Ecological Modelling 449 (2021) 109553

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

Modeling lives saved from extreme heat by urban tree cover☆

Paramita Sinha [a,*], Robert C. Coville [b], Satoshi Hirabayashi [b], Brian Lim [a], Theodore A. Endreny [c], David J. Nowak [d]

[a] RTI International, 3040 E. Cornwallis Road, Research Triangle Park, NC 27709, USA
[b] USDA Forest Service/Davey Institute, Davey Tree Expert Company, 5 Moon Library, SUNY-ESF, Syracuse, NY, 13210, USA
[c] Department of Environmental Resources Engineering, SUNY ESF, Syracuse, NY 13210, USA
[d] USDA Forest Service, Forest Inventory and Analysis, 5 Moon Library, SUNY-ESF, Syracuse, NY 13210, USA

ARTICLE INFO

Keywords:
Ecosystem services
Heat-related mortality
Vulnerability
Health impacts
Economic valuation
Human well-being
Urban heat island
Modeling temperature changes
i-Tree

ABSTRACT

Urban tree cover contributes to human well-being through a variety of ecosystem services. In this study, we focus on the role that trees can play in reducing temperature during warm seasons and associated impacts on human health and well-being. We introduce a method for quantifying and valuing changes in premature mortality from extreme heat due to the changes in urban tree cover and apply this method to Baltimore City, Maryland. The model i-Tree Cool Air uses a water and energy balance to estimate hourly changes in air temperature due to alternative scenarios of tree cover applied across 653 Census Block Groups. The changes in temperature are applied to existing temperature–mortality models to estimate changes in health outcomes and associated values. Existing tree cover in Baltimore is estimated to reduce annual mortality by 543 deaths as compared to a 0% tree cover scenario. Increasing the area of current tree cover by 10% of each Census Block Group reduced baseline annual mortality by 83 to 247 deaths (valued at $0.68 –2.0 billion applying Value of Statistical Life estimates). Over half of the reduced mortality is from the over 65 year age group, who are among the most vulnerable to extreme heat. Reductions in air temperature due to increased tree cover were greatest in downtown Baltimore where tree cover is relatively low and impervious cover is relatively high. However, the greatest reductions in mortality occurred in the outskirts of Baltimore where a greater number of people who are over 65 years in age reside. Quantifying and valuing the health benefits of changes in air temperatures due to increased tree cover can inform climate adaptation and mitigation plans by decision makers. Developing adaptation strategies to effectively address these issues will become increasingly important in the future under changing climates and an aging population.

1. Introduction

Urban tree cover provides a myriad of ecosystem services and contributes to human health and well-being at local, regional, national, and global scales. Tree cover benefits include air and water filtration; temperature, climate and water regulation; noise reduction; increased biodiversity and pollination; and esthetic improvements (Bolund and Hunhammar, 1999; Gómez-Baggethun and Barton, 2013; Nowak and Dwyer, 2007). Through quantification and valuing of these services, tree cover effects can be incorporated within city actions to improve public health (Haase et al., 2014). Estimates of monetary benefits provide a common metric that can be compared with costs of implementing the policies and support the development and prioritization of optimal policies. Thus, efforts to expand and improve the quantification and valuation of urban tree services are critical for improved decision making in urban environments, and thereby advance the United Nation's Sustainable Development Goals (U.N. General Assembly, 2015).

Air temperature reductions caused by the presence of trees are getting increasing attention due to changing climates (NPR, 2019). Although based on different data and methods (and thus not directly comparable), existing studies provide insights on the issue of heat-related mortality. In the United States, an average of 702 heat-related deaths occurred annually between 2004 and 2018 (Vaidyanathan et al., 2020). However, this estimate uses data from medical records, which often do not capture the role of heat in exacerbating other causes of death not explicitly categorized as heat-related

☆Declarations of interest: None.

* Corresponding author.
E-mail address: psinha@rti.org (P. Sinha).

https://doi.org/10.1016/j.ecolmodel.2021.109553
Received 1 October 2020; Received in revised form 30 March 2021; Accepted 1 April 2021

(USGCRP, 2016). A study using statistical approaches estimated more than 1,300 deaths per summer during the 1975–2004 period (Kalkstein et al., 2011). More recent studies provide evidence of even higher estimates. For example, Weinberger et al. (2020) estimate over 5,000 annual deaths between 1997 and 2006 in 297 counties (representing 61.9% of the total population in the country), and Shindell et al. (2020) estimate about 12,000 premature deaths annually due to heat-related deaths over the last decade. During a heat wave year, the total number of deaths is estimated to be substantially larger. For example, a heat wave in Chicago in July 1995 resulted in approximately 700 deaths (Kaiser et al., 2007), and one in Europe led to more than 70,000 deaths in summer 2003 (Robine et al., 2008). The number of premature heat-related deaths in the summer is projected to increase by the thousands under climate change scenarios in the United States and similar trends would be seen in different parts of the world (USGCRP, 2016; Gasparrini et al., 2017). Extreme heat can also result in morbidity impacts such as heat exhaustion and heat cramps, as well as exacerbate respiratory and cardiovascular illnesses (Guo et al., 2018).

People with specific demographic and socioeconomic characteristics are more sensitive to extreme heat (Gamble et al., 2016). Among them are adults above the age of 65, who are more sensitive to extreme heat due to issues related to thermoregulation, preexisting diseases, need to rely on others, and limited mobility (Balbus and Malina, 2009; Basu and Samet, 2002; Benmarhnia et al., 2015; Gamble et al., 2013). Projected increases in heat-related health impacts and differences in population vulnerability to extreme heat have important implications for public health and environmental justice. Developing adaptation strategies to effectively address these issues will become increasingly important in the future.

Quantifying and valuing the health benefits of changes in air temperatures due to increased tree cover can inform climate adaptation and mitigation plans made by decision makers. Evidence from the literature suggests that increasing tree cover in cities can reduce air temperatures and urban heat island effects (e.g., Akbari et al., 2001), yet these findings are often limited to a few small empirical studies (Bowler et al., 2010). Heavily forested parks in Baltimore have been shown to have up to 7.1 °C cooler air temperatures in the evening and about 2.7 °C cooler temperatures in the daytime relative to the inner city (Nowak and Heisler, 2010). Cooler air temperatures have direct and indirect benefits for human health (Kovats and Hajat, 2008). Even small differences in seasonal average temperatures can affect human mortality and public health (USGCRP, 2016). In New York City, deaths during heat waves were less likely among residents living in areas with more green space (Madrigano et al., 2015).

The goal of this study was to introduce and demonstrate a method and tool for quantifying and valuing changes in mortality from extreme heat due to the presence of tree cover. Existing studies that quantify temperature–mortality impacts of increased tree cover primarily use a greenspace exposure–mortality dose–response approach (e.g., Kondo et al., 2020) without directly modeling temperature changes. In our study, we employ an approach similar to Nowak et al. (2013a, 2014), who investigated air pollution removal effects of urban trees. We first estimate air temperature changes due to changes in tree cover and then link these temperature changes to changes in premature mortality by applying estimated extreme temperature–mortality relationships from the epidemiological literature. To the best of our knowledge, this direct link to temperature changes has not been explicitly modeled and incorporated in a tool before. Inclusion of this linkage can facilitate development of efficient adaptation strategies under different climate scenarios and enhanced tree cover in targeted areas to reduce human mortality.

This work adds to an existing suite of urban forest modeling tools developed by the U.S. Department of Agriculture (USDA) Forest Service and its partners in the i-Tree consortium.[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, 2013b, 2014, 2017). In this study, we expand the suite of i-Tree benefits to include air temperature and human health impacts of trees during warm seasons, and we also demonstrate how our approach can be implemented by others through use of an illustrative case study for the city of Baltimore, Maryland.

2. Methods

i-Tree generally uses a four-step process to assess and value benefits from trees: quantifying forest structure, modeling the functions of that forest structure, estimating the impacts that humans experience from those forest functions, and applying economic valuation to those impacts. In our study, while keeping the same broad approach, we tailor these steps for assessing the heat-related mortality impacts and associated economic values due to tree cover change. Our first step is to quantify relevant structural features, which include the amount of tree canopy cover and impervious cover present and baseline reference meteorological observations. In the second step, we estimate the impact of current and alternative tree cover scenarios on air temperature using the i-Tree Cool Air model (Yang et al., 2013). The third step applies relationships between extreme temperature and mortality from the epidemiological literature to the population that is exposed to air temperature changes. The last step involves conducting benefits transfers to value changes in premature mortality using evidence from economic valuation literature. The methodology for this study was designed to work in cities across the United States and is demonstrated using the study area of Baltimore, MD. The city of Baltimore consists of 653 Census Block Groups and these polygon areas were used as the spatial unit for implementing each of the four steps (U.S. Census Bureau, 2010). Census Block Groups were chosen to balance computational time and spatial resolution. Change in mortality results were aggregated up to the entire city area, rounding to whole numbers as a last step in reporting.

2.1. Quantify urban tree and impervious cover

Existing 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). Finer resolution land cover data was available in Baltimore, but the dataset used was selected because its coverage extends throughout the United States and our goal is to develop a method that can be applied to other cities across the country. Zonal Statistics in ArcMap was applied to the 30-m resolution NLCD data to assign mean percent tree cover and impervious cover to each Census Block Group polygon area and this defined the baseline conditions. Other land cover types, including surface water, may be present, but only tree cover and impervious cover were simulated to isolate the effects of those land cover types for land management decision support. The most important land cover types driving air temperature are impervious and tree canopy. In a detailed field study of the urban heat island in Madison, WI, the land cover types of impervious and tree canopy had the greatest effect on air temperature, with no observed effects of elevation and the effect of three large adjacent water bodies limited to an average of 0.25 C along the shoreline (Ziter et al., 2019). Where tree cover percent and impervious cover percent summed to less than 100%, remaining land cover was assumed to be bare soil as inputs for temperature modeling.[2]

[1] www.iTreeTools.org

[2] This simplifies comparisons between land cover scenarios by avoiding evapotranspiration energy fluxes from short vegetation.

Table 1
Studies examining relationships between temperature and mortality.

Heat Metric	Months	Geography	Age Groups	Mortality Classification (Epidem. Study)	Mortality Classification (Incidence Data)	Control for Ozone	Beta Coefficient	St. Error
Basu et al. (2005)								
Daily mean temp.	Jun-Aug	Northeast	65–99	Cardiorespiratory mortality	Mortality, Cardiopulmonary	No	0.0105	0.0052
Medina-Ramon & Schwartz (2007)								
Binary variable indicating extremely hot day or not*	May-Sep	All of US	0–99	Mortality, All Cause	Mortality, All Cause	No	0.0558	0.0115
						Yes	0.0479	0.0107
Piecewise linear metricˆ	May-Sep	All of US	0–99	Mortality, All Cause	Mortality, All Cause	No	0.0052	0.0010
						Yes	0.0043	0.0009
Medina-Ramon et al. (2006)								
Binary variable indicating extremely hot day or not*	Apr-Oct	All of US	0–99	Pneumonia	Mortality, Respiratory	No	0.0080	0.0334
				Stroke	Mortality, Cardiopulmonary	No	0.0257	0.0144
				Cardiovascular Diseases	Mortality, Cardiopulmonary	No	0.0100	0.0131

* Extremely hot days are those with daily minimum temperature at or greater than the 99th percentile.
ˆ Heat metric takes value zero when the daily minimum temperature is <= 17 °C and varies linearly with minimum temperature when minimum temperature is above 17 °C.
Note: Results presented here do not represent all results in each study. Several studies presented results for multiple Mortality Classifications, Study Populations, Thresholds, and/or Temperature Metrics. For further information, see the individual studies.

With impervious cover held constant in each Census Block Group, the effects of three alternative tree cover change scenarios on air temperature were assessed: 1) increasing the existing tree cover by 10% of each Census Block Group's area, 2) removing 10% of each Census Block Group's area from existing tree cover, and 3) removing all existing tree cover in each Census Block Group. The alternative of increasing tree cover by 10% is intended to demonstrate a simple scenario that is broadly applicable and in line with goals historically adopted by cities. For example, Baltimore's goal is to establish 40% tree cover by 2030. Other assessments of increasing tree cover also use similar scenarios. Philadelphia has a goal of at least 30% tree cover in each of the city's neighborhoods and impacts of this goal were assessed by Kondo et al. (2020). For approaches on more nuanced development of canopy goals, see Leff (2016). The 0% tree cover alternative is commonly used by i-Tree to assess impact and costs avoided due to current tree cover. The baseline tree and impervious cover and alternative tree and impervious cover scenarios served as the inputs to modeling temperature changes as described in Section 2.2.

2.2. Modeling temperature changes due to tree cover

Air temperature and humidity for baseline and alternative scenarios were estimated using the i-Tree Cool Air model based on methods detailed by Yang et al. (2013) and an interpolation routine. The Cool Air model estimates this weather at approximately 2 m elevation, within the urban canopy layer, using observed meteorological data, land cover and topography data, and hydrology and energy budget parameters.[3] The model assumes that all simulated locations within the city area have the same overlying mesoscale climate and uses the weather station record from one location to estimate the properties of temperature and humidity for all other locations. The approach involves solving 10 coupled energy and water balance equations and is designed to consider effects of land cover albedo, roughness height, topographic slope and aspect, and water storage in soil, surface depressions, and the tree canopy. To clarify the impact of tree cover on temperature for this study, simulations were simplified so that all Census Block Groups used the same reference weather station, neglected topographic slope effects on solar exposure, and used the same set of parameters related to water and energy budget equations.

Weather data from the Baltimore-Washington International Airport (WBAN 93,721) station 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). Weather inputs for the i-Tree Cool Air model include hourly air temperature, dew point temperature, wind speed, precipitation, observed and net radiation, and direct and diffuse solar radiation estimated at the reference weather station. For this case study, 3 years of meteorology inputs were used to assess model sensitivity to weather year. For the decade of 2007–2017 the typical, maximum, and minimum yearly average air temperatures nationwide were identified.[4] 2011 represents the typical annual average nationwide for that period, 2012 represents the hottest annual average, and 2008 represents the coolest annual average.

The i-Tree Cool Air model simulated hourly air temperature for the warm season months of April and October for what are identified as four edge cases of tree cover and impervious cover (0% tree cover and 0% impervious cover, 100% tree cover and 0% impervious cover, 0% tree cover and 100% impervious cover, and 100% tree cover and 100% impervious cover). Percent impervious and tree cover in each Census Block Group are not mutually exclusive in the NLCD dataset used as an input in this study. It is possible that impervious cover and tree cover can sum to values greater than 100%, since tree canopy cover can overlap impervious cover. The impervious cover under tree canopy is not explicitly represented in the energy-balance simulation because i-Tree Cool Air represents only one layer in the energy balance (Yang et al., 2013). Therefore, the edge case of 100% tree cover and 100% impervious cover yields the same results and effectively we simulate three edge cases. The reference weather defines the mesoscale climate that drives the energy budget of the three edge cases. Those edge case results were used to linearly interpolate hourly results for all 1% increments of impervious cover and tree cover from 0% to 100%. The purpose of estimating results for a full range of tree cover and impervious cover combinations was to enable users to assess a range of land cover change scenarios when this model is incorporated into i-Tree Tools. Interpolation was used to simplify, smooth, and improve efficiency of temperature results for the 10,201 land cover scenarios assessed (101 × 101 combinations of tree cover and impervious cover incremented from 0% to 100% at 1% intervals). A lookup table was used to link the estimated

[3] See table of temperature calculation parameters for i-Tree Cool Air in Supplementary Material.

[4] Nationwide temperatures were used for consistency when expanding this modeling framework to cities of various climates in a future study.

air temperature and humidity data for the combinations of tree and impervious cover under baseline and alternative scenarios identified for each Census Block Group using Zonal means of the NLCD data. The temperature and humidity records were used as inputs for the analysis of premature mortality as described in Section 2.3.

2.3. Estimating the changes in premature mortality

Our approach for modeling the connection between human health, extreme temperature, and tree cover is similar to the connection developed between human health, air pollution, and tree cover, in which epidemiological studies use either air pollution or extreme temperature as inputs and not the tree cover (Nowak et al., 2013a, 2014). We selected a set of studies from the epidemiological literature that estimated the relationship between extreme heat exposure and mortality, ensuring they were applicable to the study area (Table 1). Basu et al. (2005) included data from 20 metropolitan areas across the country and covers a range of temperature conditions. This study provides estimated coefficients for different regions and the coefficient for the Northeast was applied to Baltimore. Medina-Ramon et al. (2006) and Medina-Ramon and Schwartz (2007) include data from Baltimore in their analysis and provide nationwide estimates which we apply. City-specific studies, although ideal, are unavailable for all cities in the country. Since our goal is to provide a method that can be applied to different locations, we apply these three studies as a starting point. These relationships were then applied to the relevant population in each Census Block Group.

A wide variety of definitions and measures—including ambient temperature, heat index (a combination of temperature and dew point), and heat waves (exceeding predefined thresholds over a number of days)—represent extreme heat in the epidemiological literature. Different metrics such as average, minimum, or maximum daily temperatures, nighttime temperatures, or daytime temperatures have been used to define extremes. Predefined thresholds vary from specific temperatures such as 35 °C to historical local averages or percentiles. Studies have shown that people can adapt at least partly to the temperature they are used to due to infrastructure and physiological acclimatization and that the health impact of temperature can vary with location (Medina-Ramon et al., 2006; Sarofim et al., 2016). In other words, a 35 °C air temperature will impact people in Phoenix, Arizona differently than people from Boston, Massachusetts; what is extreme is relative to the typical local conditions. However, there is also evidence suggesting that there are heat tolerance limits (Sherwood and Huber, 2010). This lack of a standard definition is well documented in the research on climate impacts on human health (Smith et al., 2013; Sarofim et al., 2016).

The epidemiological studies selected for this study (Table 1) represent a range of extreme heat metrics. The heat metrics were calculated as per the definitions in the epidemiological studies. Basu et al. (2005) use daily mean temperature as the heat metric. Medina-Ramon et al. (2006) employ a city-specific binary variable to determine whether it is an extremely hot day. In this study, extremely hot days are defined as those with daily minimum temperature at or greater than the 99th percentile for Baltimore.[5] The minimum temperature is used as an indication of nighttime relief from heat. Medina-Ramon and Schwartz (2007) used the same heat metric as Medina-Ramon et al. (2006) but also used a piecewise linear metric where there are no impacts if the daily minimum temperature is 17 °C or less and impacts are linear above that temperature. As shown in Table 1, the three studies encompass different months.

The data for these heat metric calculations were obtained from the baseline and alternative scenarios' hourly temperature estimates from i-Tree Cool Air as described in Section 2.2. Changes in each heat metric (ΔHEAT) were obtained by taking the difference in the heat metric under the alternative scenario and the baseline tree cover–impervious cover conditions[6] as follows:

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

Mathematically, estimating the changes in mortality (Δy) due to change in each heat metric entails applying a health impact function (Voorhees et al., 2011) that transforms a change in heat exposure to a change in mortality as follows:

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

where y_0 is the baseline health incidence rate for mortality for each age group; ΔHEAT is the change in the heat metric; P is the exposed population for each age group; and β represents the relationship between the change in the heat metric and mortality for the relevant age group and was derived from the heat exposure-mortality response relationships in the selected epidemiological studies. Information on the functional form of the exposure-response relationships in each study was used to mathematically derive β and the associated confidence interval. Studies use various functional forms and covariates including air pollution that may be correlated with heat exposures. As we are focusing on warm seasons, ozone levels are likely to be high and there is emerging evidence of interactions between air pollution and temperature which impact human physiological response to each of those stressors (Analitis et al., 2014; Fann et al., 2016; Jhun et al., 2014; Madrigano et al., 2015; Medina-Ramon, and Schwartz, 2007). Not controlling for ozone, which is correlated with temperature, would result in biased estimates for the β coefficient on the heat metric. Medina-Ramon and Schwartz (2007) find that controlling for ozone reduces the β coefficient on the heat metric. Applying coefficients without ozone controls would therefore result in overestimates of mortality reduction.

County-level baseline incidence rates for cause-specific mortality were obtained for each age group from BenMAP-CE (CDC 2015; Sacks et al., 2018). Mortality classifications in the incidence data and epidemiological studies did not match exactly so we made the closest match possible as shown in the two columns for mortality classification (one for the epidemiological study and the other for incidence data) in Table 1.

Population for 5-year age groups at the Census Block Group level was obtained from the 2010 decennial census (Manson et al., 2020). Representing different age groups accurately is crucial because baseline incidence rates for cause-specific mortality vary across age groups and exposure-response functions are age-specific. Since the younger age groups in data sources for baseline incidence rates and for population were not completely aligned, an adjustment was performed. More specifically, BenMAP-CE has baseline incidence rates for ages 0 and 1 to 17, while the decennial census has population for ages under 5, 5 to 9, 10 to 14, and 15 to 17 years. Assuming that the population under 5 is uniformly distributed across the ages 0 to 4, 1/5 of the population under 5 years was used for the population for age 0. Similarly, 4/5 of the population under 5 years was used for the population for ages 1–4, which was summed with populations for 5 to 9, 10 to 14, and 15 to 17 years to obtain the population for ages 1 to 17. Above 18 years, the age groups in the two data sources were matched, and thus no adjustment was performed.

When applying each epidemiological study to calculate the mortality impacts, we use the relevant months, population age groups, heat

[5] Since the estimated β coefficients of the study represented deviations from the 99th percentile for 1989–2000, we used hourly measurements at the reference weather station (WBAN: 93721) for the same time period and our computed value for the 99th percentile of daily minimum temperature was 24°C.

[6] For the heat metric corresponding to Medina-Ramon et al. (2006) that was based on the 99th percentile threshold, binary indicator variables were used to calculate whether the threshold was exceeded under the baseline and alternative scenarios.

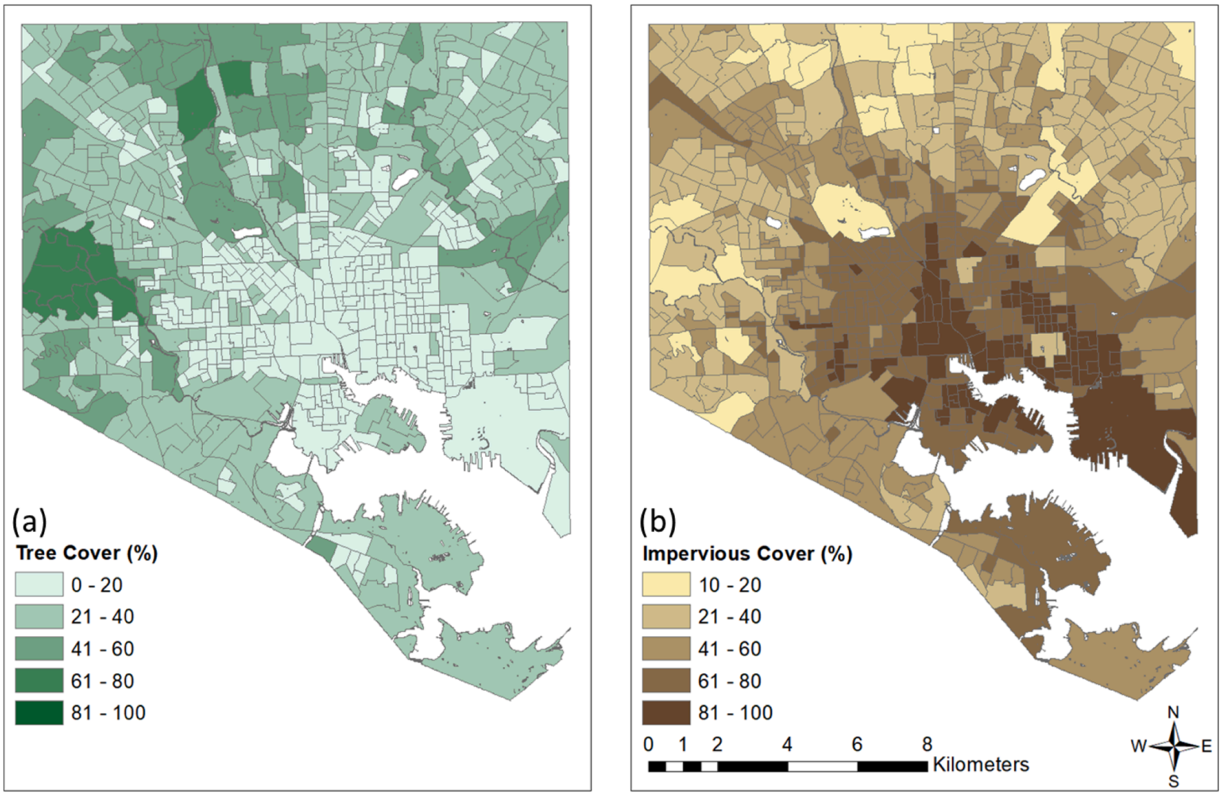

Fig. 1. Baseline land cover conditions (a) Tree cover (b) Impervious cover.

metrics, and β. 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 {Δy_{UB}, Δy_{LB}} using the confidence interval {β_{UB}, β_{LB}} to represent the uncertainty in β estimates. Results for each specification of the model run (heat metric - health endpoint - β - population) are presented separately. Since the model runs represent different heat metrics, health endpoints, and population groups, it is not appropriate to average or aggregate results. Further, retaining the full range of the results for different model runs allows us to compare results across the model specifications and provides options for considering research questions that are interesting to the reader.

2.4. Estimating the monetary value of human health benefits

The monetary benefit of the change in mortality (B) was estimated using the above computed change in mortality (Δy) along with the Value of a Statistical Life (V), and calculated as:

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

The Value of a Statistical Life is defined in the economics literature as the willingness to pay for a small reduction in risk of death in the population for a group of people. The estimate that is typically used in benefits analysis conducted by the U.S. EPA (2018) was applied in this study ($7.4 million in 2006 dollars). We adjusted this value to 2011 dollars using the Consumer Price Index Inflation Calculator from the U. S. Bureau of Labor Statistics, 2020 and obtained a value of $8.22 million. As per the guidance of U.S. EPA, this same value is applied to the whole population regardless of age, income, or other population characteristics.

3. Results and discussion

3.1. Quantify urban tree and impervious cover

The amount of tree cover and impervious cover under baseline conditions in each of Baltimore City's 653 Census Block Groups in 2011 is shown in Figs. 1a and 1b respectively. Tree cover estimates are conservative as NLCD is known to underestimate tree cover (Nowak and Greenfield, 2010). We expect that the NLCD underestimation of tree cover does not affect the impacts of adding tree cover, because tree cover effects are linearly interpolated as described in Section 2.2. The 0% tree cover scenario is affected by the NLCD underestimation of tree cover, where the estimated impacts and economic values for the 0% tree cover scenario represent change from an underestimated baseline tree cover and therefore are a lower boundary of results. Tree cover in downtown Baltimore was low (≤20%) and higher in the city's outskirts (≥20%). The most forested Census Block Group had 73% tree cover and the least forested had 0% tree cover. There were 93 Census Block Groups with less than 10% tree cover and 81 of those had 0% tree cover. Conversely, impervious cover in downtown Baltimore tended to be high (>60%), while it was lower in the city's outskirts (≤40%). The most impervious Census Block Groups had 100% impervious cover and the least impervious had 10% impervious cover. There were 55 Census Block Groups with impervious cover of 90% or more and 3 of those had 100% impervious cover. The effect on tree cover of removing or adding 10% tree cover in each of Baltimore City's Census Block Groups is shown in

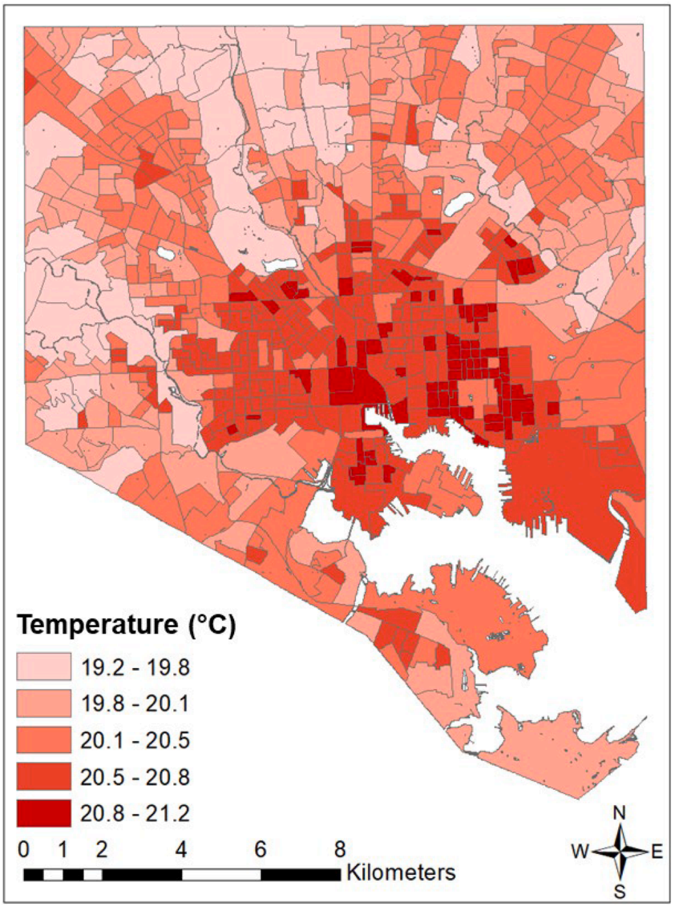

Fig. 2. Baseline temperature for each Census Block Group averaged over April to October.[8]

Appendix Figs. A1.a and A1.b.[7] As described in Section 2.1, surface water cover was not accounted for in this model, and of the 653 Census Block Groups in Baltimore, only 29 (4%) included water bodies.

3.2. Modeling temperature changes due to tree cover

Baseline average air temperatures from April to October for Baltimore City's Census Block Groups range from 19.2 °C to 21.2 °C, with highest impervious cover and lowest tree cover being the hottest (Fig. 2). A time series of baseline minimum, average, and maximum air temperature among all Census Block Groups for the same period shows the months of May, June, and July have some of the hottest weather, with maximum temperatures reaching 40 °C (Fig. 3). Although the average temperature (shown by the red line in Fig. 3) reaches its highest value near 35 °C on July 22, approximately midway through the warm season, there is considerable variation across the period and within each month. The difference between the baseline minimum and maximum temperatures ranges from 1.2 °C on September 6 to 22.7 °C on April 4.

Analysis of the simulated years of 2008, 2011, and 2012 showed common patterns in temperature changes between the baseline tree cover and the alternative scenarios, and 2011 was selected as a representative case. Although we conduct our analysis for all three alternative scenarios, we primarily focus on the alternative of increasing tree cover by 10% for the purposes below.[9]

As summarized in Table 2, the heat metrics derived from the i-Tree Cool Air model results vary across the selected epidemiological studies and are based on either average or minimum temperatures. Maps of the reductions in average and minimum air temperatures with 10% increases in tree cover are shown for the hottest day of the season, July 22, 2011 (Fig. 4a and 4b). While the spatial distribution of the reductions is similar for both the average and the minimum, the reductions in average temperature range from 0.33 °C to 0.57 °C, while the reductions in minimum temperature range from 0.09 °C to 0.33 °C. This indicates that if other parameters including β in Eq (2) are held constant, the health impacts would be lower for a heat metric that uses the minimum temperature. The same pattern holds for reductions in the daily average and daily minimum air temperatures averaged across all the months between April and October (Figs. 4c and 4d). The greater magnitude reduction in average temperatures compared with minimum temperatures fits trends in the i-Tree Cool Air model where maximum temperatures (and thus averages) are more sensitive to changes in tree cover than are minimum temperatures. All four maps show temperature change to be higher downtown, which has a higher impervious cover and lower tree cover, indicating the higher impact of increased tree cover in areas where the baseline tree cover is low and impervious cover is high.

To better understand how changes in premature mortality vary across the warm season months, the monthly reductions in average and minimum air temperatures caused by increased tree cover are presented in Figs. 5a and 5b. Overall a U-shaped trend is seen where the temperature reduction is smallest in April and October and the greatest reduction in temperature is in July for both average and minimum. These monthly average temperature reductions smooth out the much larger hourly and daily temperature reductions caused by increasing tree cover. Across all days and Census Block Groups in the warm season, the maximum reduction in average (minimum) temperature is 0.63 °C (0.56 °C) and the minimum reduction in average (minimum) temperature is 0.01 °C (0.06 °C). There is high variance across the Census Block Groups with July having the greatest variance for both average and minimum air temperatures.

3.3. Estimating the changes in premature mortality

3.3.1. Changes in heat metrics

The heat metric of Basu et al. (2005) focuses on June, July, and August, the summer season's three hottest months. The heat metric in this study is the daily average temperature and as seen in Fig. 3, this metric (averaged across all Census Block Groups) ranges from 20 °C to 35 °C during these three months in our study year of 2011. Under the alternative scenario of increased tree cover, the maximum and minimum reductions in the monthly mean of the average temperature for the three summer months of June, July, and August are 0.40 °C and 0.19 °C,

[7] When removing 10% tree cover, the extent of tree cover for the 93 Census Block Groups that had less than 10% tree cover was set at or left at 0% and thus not reduced by a full 10%. This asymmetry is indicative of a limitation in simple alternative scenarios being broadly applied to all Census Block Groups. For example, assessing the removal of 10% tree cover is irrelevant in the 81 out of 653 Census Block Groups that have a baseline of 0% tree cover. This asymmetry does not prevent the identification of overall trends in impact for this case study.

[8] Temperatures are based on mesoscale climate calculated from a reference weather station (Baltimore/Washington International Thurgood Marshall Airport) located outside of the study area, as described in section 2.2.

[9] The asymmetry of alternative scenario changes to tree cover has only a small effect on temperature impacts for all years and alternative scenarios. When adding or removing 10% of tree cover from each Census Block Group's area, the interquartile range of impact on air temperature is equivalent with one significant figure of precision: the 25th and 75th percentile impact for both alternative scenarios ranges from a 0.4°C to a 0.5°C change in mean temperature across all Census Block Groups for the hottest day, July 22, 2011.

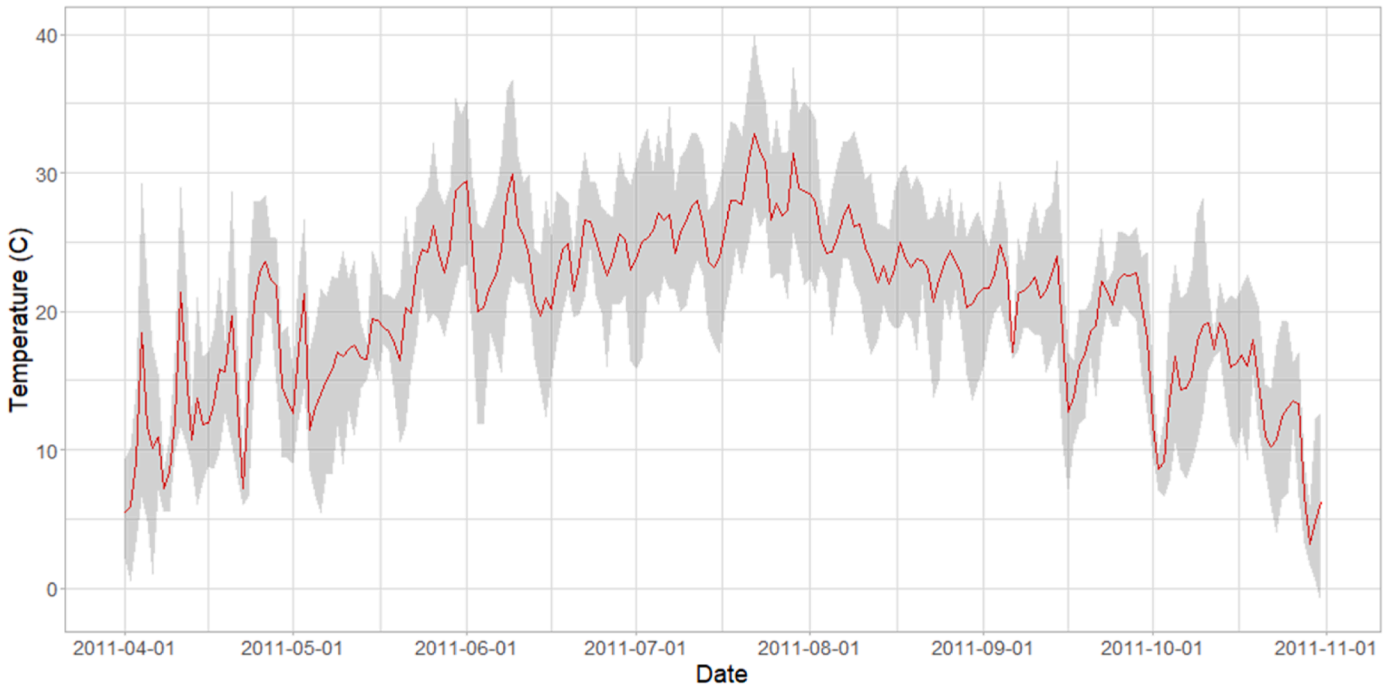

Fig. 3. Time series of baseline daily temperature range (in gray) and average (in red), averaged over the 653 Census Block Groups.

Table 2
Change in Mortality† and Associated Monetary Benefits Under the Alternative Scenario of Increasing Tree Cover by 10% of Census Block Group Area.

Study	Heat Metric	Mortality Classification	Age Groups	Control for Ozone	Change in Incidence			Economic Value (2011 $billions)		
					LB*	Center*	UB*	LB*	Center*	UB*
Basu et al. (2005)	Daily mean temperature	Cardiorespiratory mortality	Over 65	No	−213	−423	−632	-$1.751	-$3.473	-$5.193
Medina-Ramon & Schwartz (2007)	Binary variable indicating extremely hot day or not	Mortality, All Cause	All ages	No	−58	−96	−133	-$0.476	-$0.790	-$1.096
				Yes	−47	−83	−118	-$0.386	-$0.681	-$0.969
	Piecewise linear metric	Mortality, All Cause	All ages	No	−181	−298	−416	-$1.488	-$2.453	-$3.417
				Yes	−141	−247	−353	-$1.158	-$2.029	-$2.900
			Over 65	No	−105	−172	−240	-$0.860	-$1.418	-$1.975

†Under the alternative scenarios of increasing tree cover by 10%, mortality is reduced from baseline conditions. Hence the table shows negative values.
*Center uses the estimated Beta coefficient. LB and UB denote estimates using lower and upper bounds of the 95% Confidence Interval for the estimated Beta coefficient.

respectively (Fig. 5).

As with Basu et al. (2005), the heat metric of Medina-Ramon and Schwartz (2007) is also linear but is based on daily minimum temperature and assumes no heat exposure unless the minimum temperature exceeds 17 °C. The minimum temperature (averaged across all Census Block Groups) ranged from 5.4 °C to 27.4 °C between May and September. The maximum and minimum reductions in the monthly mean of the minimum temperature for the five months are 0.17 °C and 0.04 °C respectively as shown in Fig. 5.

Comparing the metrics from the two studies, we see that as summarized in Section 3.2, the reduction in minimum temperatures is less than that of average temperatures. In addition, the Medina-Ramon and Schwartz (2007) study assumes a truncated heat metric, where any health impacts below a minimum temperature of the 17 °C threshold are zero.[10] In our study, for about 33% of the time the minimum temperatures were below 17 °C for both the baseline and alternative scenarios across the Census Block Groups. The change in heat metric in such instances is zero. Further, about 0.4% of the time, increased tree cover under the alternative scenario results in temperatures dropping from above 17 °C to below 17 °C. In such cases the impacts on heat metrics are

[10] Figure A.2 in the appendix shows that the drop in heat metric values (averaged across Census Block Groups) representing the piecewise linear metric from Medina-Ramon and Schwartz (2007) is always less than the Basu et al. (2005) metric, since the line showing the latter is always below the former. For Medina-Ramon and Schwartz (2007), the line coincides with the horizontal axis for some days, which denotes a no changes in the heat metric.

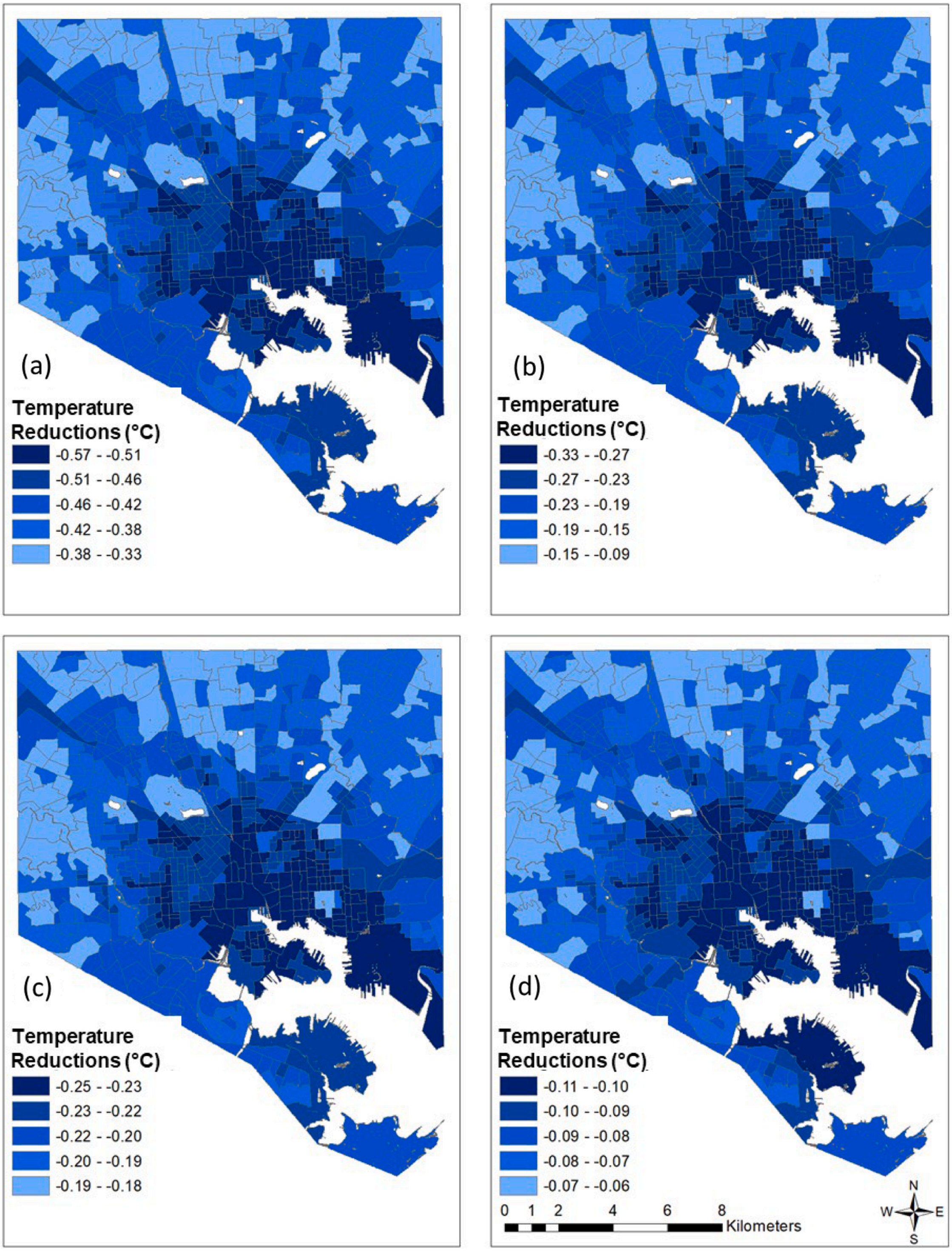

Fig. 4. Reductions in (a) average and (b) minimum temperature on hottest day (7/22/2011), and (c) average and (d) minimum temperature averaged over April to October, under the alternative scenario of a 10% increase in tree cover.

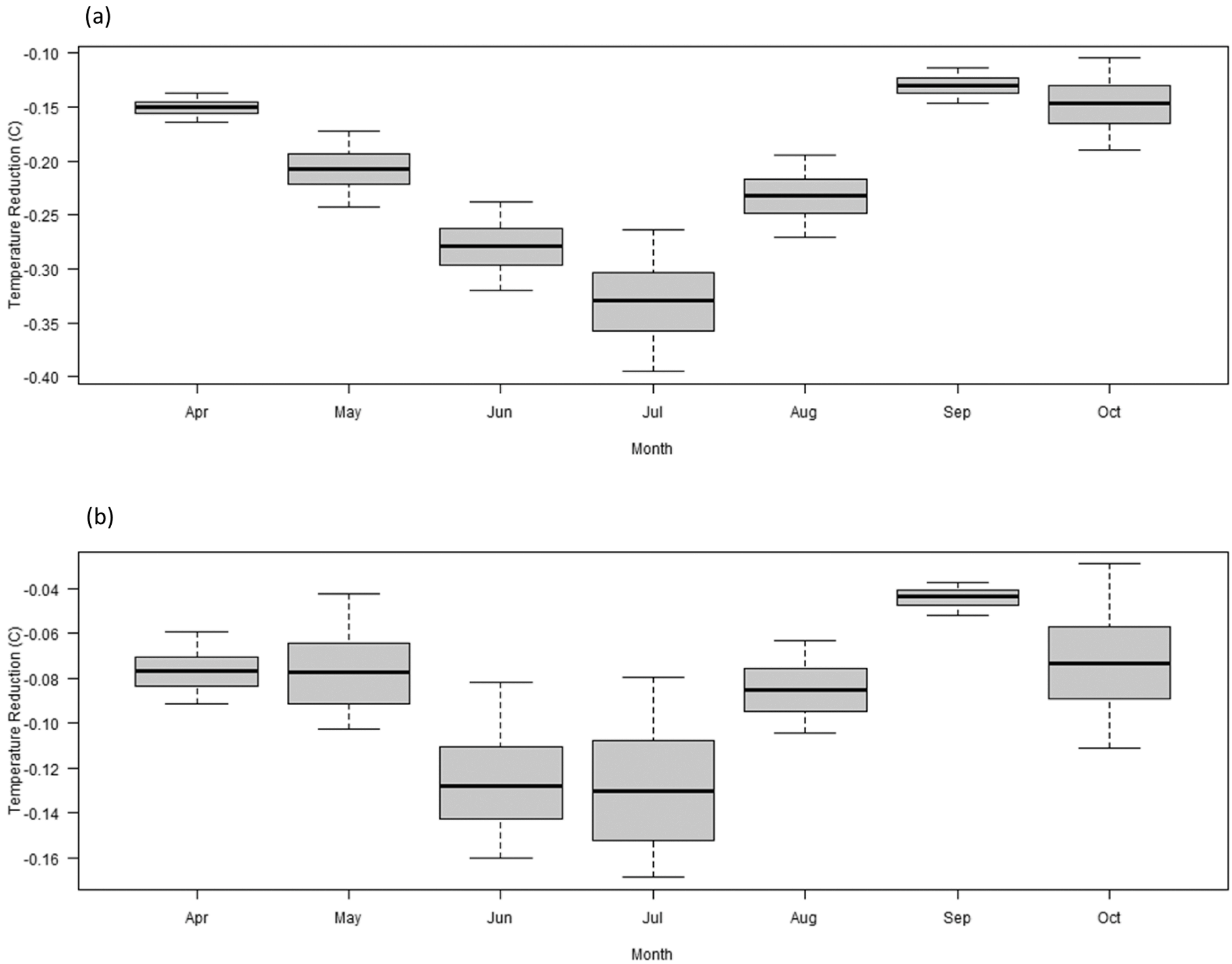

Fig. 5. Spatial distribution across all Census Block Groups for monthly average of reductions in daily (a) average and (b) minimum temperature under the alternative scenario of a 10% increase in tree cover.

limited by the 17 °C threshold.[11]

The Medina-Ramon et al. (2006) and Medina-Ramon and Schwartz (2007) studies both use a binary heat metric to define extremely hot days. For these studies, reductions in heat metrics only occur if the increase in tree cover causes the minimum temperature to drop from above the historical threshold to below the threshold. For this to happen, two conditions must be satisfied. First, the minimum temperature under the baseline conditions must be above 24 °C, and second, the increase in tree cover must cause enough of a temperature drop to change the binary heat metric from 1 to 0. Extremely hot days are defined as days where minimum temperatures cross historical thresholds, so a priori we expect that the number of days with temperature conditions satisfying the first condition for each Census Block Group will be small. This is evidenced in our data where there are 10 days where minimum temperature is above 24 °C. The number of days that the binary heat metric switched from a value of 1 to 0 varied across the study area, with only 28% of Census Block Groups experiencing a change of 1 or 2 days; 151 (23%) had a change on 1 day, 33 (5%) had a change on 2 days; and the remainder experienced no change (Fig. 6).

3.3.2. Changes in premature mortality

Estimated heat metric results applied using the Medina-Ramon and Schwartz (2007) approach provide impacts for the broadest range of health endpoints (all-cause mortality) and all age groups. Further, this study also estimates exposure-response relationships controlling for ozone. Applying the β coefficient on the piecewise linear heat metric in Medina-Ramon and Schwartz (2007), we find that the estimated number of deaths avoided when tree cover is increased by 10% of Census Block Group area is 247 with a 95% confidence interval of 141 to 353

[11] Figure A.3 shows the number of days that minimum temperature was below 17°C under both the baseline and alternative scenarios for each Census Block Group. Figure A.4 shows the number of days that minimum temperature changed from above 17°C to below 17°C under the alternative scenario of increasing tree cover by 10% of the Census Block Group area.

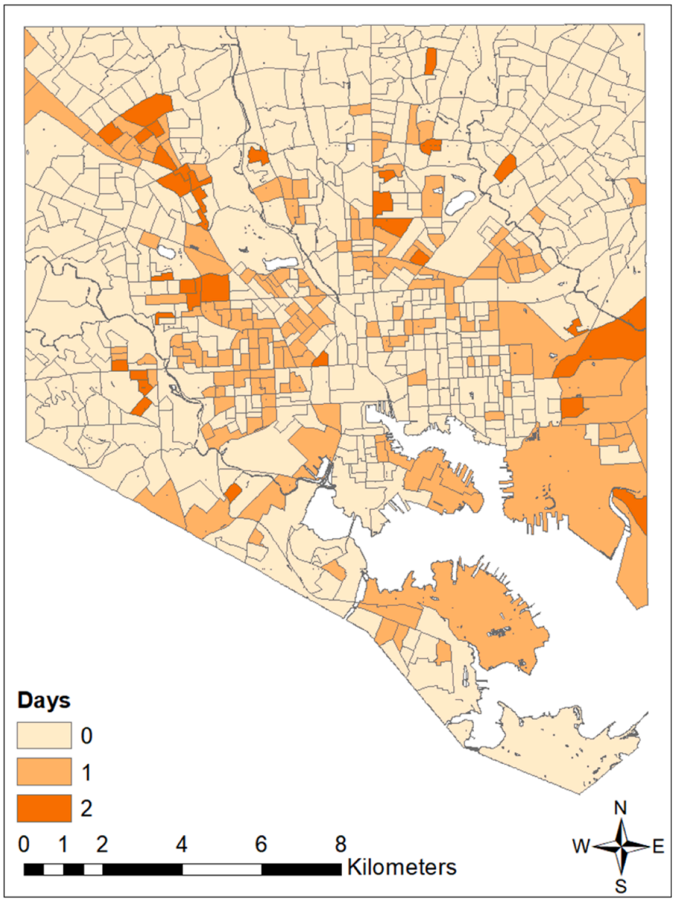

Fig. 6. Number of days for each Census Block Group when 10% increase in tree cover caused daily minimum temperature to drop from above historical threshold (24 °C) to below threshold for May through September.

(Table 2).[12] These impacts are 17% lower than when applying β coefficients without controlling for ozone to the same piecewise linear metric, which yields 298 avoided deaths.

To incorporate another type of heat metric typically used in the public health literature, we apply the binary metric from Medina-Ramon and Schwartz (2007) to assess the health impacts of the alternative scenario of increasing tree cover. The β coefficient for this binary metric is roughly 10 times higher than that of the piecewise linear metric from the same study, indicating a much stronger mortality response to an extremely hot day as compared to less extreme temperatures. However, the number of extremely hot days are limited (in 2011, this was 10). Hence, whether smaller or larger health impacts in total are expected with binary metrics versus piecewise linear metrics is an empirical question and will depend on the number of days that the binary heat metric changes from 1 to 0. Applying the β coefficient on the binary heat metric that also controls for ozone, the mortality reduction is 83 with a confidence interval of 47 to 118.[13] Although this is a much smaller impact compared to the estimated avoided deaths from applying the piecewise linear metric, this result is not surprising given the small number of days that the binary heat metric changes from 1 to 0 in 2011 as illustrated in Fig. 6 and described in detail in Section 3.3.1. If the study year included a higher number of extreme heat days (e.g., in a heat wave year), the estimates would be much higher.

The public health literature shows that the population over 65 is more sensitive to extreme heat, so we also show results for the Basu et al. (2005) approach, which represents cardiorespiratory mortality for adults in this age group. Basu et al. (2005) and Medina-Ramon and Schwartz (2007) differ in terms of the age groups, months covered, data and methods, heat metrics, and mortality causes, thus making a direct comparison of results challenging. The most meaningful comparison between the two is to consider the β coefficient on the piecewise linear metric of Medina-Ramon and Schwartz (2007) that does not control for ozone with the linear metric of Basu et al. (2005).

Given the lower baseline incidence rates for cardiorespiratory mortality[14] and the reduced population represented by the elderly, along with fewer months assessed, smaller impacts were expected using Basu et al. (2005). However, the larger β coefficient in Basu et al. (2005) would be expected to result in greater impacts, potentially due to a greater response for the hottest months and/or vulnerability to the heat exposures for the population over 65. Further, as described in Section 3.3.1, because the change in heat metrics is larger for Basu et al. (2005), reductions in mortality would also be expected to be lower using the Medina-Ramon and Schwartz (2007) study. Which study yields a higher net impact is therefore an empirical question.

When applying the Medina-Ramon and Schwartz (2007) β coefficient for all ages to only the adults over 65, the avoided mortality is 172 (95% confidence interval is between 105 and 240) while the avoided mortality for Basu et al. (2005) is 423 (95% confidence interval is between 213 and 632). The mean estimates for Medina-Ramon and Schwartz (2007) are lower despite being applied to a higher baseline incidence for all-cause mortality and to a larger number of months. This lower estimate is potentially due to a combination of the smaller reduction in heat metrics (as described in Section 3.3.1) and smaller β coefficient of Medina-Ramon and Schwartz (2007). Even if the same heat metrics were used, the fact that the β coefficient for Medina-Ramon and Schwartz (2007) is roughly half of Basu et al. (2005) highlights the importance of distinguishing vulnerable age groups and applying the age-specific coefficients relevant for vulnerable age groups.

In addition to the mortality impacts, another question that is extremely relevant for decision makers is the spatial distribution of the impacts. The mortality impacts estimated with Basu et al. (2005) tend to be lowest near Baltimore downtown and higher in the outskirts (Fig. 7a). This result is not in line with the temperature reductions, which occur more in the downtown area (Fig. 4). However, as Fig. 8a shows, the population over 65 is more concentrated in the outskirts, and the spatial distribution of impacts lines up closely with that of the population (the magnitude of the Pearson's correlation coefficient is 0.94). As shown in Fig. 7b, the distribution of mortality impacts using Medina-Ramon and Schwartz (2007) but applied to the population over 65 shows a similar pattern (the magnitude of the Pearson's correlation coefficient is 0.93).[15] Further, applying the Medina-Ramon and Schwartz (2007) approach to all age groups, we see that the mortality impacts (Fig. 7c) and total population (Fig. 8b) have similar spatial distribution patterns (the magnitude of the Pearson correlation coefficient is 0.58), with more impacts downtown than for the population over 65 years in age. In comparison, heat metric changes showed very low correlation with the mortality impacts estimated for the total population using the

[12] Table A.1 in the appendix also provides mortality impacts associated with the other 2 alternative scenarios.

[13] As shown in Table 2, estimates with ozone controls for the binary metric are lower than with no controls by about 14%.

[14] Mortality rates from all causes includes cardiorespiratory causes as well as other causes, hence cardiorespiratory incidence rates are smaller.

[15] We expect the correlation between population and mortality impacts for Medina-Ramon and Schwartz (2007) to be different from Basu et al. (2005). This is because the spatial distribution of impacts, although similar, is not identical. The different heat metrics used in the two studies combined with different β coefficients account for the difference in the spatial distribution of impacts.

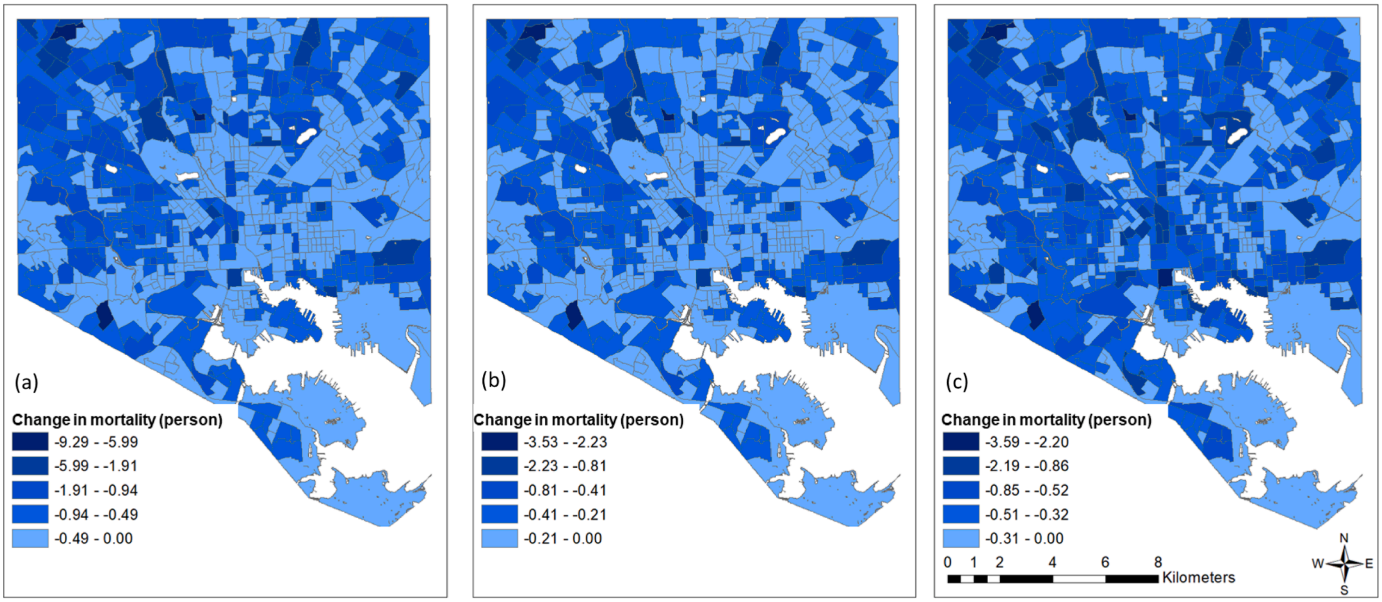

Fig. 7. Changes in mortality for (a) cardiorespiratory causes over 65 years old (Basu et al., 2005), (b) all causes for over 65 years old (Medina-Ramon and Schwartz, 2007), and (c) all causes for all ages (Medina-Ramon and Schwartz, 2007) due to 10% increase in tree cover. Note: Under the alternative scenario of increasing tree cover by 10%, mortality is reduced from baseline conditions. Hence the maps show negative values.

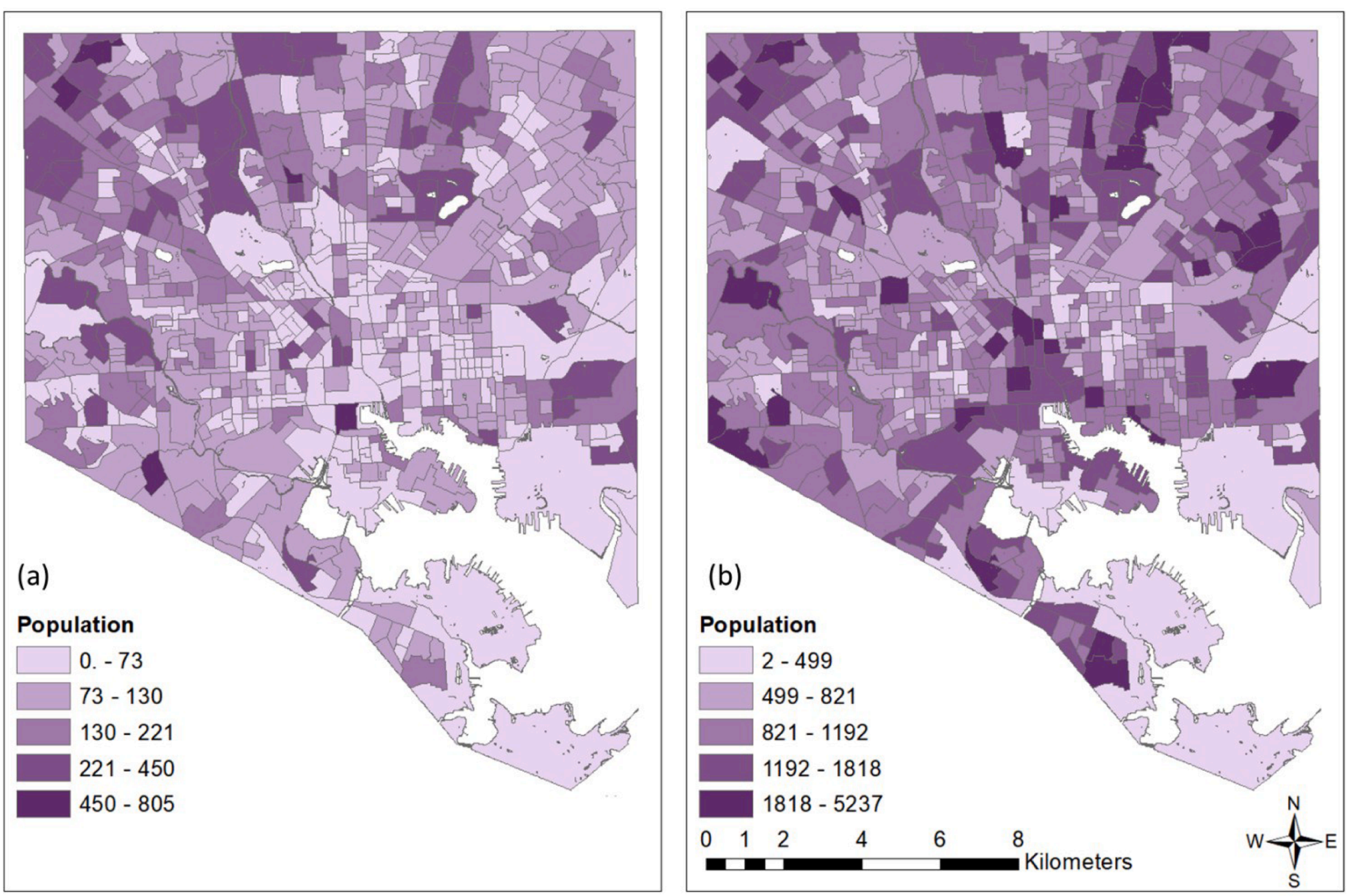

Fig. 8. Population (a) over 65 years old and (b) all ages.

Medina-Ramon and Schwartz (2007) approach (the magnitude of the Pearson correlation coefficient is 0.001). A key implication of these results is that in Baltimore, the largest impacts of increased tree cover are seen where the exposed population resides, not necessarily where the temperature changes are the greatest. If a policy goal is to reduce temperature risks to vulnerable populations, it is important to increase tree cover in areas where susceptible populations reside, not necessarily where there is low tree cover or where temperature reductions can be the greatest.

Given the difference in estimates among the various studies and metrics, the question is which metric is appropriate for decision makers? The answer depends on the audience and context of the analysis. As the piecewise linear metrics used by Medina-Ramon and Schwartz (2007) represent the entire population and all mortality causes, it would provide average city-wide estimates. These estimates would be appropriate for decision makers such as city planners in typical years (i.e., without heat waves). The binary metric in this study assumes that there is no mortality impact of warmer temperatures unless they are extreme. Given that the piecewise linear metrics provide significant results for less extreme temperatures, the use of binary metrics is more restrictive. However, in the context of climate change, where the number of extremely hot days is projected to increase significantly, assessments using the binary heat metric can potentially inform preparedness efforts (e.g., cooling centers) and response plans for heat waves and thus provide useful information to the public health community. The results may be closer using these two types of metrics for heat wave years if minimum temperatures stay the same on average but there are more days with extreme heat. If the focus is on the population over 65, the linear Basu et al. (2005) metric would yield estimates that can be considered as upper bounds for cardiorespiratory mortality specific to this age group, and policies based on these estimates would be most protective of that group. More detailed information about impacts on specific causes of mortality, such as pneumonia, stroke, and cardiovascular diseases, might be useful for the public health community as well. We applied the same binary heat metric from Medina-Ramon et al. (2006) to calculate reductions in pneumonia, stroke, and cardiovascular disease-related mortality, which were 1, 18, and 7 deaths, respectively, under the scenario of increasing trees.[16]

Though this case study focuses primarily on impacts for the scenario of increasing tree cover by 10%, two other scenarios were assessed (described in Section 2.1). For city-wide mortality using the Medina-Ramon and Schwartz (2007) study, while the scenario of increasing tree cover by 10% of each Census Block Group's area was estimated to result in 251 deaths avoided, reducing tree cover by 10% of each Census Block Group's area was estimated to result in 220 more deaths. The asymmetry of health impacts when increasing and reducing tree cover by the same amount is expected because the health impact function is non-linear and because of the asymmetry in structure and temperature impacts of these alternative scenarios as described in Sections 3.1 and 3.2.[17] Removing all tree cover from each Census Block Group was estimated to result in 551 more deaths. This 0% tree cover scenario indicated that Baltimore's baseline tree cover in 2011 avoids 551 deaths from mortality city-wide per year.

3.4. Estimating the monetary value of human health benefits

The mean estimate for monetary values of reductions in mortality (shown in Table 2) using the Medina-Ramon and Schwartz (2007) piecewise linear approach (when controlling for ozone and applied to all age groups) is $2.06 billion with a 95% confidence interval of $1.18 billion to $2.95 billion. Applying the binary heat metric from the same study, the estimate is $692.63 million with a 95% confidence interval of $393 million to $986.04 million.

The monetary value of the reduced mortality for the population over 65 using the Basu et al. (2005) approach is $3.47 billion (95% confidence interval between $1.75 billion and $5.19 billion) and using the Medina-Ramon and Schwartz (2007) piecewise linear approach is $1.42 billion (95% confidence interval between $0.86 billion and $1.98 billion). Estimates from the Basu et al. (2005) study may be considered as upper bounds for cardiorespiratory mortality. Table A.1 in the appendix also provides monetary values associated with the other two alternative scenarios for Basu et al. (2005) and Medina-Ramon and Schwartz (2007). Table A.2 shows the health and monetary impacts using the Basu et al. (2005) approach for all three years and Fig. A.5 shows the spatial distribution for mortality reductions in 2008 and 2012.

To place these results in context with other impacts of ecosystem services provided by urban tree cover, the monetary benefits of Baltimore's current tree cover from reducing heat are more than 100 times larger than from reducing $PM_{2.5}$ concentrations on average (Nowak et al., 2013a). The study of $PM_{2.5}$ reduction is comparable in that both studies represented all causes of mortality associated with an environmental factor ($PM_{2.5}$ or heat metrics), assessed a 0% tree cover alternative to estimate the impact of current tree cover, and used the Value of Statistical Life to estimate monetary benefits. The studies differ in that Nowak et al. (2013a) used different age group delineations (0–1 and 25–99), analysis year (2010 instead of 2011), dollar year (2015 instead of 2011), scale of result (by city instead of by Census Block Group), and source of tree cover data (2005 field samples instead of 2011 NLCD). Although $PM_{2.5}$ levels vary across cities and therefore the benefits of pollutant removal also vary, baseline levels of pollution in the United States are in the range of the National Ambient Air Quality Standards and thus the marginal benefits of reducing $PM_{2.5}$ are relatively small as compared to heat-related mortality, which is a leading cause of death from natural weather or environmental events in the United States (APHA, 2018). Increasing tree cover can therefore play a critical role in reducing heat-related mortality impacts under current conditions and an even bigger role under future climate scenarios.

4. Conclusion and future research

The goal of this study was to introduce and demonstrate a method for quantifying and valuing changes in mortality from extreme heat due to the presence of tree cover. This method provides the foundation for the spatially-explicit decision-support tool i-Tree to incorporate heat-related mortality. This method will be implemented in the i-Tree model to allow users to assess mortality impacts of changes in tree cover across the warm season and provide valuable information to city planners and the public health community. Future work will explore the potential for i-Tree to include a range of health impact functions (e.g., different heat metrics, coefficients that are specific to vulnerable populations) that will allow users to assess a wide set of research questions such as the role trees can play in reducing mortality impacts under different climate and population scenarios.

To further facilitate environmental policymaking, we apply the

[16] These estimates are not additive with the overall estimates from the other two studies; rather, they provide impacts on more detailed causes of mortality.

[17] Each source of asymmetry acts in a different direction: ΔHEAT used as an exponential in the health impact function means reducing tree cover (resulting in positive ΔHEAT) is expected to have a larger health impact, but asymmetry when removing tree cover (due to 14.2% of Census Block Groups having <10% baseline tree cover) reduces the city-wide impact of the reduced tree cover scenario.

National Ecosystem Services Classification System (NESCS) Plus classification system (Newcomer-Johnson et al., 2020) to the ecosystem service we quantify and value in this study. Mortality impacts of temperature reductions due to increased tree cover can be assigned a NESCS Plus code of 27.1.1092.211 (Environment Class: Urban/-Suburban (27); Ecological End-Product: Atmosphere (1); Direct Use: Support of human health and life (1092); Direct User: Households (211)). Using a common classification code can support policymaking by helping organize measures of ecosystem service benefits and providing a common language across disciplines.

Results indicate that approximately 251 deaths (95% confidence interval of 143 to 358) can be avoided in the city of Baltimore (total population of 620,961) with a 10% increase in tree cover. We also find that more than half of the reduced mortality impacts are for the population over the age of 65 (which is about 12% of the total population) who are known to be vulnerable to extreme heat. Controlling for ozone is important to account for interaction effects with temperature and we find that impacts on premature mortality are lower but remain in a similar range. Even under the most conservative approach, with only extreme temperatures above 24 °C assumed to have a mortality impact (and therefore impacts in 2011, which is not a heat wave year, are limited to a few days and Census Block Groups), 84 (95% confidence interval of 48 to 120) deaths are avoided annually in Baltimore alone. The economic value of these avoided deaths is large, ranging from $690 million to $2.1 billion when we consider ozone effects. There is potential for even larger benefits given that tree cover can be increased by much more in some areas. Spatial distribution of impacts shows that the greatest reductions in mortality occurred in the outskirts of Baltimore (where a greater number of people who are over 65 years in age reside) rather than downtown (where the temperature reductions are greatest). These spatial patterns have important policy implications. For example, our analysis highlights the importance of identifying areas with plantable space and vulnerable populations to maximize human health benefits from urban forests in each city. Further, assessing spatially-explicit impacts of alternative tree cover scenarios can help develop more targeted and efficient policies to promote environmental justice and equity.

Our estimated results are broadly consistent with other studies that quantify mortality impacts of increased tree cover using different methods. For example, Kondo et al. (2020) project reducing premature deaths by about 400 (95% confidence interval of 298 to 618) by increasing Philadelphia's tree cover to 30%. Given that the spatial and temporal aspects as well as the study data and methods (including the extent of tree cover change assessed) are different between the two studies, a direct comparison is difficult. However, the results appear to be in a similar range.

While this study is a first step to modeling temperature impacts of trees on human health, there are several ways in which a more comprehensive assessment can be made. In subsequent analysis on the temperature modeling side, i-Tree Cool Air could be modified to simulate anthropogenic contributions to the urban heat island. This would include heat released from human activities, such as from combustion of fuels, friction from machines, and human metabolism. The signature of anthropogenic heating is often clearest in nighttime temperatures where it can add 2 °C to 3 °C, and during peak activity it can contribute on the order of 100 W/m^2 to net heat inputs (Sailor, 2011).

Although the monetary value of avoided mortality impacts from increasing tree cover is large, mortality is not the only impact of temperature on human well-being. Further research should investigate temperature impacts on other health conditions such as heat stroke, heat exhaustion, heat cramps, as well as respiratory and cardiovascular illnesses, low birth weight, and mental distress. Research could also investigate how these changes in air temperature affect human comfort (e.g., Sinha et al., 2018).

Estimating the impacts of tree cover for different U.S. cities will also expand our knowledge on the variation of potential impacts of urban trees on air temperature and human health. Exploring whether the binary metrics and the piecewise linear metrics yield results that are more similar in analysis conducted for a heat wave year would be interesting. Further, we find that more than half the impacts are for a vulnerable age group (population over 65). For a more comprehensive assessment, future models will need to incorporate other demographic and socioeconomic factors associated with health impacts from extreme heat (USGCRP, 2016).

Our findings for Baltimore suggest that temperature reductions can potentially contribute to human health and well-being significantly in the light of the large number (approximately 12,000) of heat-related deaths in the United States each year and the projected increases in such deaths due to changing climates. Increasing tree cover can therefore play an important role in adaptation strategies for cities to mitigate the effects of rising temperatures and reduce urban heat island effects. The method demonstrated here can be applied to inform the development of climate adaptation strategies in an optimal manner. For example, estimates of monetary benefits provide a common metric that can be compared with the costs of implementing the policies. Further, such holistic assessments of benefits provide evidence-based support for policies, which can provide significant public health and economic benefits to cities. Examining spatial variations of impacts among different socioeconomic and demographic groups could also help address public health, environmental justice, and equity issues and reduce risks to vulnerable populations.

Credit author statement

Paramita Sinha: Conceptualization, Methodology, Investigation, Formal analysis, Writing - Original Draft, Supervision, Visualization, Project administration, Funding acquisition **Robert C. Coville:** Formal analysis, Software, Data Curation, Validation, Investigation, Writing - Original Draft, Visualization, Funding acquisition **Satoshi Hirabayashi:** Formal analysis, Software, Data Curation, Visualization, Writing-Reviewing and Editing, **Brian Lim:** Formal analysis, Investigation, Visualization, **Theodore A. Endreny:** Supervision, Methodology, Investigation, Formal analysis, Software, Validation, Writing- Reviewing and Editing, Funding acquisition **David J. Nowak:** Conceptualization, Supervision, Writing- Reviewing and Editing, Funding acquisition

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.

Acknowledgments

We acknowledge financial support from the 2018 U.S. Forest Service National Urban and Community Forestry Challenge Cost-Share Grant Program (Federal Award Identification Number 18DG-11132544–014) and an RTI internal grant. We thank Jennifer Richkus for coordination support for the project collaborators.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2021.109553.

Appendix

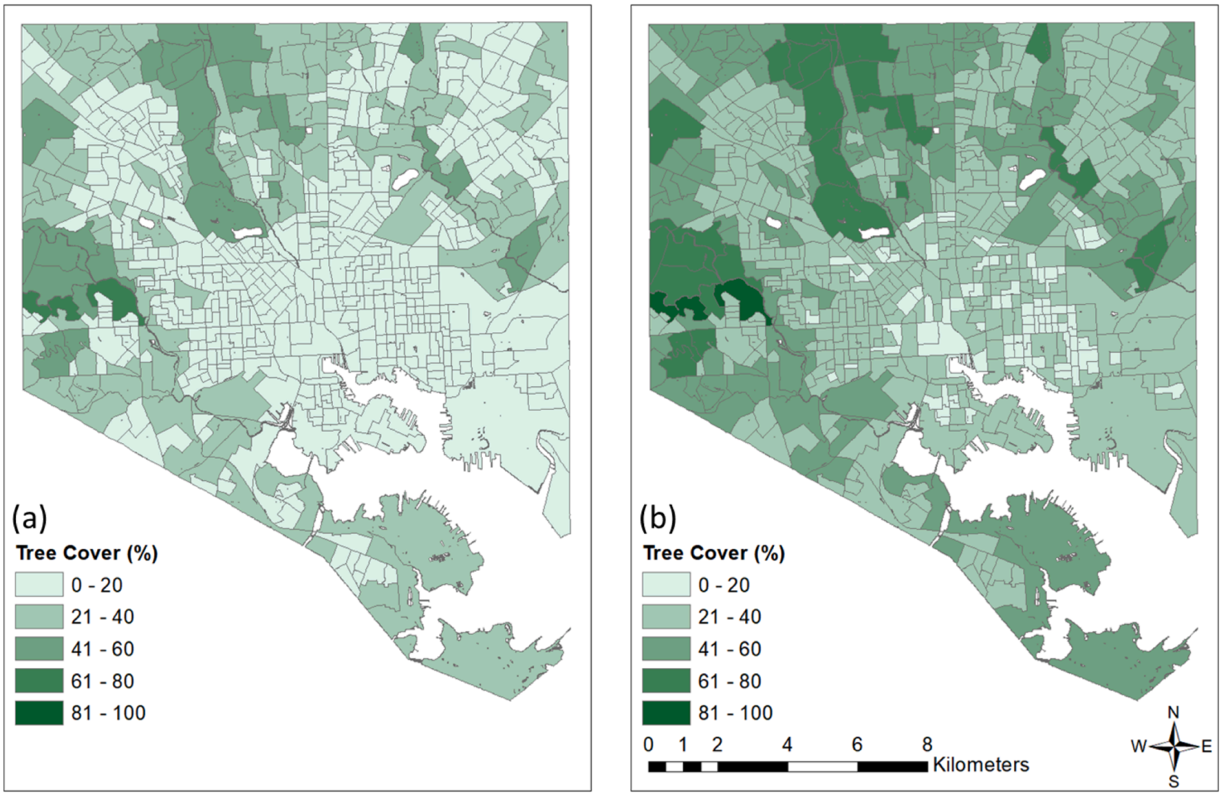

Fig. A.1. Alternative Tree Cover Scenarios (a) Baseline tree cover - 10% of Census Block Group area (b) Baseline tree cover +10% of Census Block Group area.

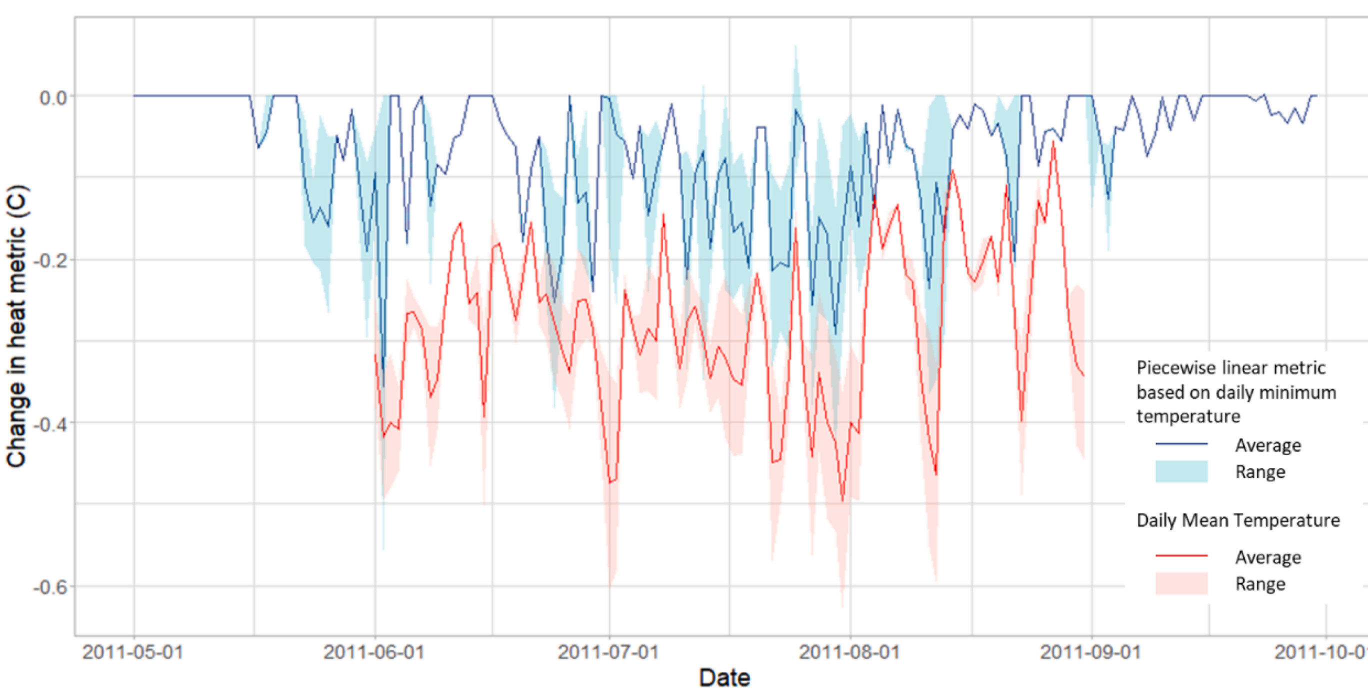

Fig. A.2. Time series of change in daily heat metrics over 653 Census Block Groups for alternative scenario of a 10% increase in tree cover versus baseline.

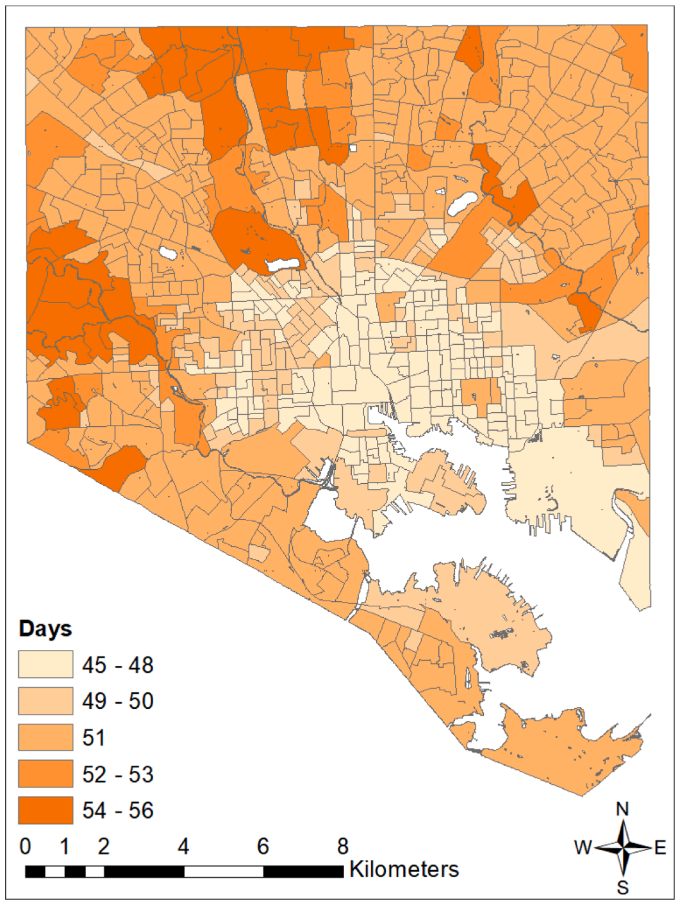

Fig. A.3. Number of days at each Census Block Group when daily minimum temperature for baseline and alternative scenario of a 10% increase in tree cover is below threshold (17 °C) for May through September.

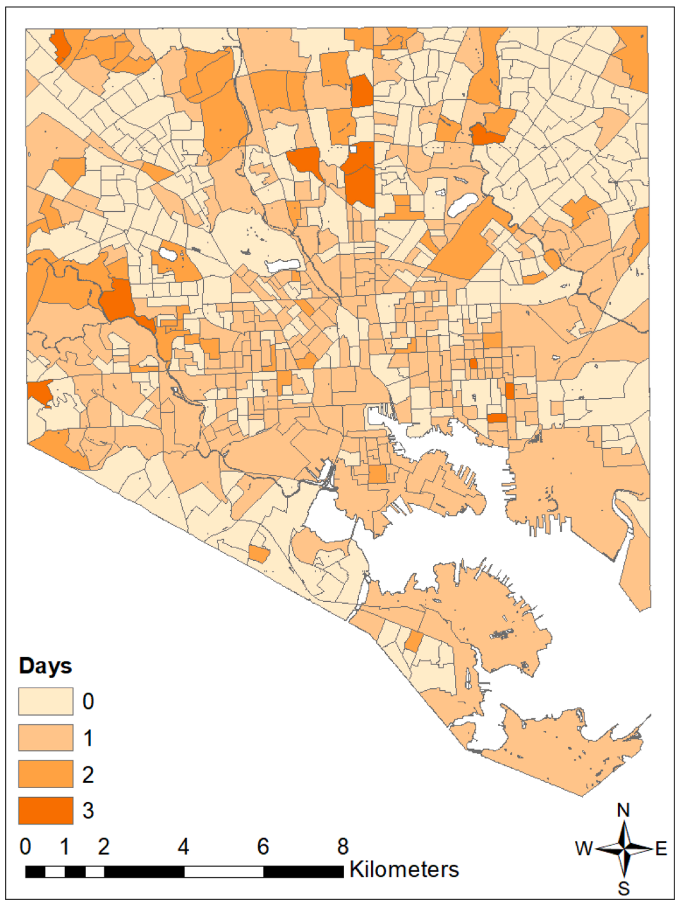

Fig. A.4. Number of days for each Census Block Group when 10% increase in tree cover caused daily minimum temperatures to change from above 17 °C to below 17 °C for May through September.

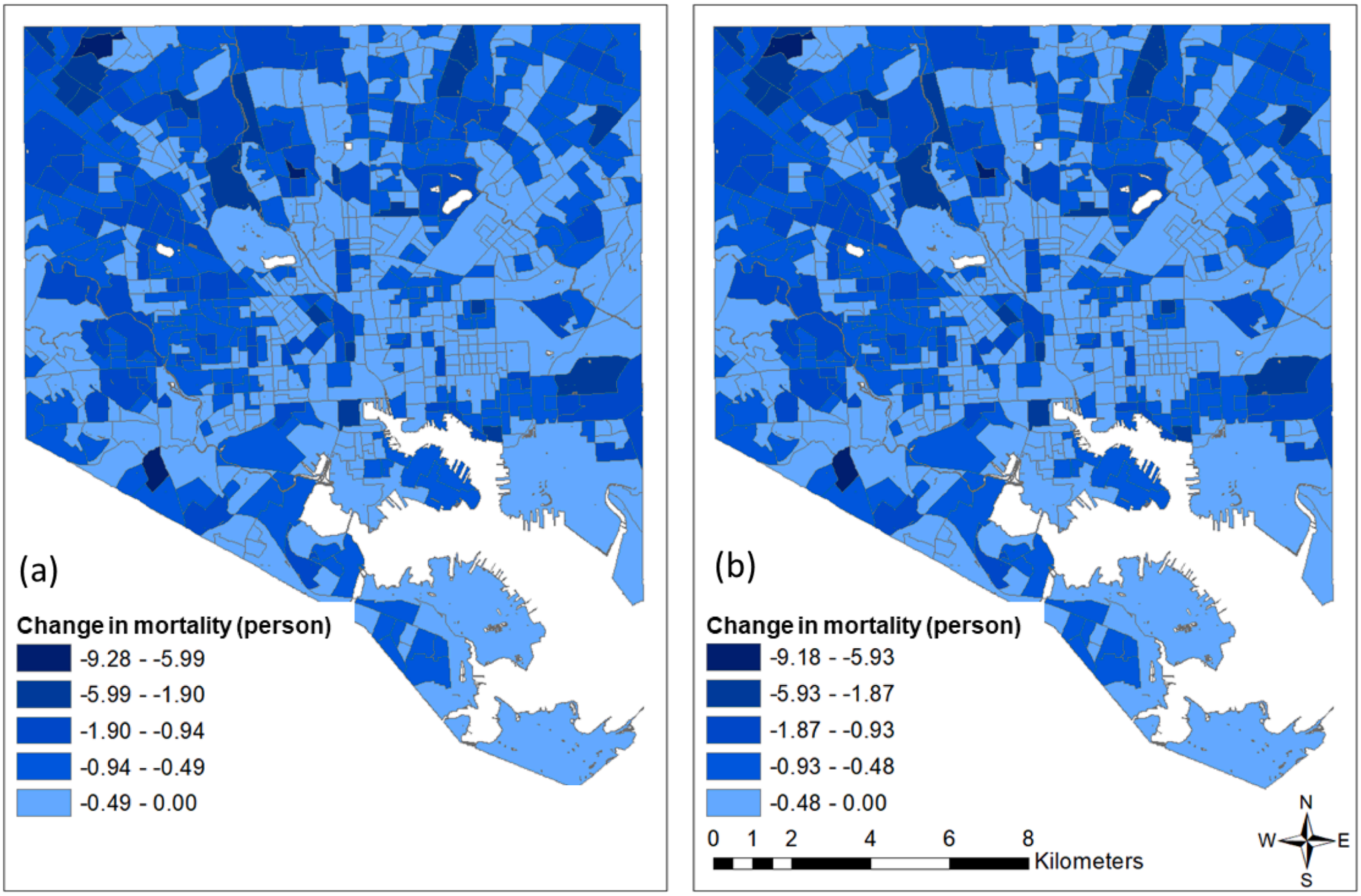

Fig. A.5. Changes in cardiorespiratory mortality for population over 65 years old (Basu et al., 2005) due to 10% increase in tree cover using weather data for (a) 2008 and (b) 2012. Note: Under the alternative scenario of increasing tree cover by 10%, mortality is reduced from baseline conditions. Hence the maps show negative values.

Table A1
Change in Mortality† and Associated Monetary Benefits Under the Alternative Scenarios of Reducing Tree Cover by 10% of Census Block Group Area and of Zero Tree Cover.

Study	Heat Metric	Mortality Classification	Age Groups	Control for Ozone	Change in Incidence			Economic Value (2011 $billions)		
					LB*	Center*	UB*	LB*	Center*	UB*
Reducing Tree Cover by 10% of Census Block Group Area										
Basu et al. (2005)	Daily mean temperature	Cardiorespiratory mortality	Over 65	No	191	380	569	$1.571	$3.121	$4.674
Medina-Ramon & Schwartz (2007)	Binary variable indicating extremely hot day or not	Mortality, All Cause	All ages	No	59	101	143	$0.487	$0.827	$1.175
				Yes	48	86	125	$0.393	$0.708	$1.029
	Piecewise linear metric	Mortality, All Cause	All ages	No	159	262	364	$1.304	$2.150	$2.995
				Yes	123	216	309	$1.015	$1.778	$2.548
			Over 65	No	94	155	215	$0.771	$1.271	$1.771
Zero Tree Cover										
Basu et al. (2005)	Daily mean temperature	Cardiorespiratory mortality	Over 65	No	505	1005	1507	$4.150	$8.258	$12.385
Medina-Ramon & Schwartz (2007)	Binary variable indicating extremely hot day or not	Mortality, All Cause	All ages	No	181	308	437	$1.490	$2.529	$3.592
				Yes	146	263	383	$1.202	$2.163	$3.145
	Piecewise linear metric	Mortality, All Cause	All ages	No	398	657	915	$3.273	$5.397	$7.522
				Yes	310	543	776	$2.546	$4.464	$6.383
			Over 65	No	240	396	552	$1.973	$3.253	$4.535

†Under the alternative scenarios of reducing tree cover by 10% and no tree cover, mortality is increased from baseline conditions. Hence the table shows positive values.
*Center uses the estimated Beta coefficient. LB and UB denote estimates using lower and upper bounds of the 95% Confidence Interval for the estimated Beta coefficient.

Table A2
Change in Mortality† and Associated Monetary Benefits due to 10% increase in tree cover for 2008, 2011 and 2012.

Study	Year	Mortality Classification	Age Group	Change in Incidence			Economic Value (2011$billions)		
				LB*	Center*	UB*	LB*	Center*	UB*
Basu et al. (2005)	2008	Cardiorespiratory mortality	Over 65	−213	−422	−631	-$1.749	-$3.469	-$5.186
	2011			−213	−423	−632	-$1.751	-$3.473	-$5.193
	2012			−210	−417	−623	-$1.727	-$3.425	-$5.120

†Under the alternative scenario of increasing tree cover by 10%, mortality is reduced from baseline conditions. Hence the table shows negative values.
*Center uses the estimated Beta coefficient. LB and UB denote estimates using lower and upper bounds of the 95% Confidence Interval for the estimated Beta coefficient.

References

Akbari, H., Pomerantz, M., Taha, H., 2001. cool surfaces and shade trees to reduce energy use and improve air quality in urban areas. Solar Energy 70, 295–310. https://doi.org/10.1016/S0038-092X(00)00089-X.

Analitis, A., Michelozzi, P., D'Ippoliti, D., De'Donato, F., Menne, B., Matthies, F., Atkinson, R.W., Iniguez, C., Basagana, X., Schneider, A., Lefranc, A., Paldy, A., Bisanti, L., Katsouyanni, K., 2014. Effects of heat waves on mortality: effect modification and confounding by air pollutants. Epidemiol 25 (1), 15–22.

APHA, 2018, Differences in Heat-Related Mortality by Citizenship Status: United States 2005–2014. https://www.apha.org/-/media/files/pdf/topics/climate/heat_related_deaths.ashx?la=en&hash=2C87CFBF6E38A710EC27E607675DDD1ECAA477F6 (accessed 24 September 2020).

Balbus, J.M., Malina, C., 2009. Identifying vulnerable subpopulations for climate change health effects in the United States. J. Occup. Environ. Med. 51 (1), 33–37.

Basu, R., Samet, J.M., 2002. Relation between elevated ambient temperature and mortality: a review of the epidemiologic evidence. Epidemiol. Rev. 24 (2), 190–202.

Basu, R., Dominici, F., Samet, J.M., 2005. Temperature and mortality among the elderly in the United States: a comparison of epidemiologic methods. Epidemiol 16 (1), 58–66.

Benmarhnia, T., Deguen, S., Kaufman, J.S., Smargiassi, A., 2015. Review article: vulnerability to heat-related mortality: a systematic review, meta-analysis, and meta-regression analysis. Epidemiol 26 (6), 781–793.

Bolund, P., Hunhammar, S., 1999. Ecosystem services in urban areas. Ecol. Econ. 29 (2), 293–301.

Bowler, D.E., Buyung-Ali, L., Knight, T.M., Pulin, A.S., 2010. Urban greening to cool towns and cities: a systematic review of the empirical evidence. Landsc Urban Plan 97 (3), 147–155.

Centers for Disease Control and Prevention (CDC), National Center for Health Statistics, 2015, Underlying cause of death 1999-2014 on CDC WONDER online database. Data are from the Multiple Cause of Death Files, 1999–2014, as Compiled from Data Provided by the 57 Vital Statistics Jurisdictions Through the Vital Statistics Cooperative Program. http://wonder.cdc.gov/ucd-icd10.html.

Fann, N., Brennan, T., Dolwick, P., Gamble, J.L., Ilacqua, V., Kolb, L., Nolte, C.G., Spero, T.L., Ziska, L., 2016. Air quality impacts. The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment. U.S. Global Change Research Program, Washington, DC, pp. 69–98. https://health2016.globalchange.gov/air-quality-impacts. accessed 24 September 2020.

Gamble, J.L., Hurley, B.J., Schultz, P.A., Jaglom, W.S., Krishnan, N., Harris, M., 2013. Climate change and older Americans: state of the science. Env. Health Perspect. 121 (1), 15–22. https://doi.org/10.1289/ehp.1205223.

Gamble, J.L., Balbus, J., Berger, M., Bouye, K., Campbell, V., Chief, K., Conlon, K., Crimmins, A., Flanagan, B., Gonzalez-Maddux, C., Hallisey, E., Hutchins, S., Jantarasami, L., Khoury, S., Kiefer, M., Kolling, J., Lynn, K., Manangan, A., McDonald, M., Morello-Frosch, R., Redsteer, M.H., Sheffield, P., Thigpen Tart, K., Watson, J., Whyte, K.P., Wolkin, A.F., 2016. Populations of concern. The Impacts of Climate Change On Human Health in the United States: A Scientific Assessment. U.S. Global Change Research Program, Washington, DC, pp. 247–286. https://doi.org/10.7930/J0Q81B0T accessed 24 September 2020.

Gasparrini, A., Guo, Y., Sera, F., Vicedo-Cabrera, A.M., Huber, V., Tong, S., de Sousa Zanotti Stagliorio Coelho, M., Nascimento Saldiva, P.H., Lavigne, E., Matus Correa, P., Valdes Ortega, N., Kan, H., Osorio, S., Kyselý, J., Urban, A., Jaakkola, J.J.K., Ryti, N.R.I., Pascal, M., Goodman, P.G., Zeka, A., Michelozzi, P., Scortichini, M., Hashizume, M., Honda, Y., Hurtado-Diaz, M., Cesar Cruz, J., Seposo, X., Kim, H., Tobias, A., Iñiguez, C., Forsberg, B., Åström, D.O., Ragettli, M.S., Guo, Y.L., Wu, C.F., Zanobetti, A., Schwartz, J., Bell, M.L., Dang, T.N., Van, D.D., Heaviside, C., Vardoulakis, S., Hajat, S., Haines, A., Armstrong, B., 2017. Projections of temperature-related excess mortality under climate change scenarios. Lancet Planet Health 1 (9), E360–E367. https://doi.org/10.1016/S2542-5196(17)30156-0.

Gómez-Baggethun, E., Barton, D.N., 2013. Classifying and valuing ecosystem services for urban planning. Ecol. Econ. 86, 235–245. https://doi.org/10.1016/j.ecolecon.2012.08.019.

Guo, Y., Gasparrini, A., Li, S., Sera, F., Vicedo-Cabrera, A.M., Coelho, M., Saldiva, P., Lavigne, E., Tawatsupa, B., Punnasiri, K., Overcenco, A., Correa, P.M., Ortega, N.V., et al., 2018. Quantifying excess deaths related to heatwaves under climate change scenarios: a multicountry time series modelling study. PLoS Med. 15 (7), e1002629.

Haase, D., Larondelle, N., Andersson, E., Artmann, M., Borgström, S., Breuste, J., Gomez-Baggethun, E., Gren, A., Hamstead, Z., Hansen, R., Kabisch, N., Kremer, P., Langemeyer, J., Lorance Rall, E., McPhearson, T., Pauleit, S., Qureshi, S., Schwarz, N., Voigt, A., Wurster, D., Elmqvist, T., 2014. A quantitative review of urban ecosystem service assessments: concepts, models, and implementation. Ambio 43 (4), 413–433. https://doi.org/10.1007/s13280-014-0504-0.

Hirabayashi, S., Endreny, T.A., 2016, Surface and Upper Weather Pre-Processor for i-Tree Eco and Hydro. https://www.itreetools.org/documents/554/Surface_and_Upper_Weather_Pre-processor_Description.pdf (accessed 24 September 2020).

Jhun, I., Fann, N., Zanobetti, A., Hubbell, B., 2014. Effect modification of ozone-related mortality risks by temperature in 97 US cities. Env. Int. 73, 128–134. https://doi.org/10.1016/j.envint.2014.07.009.

Kaiser, R., Le Tertre, A., Schwartz, J., Gotway, C.A., Daley, W.R., Rubin, C.H., 2007. The effect of the 1995 heat wave in Chicago on all-cause and cause-specific mortality. Am. J. Public Health 97, S158–S162. https://doi.org/10.2105/ajph.2006.100081.

Kalkstein, L.S., Greene, S., Mills, D.M., Samenow, J., 2011. An evaluation of the progress in reducing heat-related human mortality in major U.S. cities. Natural Hazards 56, 113–129. https://doi.org/10.1007/s11069-010-9552-3.

Kondo, M.C., Mueller, N., Locke, D.H., Roman, L.A., Rojas-Rueda, D., Schinasi, L.H., Gascon, M., Nieuwenhuijsen, M.J., 2020. Health impact assessment of Philadelphia's 2025 tree canopy cover goals. Lancet, Planet. Health 4 (4), e149–e157. https://doi.org/10.1016/S2542-5196(20)30058-9.

Kovats, R.S., Hajat, S., 2008. Heat stress and public health: a critical review. Annu. Rev. Public Health 29 (41). https://doi.org/10.1146/annurev.publhealth.29.020907.090843.

Leff, M., 2016, The sustainable urban forest guide: a step-by-step approach. Davey Inst./USDA Forest Serv.. http://www.itreetools.org/resources/content/Sustainable_Urban_Forest_Guide_14Nov2016.pdf (accessed 15 March 2021).

Madrigano, J., Jack, D., Anderson, G.B., Bell, M.L., Kinney, P.L., 2015. Temperature, ozone, and mortality in urban and non-urban counties in the northeastern United States. Env. Health 14 (1), 3. https://doi.org/10.1186/1476-069X-14-3.

Manson, S., Schroeder, J., Van Riper, D., Kugler, T., Ruggles, S., 2020, IPUMS National historical geographic information system: version 15.0 [nhgis0088_ds172_2010_blck_grp]. Minneapolis, MN: IPUMS, 10.18128/D050.V15.0.

Medina-Ramon, M., Schwartz, J., 2007. Temperature, temperature extremes, and mortality: a study of acclimatisation and effect modification in 50 US cities. Occ. Env. Med. 64 (12), 827–833. https://doi.org/10.1136/oem.2007.033175.

Medina-Ramon, M., Zanobetti, A., Cavanagh, D.P., Schwartz, J., 2006. Extreme temperatures and mortality: assessing effect modification by personal characteristics and specific cause of death in a multi-city case-only analysis. Env. Health Persp. 114 (9), 1331–1336. https://doi.org/10.1289/ehp.9074.

Multi-Resolution Land Characteristics Consortium (MRLC), 2015, National Land Cover Database 2001 (NLCD 2001). http://www.mrlc.gov/nlcd01_data.php (accessed 31 July 2015).

National Public Radio (NPR), 2019, Heat and Health in American Cities: As Rising Heat Bakes U.S. Cities, The Poor Often Feel It Most.

Newcomer-Johnson, T., Andrews, F., Corona, J., DeWitt, T.H., Harwell, M.C., Rhodes, C., Ringold, P., Russell, M.J., Sinha, P., Van Houtven, G., 2020. National Ecosystem Services Classification System (NESCS) Plus. U.S. Environmental Protection Agency. EPA/600/R-20/267.

Nowak, D.J., Dwyer, J.F., 2007. Understanding the benefits and costs of urban forest ecosystems. In: Kuser, J. (Ed.), Urban and Community Forestry in the Northeast. Springer, New York, pp. 25–46. https://doi.org/10.1007/978-1-4020-4289-8_2.

Nowak, D.J., Greenfield, E.J., 2010. Evaluating the national land cover database tree canopy and impervious cover estimates across the conterminous United States: a comparison with photo-interpreted estimates. Environ. Manage. 46 (3), 378–390. https://doi.org/10.1007/s00267-010-9536-9.

Nowak, D., Heisler, G., 2010, Air Quality Effects of Urban Trees and Parks. National Recreation and Park Association.

Nowak, D.J., Hoehn, R.E., Crane, D.E., Stevens, J.C., Walton, J.T., Bond, J., 2008. A ground-based method of assessing urban forest structure and ecosystem services. Arboric. Urban For. 34 (6), 347–358.

Nowak, D.J., Hirabayashi, S., Bodine, A., Hoehn, R., 2013a. Modeled PM2.5 removal by trees in ten U.S. cities and associated health effects. Env. Poll. 178, 395–402.

Nowak, D.J., Greenfield, E.J., Hoehn, R.E., Lapoint, E., 2013b. Carbon storage and sequestration by trees in urban and community areas of the United States. Env. Poll. 178, 229–236. https://doi.org/10.1016/j.envpol.2013.03.019.

Nowak, D.J., Hirabayashi, S., Bodine, A., Greenfield, E., 2014. Tree and forest effects on air quality and human health in the United States. Env. Poll. 193, 119–129. https://doi.org/10.1016/j.envpol.2014.05.028.

Nowak, D.J., Appleton, N., Ellis, E., Greenfield, E., 2017. Residential building energy conservation and avoided power plant emissions by urban and community trees in the United States. Urban For. Urban Green 21, 158–165. https://doi.org/10.1016/j.ufug.2016.12.004.

Robine, J.M., Cheung, S.L., Le Roy, S., Van Oyen, H., Griffiths, C., Michel, J.P., Herrmann, F.R., 2008. Death toll exceeded 70,000 in Europe during the summer of 2003. C. R. Biol. 331, 171–178.
Sacks, J.D., Lloyd, J.M., Zhu, Y., Anderton, J., Jang, C.J., Hubbell, B., Fann, N., 2018. The Environmental Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE): a tool to estimate the health and economic benefits of reducing air pollution. Env. Model. Softw. 104, 118–129. https://doi.org/10.1016/j.envsoft.2018.02.009.
Sailor, D.J., 2011. A review of methods for estimating anthropogenic heat and moisture emissions in the urban environment. Int. J. Climatol. 31, 189–199. https://doi.org/10.1002/joc.2106.
Sarofim, M.C., Saha, S., Hawkins, M.D., Mills, D.M., Hess, J., Horton, R., Kinney, P., Schwartz, J., St. Juliana, A., 2016, Temperature-related death and Illness. The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment (pp. 43–68). Washington, DC: U.S. Global Change Research Program. 10.7930/J0MG7MDX.
Sherwood, S.C., Huber, M., 2010. An adaptability limit to climate change due to heat stress. Proc. Natl. Acad. Sci. USA 107 (21), 9552–9555. https://doi.org/10.1073/pnas.0913352107.
Shindell, D., Zhang, Y., Scott, M., Ru, M., Stark, K., Ebi, K.L., 2020. The effects of heat exposure on human mortality throughout the United States. GeoHealth 3. https://doi.org/10.1029/2019GH000234.
Sinha, P., Caulkins, M., Cropper, M., 2018. Household location decisions and the value of climate amenities. J. Environ. Econ. Manag. 92, 608–637. https://doi.org/10.1016/j.jeem.2017.08.005.
Smith, T.T., Zaitchik, B.F., Gohlke, J.M., 2013. Heat waves in the United States: definitions, patterns and trends. Clim. Chang. 118 (3–4), 811–825. https://doi.org/10.1007/s10584-012-0659-2.
U.N. General Assembly, 2015, Transforming Our world: the 2030 Agenda for Sustainable Development, available at: https://www.refworld.org/docid/57b6e3e44.html (accessed 25 February 2021).
U.S. Bureau of Labor Statistics, n.d., CPI Inflation Calculator. https://www.bls.gov/data/inflation_calculator.htm (accessed 22 September 2020).
U.S. Census Bureau, 2010, 2010 TIGER/Line Shapefiles (Machine-Readable Data Files). https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2010.html (accessed 26 March 2021).
U.S. Environmental Protection Agency (EPA), 2018, Mortality Risk Valuation. https://www.epa.gov/environmental-economics/mortality-risk-valuation (accessed 22 September 2020).
U.S. Global Change Research Program (USGCRP), 2016, The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment (A. Crimmins, J. Balbus, J. L. Gamble, C. B. Beard, J. E. Bell, D. Dodgen et al., Eds.). Washington, DC: U.S. Global Change Research Program.
Vaidyanathan, A., Malilay, J., Schramm, P., Saha, S., 2020. Heat-Related Deaths - United States, 2004-2018. MMWR 69 (24), 729–734. https://doi.org/10.15585/mmwr.mm6924a1.
Voorhees, A.S., Fann, N., Fulcher, C., Dolwick, P., Hubbell, B., Bierwagen, B., Morefield, P., 2011. Climate change-related temperature impacts on warm season heat mortality: a proof-of-concept methodology using. BenMAP. Env. Sci. Tech. 45 (4), 1450–1457. https://doi.org/10.1021/es102820y.
Weinberger, K.R., Harris, D., Spangler, K.R., Zanobetti, A., Wellenius, G.A., 2020. Estimating the number of excess deaths attributable to heat in 297 United States counties. Environ. Epidemiol. 4 (3), e096. https://doi.org/10.1097/EE9.0000000000000096.
Yang, Y., Endreny, T.A., Nowak, D.J., 2013. A physically based analytical spatial air temperature and humidity model. J. Geophys. Res., D, Atmos. 118 (18) https://doi.org/10.1002/jgrd.50803, 10,463–10,449.
Ziter, C.D., Pedersen, E.J., Kucharik, C.J., Turner, M.G., 2019. Scale-dependent interactions between tree canopy cover and impervious surfaces reduce daytime urban heat during summer. Proc. Natl. Acad. Sci. 116 (15), 7575.