore lead to inaccurate estimates of mortality benefits of increasing tree cover. To conduct accurate and credible benefits transfers from one location to another, the environmental and demographic conditions of the locations must be considered carefully.

Second, given that hotter cities potentially have higher mortality under baseline conditions, knowing whether hotter cities benefit more from an increase in tree cover is very relevant for adaptation planning. However, this study shows that this pattern does not always hold due to a variety of factors. Areas with warmer temperatures, drier air, and older populations tend to have greater benefits from increases in tree cover.

Another key policy implication of this study is for northeastern and midwestern cities that typically have relatively cooler summers compared to the rest of the country. While reductions in mortality are relatively low during average conditions throughout the season in these cooler cities, additional tree cover on extremely hot days (relative to historical conditions) may be very beneficial. Increasing tree cover can therefore be an effective adaptive strategy for addressing high mortality from unusually hot temperatures or heat waves in any particular year even in these cooler cities. This is even more relevant in the context of climate scenarios that project increases in the frequency of heat waves and associated mortality (Hayhoe et al., 2010).

Although a direct comparison between results for the two heat metrics assessed in this study is difficult because the binary metric only focuses on extremely hot days and not all days in the season, this study highlights the importance of considering acclimatization to temperature. When comparing the change in per person mortality as a percentage of change in baseline mortality for the binary heat metric versus for the piecewise linear metric, the rankings change dramatically for some cities. Interestingly, Phoenix benefits the most from increasing tree cover whether we consider impacts throughout the season or for extremely hot days. This shows how effective tree cover can potentially be in Phoenix.

More generally, our findings highlight the importance of considering trees as an adaptive strategy for both hot and cool cities. Increasing tree cover by 10% can significantly reduce heat-related deaths in the United States, which have been estimated to range between 1300 and 12,000 deaths annually (Kalkstein et al., 2011; Shindell et al., 2020; Weinberger et al., 2020). While our estimates in reductions may appear large compared to estimates of current heat-related mortality, three factors need to be kept in mind. First, the magnitude of these estimates has changed over time, with more recent studies providing evidence of underestimation in earlier studies. Second, our study models the potential changes in mortality impacts due to increases in tree cover, it does not provide absolute counts of deaths, which may be influenced by factors outside of our modeling context. Third, the importance of increasing tree cover as an adaptive strategy will increase substantially under future climate scenarios. For example, Schwartz et al. (2015) project an increase in the number of deaths by over 27,000 in 2100 compared to 1990 across 209 cities in the United States under climate change scenarios. Shindell et al. (2020) projects an increase in 36,000–97,000 heat-related deaths nationwide compared to the last decade under different climate scenarios. Accounting for adaptation reduces these estimates by about half, but still results in significant projected increases. Although it is difficult to do a direct comparison between this and other studies' results due to differences in methods and data, our study shows that even under current conditions, the potential mortality reduction in New York City alone is almost 4000 deaths annually and in Phoenix is approximately 1500. Our study found that increased tree cover could result in 3%–22% mortality reduction from baseline levels across cities. These magnitudes could potentially increase considering changing temperature, demographic, and other conditions.

5. Conclusion and future research

The goal of this study was to quantify and value the impacts of tree cover on air temperature and mortality across 10 cities in the United States with diverse climatic, land cover, and demographic conditions. We do this by establishing a direct link between increases in tree cover, reductions in temperature, and mortality reductions. Applying estimates of changes in air temperature in this way is a novel use of Yang et al. (2013)'s process-based air temperature model, providing the clarity and adaptability of a mechanistic model, whereas other modeling studies of tree effects on air temperature estimate statistical relationships. Moreover, we apply epidemiological relationships that account for acclimatization. We estimate mortality benefits due to reductions in temperature throughout the season and on extremely hot days, which have important policy implications for hot as well as cool cities. We also examine differences in impacts across cities and this analysis can inform benefit transfers conducted by policy analysts.

While these results can be used to inform climate adaptation strategies and policies to reduce temperature-related mortality, there are various limitations that need to be understood and addressed in future research. First, while we expect the broad patterns in our findings to be stable, this analysis was conducted for 2011 and as such, the estimated impacts and relative ranking of cities are reflective of temperature and other factors during that year. More analysis should be conducted to confirm whether these patterns prevail in other years and cities.

Second, the extreme heat-related impacts of trees in this study are likely conservative. This limitation is primarily because i-Tree Cool Air shows higher responsiveness to land cover change in daytime temperatures than nighttime temperatures (Fig. 3) and our study relies on heat metrics that are based on minimum temperature, which occurs during the night. While the epidemiological literature indicates that nighttime temperature is what drives mortality impacts, if future work incorporates other heat metrics based on daytime or 24-h temperatures, we may see greater impacts. Further, morbidity (USGCRP, 2016) or amenity impacts (Albouy et al., 2016; Sinha et al., 2018) are not included in this study. Other heat metrics that include humidity, for example, need to be explored. Also, i-Tree Cool Air could be modified to simulate anthropogenic contributions to the urban heat island, which are currently unaccounted for in this model. Anthropogenic heat sources include all heat released from human activities, such as from combustion of fuels, friction from machines, and human metabolism.

Third, though the results of this study are spatially explicit and provide information on who benefits more, we do not use epidemiological studies that provide coefficients for different socioeconomic groups. While Sinha et al. (2021) explores age-specific coefficients, we need to incorporate other socioeconomic and demographic characteristics in our modeling framework to address issues of environmental justice more effectively. For example, low-income population groups tend to face higher risks of exposure to extreme heat because they typically live in areas with less greenery (Gerrish and Watkins, 2018; Wen et al., 2013) and often lack resources to adapt and adjust to extreme heat.

Fourth, other conditions that change over time, such as changing tolerance to extreme heat due to increased use of air conditioning and acclimatization, must be considered when applying this method in the future. Another key factor that may change is the spatial distribution of population and demographic characteristics. These changes will be important to account for when assessing impacts of trees under future climate scenarios.

Our study illustrates where tree cover may be more effective as an adaptive strategy in terms of reducing mortality. Hotter and drier cities experience higher percentage reduction in mortality across the season. Cooler cities may benefit less across the season but tree cover can make a significant difference on extremely hot days or under heat wave conditions. More than half of the projected deaths under Schwartz et al. (2015) are in cooler northeastern and midwestern cities, followed by cities in the Pacific Region. Shindell et al. (2020) projects larger per capita heat-related premature deaths in the upper Midwest through the Pacific Northwest and smaller values in the Southeast. Although a direct detailed comparison is difficult given the differences in methods and data, our findings and methods are relevant for designing adaptive strategies to address these projected increases in heat-related deaths under climate scenarios.

This study provides information on both the total magnitude of reduced mortality due to tree cover across cities and the temporal and spatial distributions within each city. This information can support different decision-making efforts related to city planning, environmental management, and public health. For example, land use managers can use this information to optimize tree plantings, and public stakeholders can use these impact estimates for advocacy. Temporal distribution of mortality reductions across the season provides insights on when trees may be most effective while spatial distribution of mortality reductions within each city provides information on where trees are likely to be more effective within cities and who benefits from increasing tree cover. Quantitative estimates of spatial and temporal patterns from this study provide crucial information needed for designing targeted policies to address public health, equity, and environmental justice issues.

Declaration of competing 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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2021.113751.

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