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A national health impact assessment of achieving tree canopy goals in US urban areas

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1. Introduction

Urban trees and forests provide essential ecosystem services such as cleaner air, water, and soil; increased habitat and biodiversity; reduced noise, heat, and flood risks; reduced energy demands; and improved neighborhood satisfaction, aesthetics, and walkability (Wang and Banzhaf, 2018). Through these ecosystem services, extensive social, cultural, economic and human health co-benefits are provided to nearby populations (Martínez Pastur et al., 2018). For example, trees reduce adverse exposures to extreme heat (McDonald et al., 2020) and air pollution (Nowak et al., 2006), and facilitate social cohesion (Donovan et al., 2022c), which are pathways to improving human health in cities and beyond (Markevych et al., 2017). While there is an extensive body of research establishing the beneficial associations between human health and exposure to nature or green space (as a more general category), there is increasing evidence of the importance of tree canopy in particular (Wolf et al., 2020). Studies have found benefits associated with exposure to trees, including improved birth outcomes (Donovan et al., 2025), reduced violence (Kondo et al., 2017), risk of injury falls (Burford et al., 2025), odds (compared to living with no/low tree canopy cover) of developing heart disease, hypertension and diabetes (Astell-Burt and Feng, 2019b) and risk of mortality due to non-accidental causes (Donovan et al., 2022b) and due to cardiovascular and lower-respiratory-tract illness (Donovan et al., 2013). At the same time, exposure to trees may increase risk of asthma and allergic sensitization (Lovasi et al., 2013), and due to historical social processes such as segregation, there are commonly disparities in the distribution of trees within cities (Locke et al., 2021).

The evidence of largely beneficial effects has prompted local-to international-level policies and actions to increase urban trees and green space. For instance, the United Nations Sustainable Development Goal 11.7 states, “By 2030, provide universal access to safe, inclusive and accessible green and public spaces, in particular for women and children, older persons and persons with disabilities" (United Nations, 2015). Tree canopy cover (TCC) is an internationally and widely-used metric for assessing, monitoring and evaluating resources, and setting TCC targets is a popular strategy for “greening” cities (Browning et al., 2024; Morgenroth et al., 2025). In the US, cities have been adopting TCC targets over past decades in particular as a tool to address socio-geographic disparities, as well as to provide relief from climate concerns.

Health impact assessment (HIA) tools can leverage exposure-response functions (ERFs) to estimate morbidity or mortality burden in reference to policy goals such as TCC targets. Yet while studies of the association between tree canopy and mortality rates exist, they are few. Instead, epidemiologic studies linking green space exposure to risk of mortality have almost solely been conducted using the Normalized Difference Vegetation Index (NDVI) as an exposure metric, because it

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has been fully and freely available since 2008 (dating back to 1972), providing researchers across the globe a consistent green space exposure metric (Donovan et al., 2022a). NDVI was originally developed as a tool to map vegetation and ecosystem boundaries (Pettorelli et al., 2005), and is not generally used as an urban forestry management tool.

It follows, then, that many HIAs have relied on NDVI-based policy targets (Barboza et al., 2021; Brochu et al., 2022; Martin et al., 2025). For example, one HIA that modeled a uniform 1% increase in NDVI across 96 cities worldwide found a median reduction of 1.77 deaths per 100,000 people (Martin et al., 2025). Other HIAs have estimated the mental health benefits associated with not implementing specific urban greening interventions (Yañez et al., 2023). Barboza et al. (2021) used a 25% "green area" target—encompassing a modeled translation for universal access to publicly accessible parks and green spaces—and conducted the HIA using the equivalent NDVI target for each city.

Due to the policy-relevance of TCC targets, HIAs increasingly employ TCC as the target, using statistical techniques to relate TCC to NDVI. Among HIAs employing TCC as the target, most have been conducted on specific projects (Iungman et al., 2025), or specific (one or two) cities (Dean et al., 2024; Kondo et al., 2020). Dean et al. (2024) modeled the mortality burden of TCC levels in 2020, compared to policy targets of 20% in Denver, CO (200 lives annually), and 25% in Phoenix, AZ (368 lives annually). Kondo et al. (2020) estimated a mortality burden of 2014 TCC levels of 403 lives annually (approximately 3%) relative to a targeted 30% in Philadelphia. Only in one case has a TCC-focused HIA been conducted on a national-scale (Giannico et al., 2024). Of note, Qiu et al. (2025) used a percent green space measure in their estimate of mortality burden associated with green space exposures in year 2000 compared to 2020 in China; however, they also included other green landcover classes and therefore their results are not comparable.

It is important to note that NDVI and TCC are not interchangeable; NDVI reflects presence of not only trees, but other forms of vegetation, and it is sensitive to leaf-on/-off season and plant health and is therefore more temporally dynamic than TCC. Tree canopy is a major structural contributor to NDVI, and NDVI and TCC would align well in tree-dominated areas (e.g. forested parks or ecological zones, or neighborhoods with a mature tree canopy) during leaf-on season, although at higher levels of TCC, the NDVI–TCC relationship plateaus. On the other hand, they might diverge in landscapes dominated by lawns, sports fields, or crops.

Relating TCC to NDVI calls for careful interpretation of findings regarding potential mechanisms of association with health outcomes. Previous research has established numerous pathways by which greener environments in general are associated with reduced risk of mortality. When vegetated green spaces reduce multiple concurrent harms (e.g. exposure to pollution, noise and heat), and simultaneously aids in stress and attention recovery, encourages physical activity, and promotes social connection, their presence can reduce morbidity and mortality through numerous concurrent and place-dependent mechanisms (Markevych et al., 2017). These pathways may also differ in landscapes with equivalent NDVI values, but different TCC. This could be due to the fact that tree canopy is associated, more strongly than is NDVI, with reducing air pollution (Nowak et al., 2014), attenuating noise, (Zhao et al., 2021), and mitigating heat (Bowler et al., 2010). On the other hand, NDVI has been negatively associated with mortality via improved mental health outcomes (James et al., 2016), which could indicate that it is a stronger measure of visual greenness than tree canopy cover (Astell-Burt and Feng, 2019a).

Because of their tangibility and simplicity, unlike NDVI, TCC targets are common in cities across the US. The number of municipalities with TCC goals is increasing; therefore, we explored the question of what could be the magnitude of natural-cause mortality and economic burden associated with TCC levels below TCC targets. We applied previous epidemiological evidence of association between green space exposure and mortality using a quantitative HIA approach to estimate the mortality and economic burden, focused on urban areas with over 100,000 persons in the United States in 2019. We additionally applied several sensitivity analyses to check how the estimated burden would change under more conservative scenarios. Such estimates could underscore the value of the urban tree canopy specifically, and the investments that are made in maintaining and growing urban forests to achieve TCC goals.

2. Methods

We estimated the mortality burden associated with TCC below target levels in US urban areas with population >100,000. Because established ERFs linking green space to mortality have been calculated using NDVI, our approach required translating TCC targets into NDVI values using empirical urban area-specific models, then applying the ERFs. Below, we describe our study area, data sources, the TCC-to-NDVI translation process, and health impact calculations. For detailed descriptions, refer to Supplement 1.

2.1. *Study area and TCC target definition*

Our units of analysis were census tracts located within Census-defined urban areas. The US is divided into census tracts, generally containing 4000 residents and scaled in size accordingly. Because populated and built-up areas often extend beyond formal city boundaries, including areas with limited or no TCC, we used U.S. Census Bureau–designated urban areas as proxies for city boundaries. These urban areas are characterized by dense development, including residential and nonresidential land uses, and contain more than 2000 housing units or more than 5000 residents. Characteristics of each urban area (such as area, population, demographics, and mortality rates) are calculated based on the census tracts contained within them. In 2019, there were 3601 urban areas, but only 298 with a population greater than 100,000 residents. We excluded nine urban areas outside of the continental United States that lacked TCC data coverage, and 12 urban areas in arid climates with mean TCC <5%, leaving 277 urban areas in the preliminary sample. We included census tracts that intersected 30% or more with urban area boundaries (n = 37,664) to ensure inclusion of meaningful urban population presence and developed areas. In addition, we excluded 279 tracts with zero population.

We obtained TCC targets for the cities located within urban areas using an AI-assisted and manually verified search of sources such as urban forest plans or ordinances (Supplement 1 pp 1-3). For urban areas that lacked explicit goals (n = 86), we assigned an imputed value using the average TCC target within the finest-scale ecological region ("ecoregion") as defined by the U.S. Environmental Protection Agency (U.S. Environmental Protection Agency, 2025). Urban area locations with level III ecoregions are shown in Fig. 1, and level I, II and III ecoregions are shown in Fig. S1 (Supplement 1 p 4).

2.2. *Data sources*

We retrieved TCC values from the National Land Cover Database (NLCD) 2019 Tree Canopy Cover Data for the continental US (Multi-Resolution Land Characteristics Consortium, 2019(Multi-Resolution Land Characteristics Consortium, 2019). The NLCD is a 30 m × 30 m raster in which each pixel records 0–100% TCC. We assigned the mean TCC value from each pixel to each overlapping tract using zonal statistics. While more finely resolved TCC data exists (Corro et al., 2025), we opted to use 2019 data because it is available for the same year across all states.

NDVI provides a measure of vegetation density based on the difference between visible red and near-infrared surface reflectance in Land Remote-Sensing Satellite System (Landsat) images. We derived 2019 mean NDVI values within each census tract at a 30 m × 30 m spatial resolution from the US Geological Survey (Supplement 1 p 5). NDVI values range from −1 to +1, with negative values indicating water, snow or ice and higher values indicating higher density of healthy vegetation.

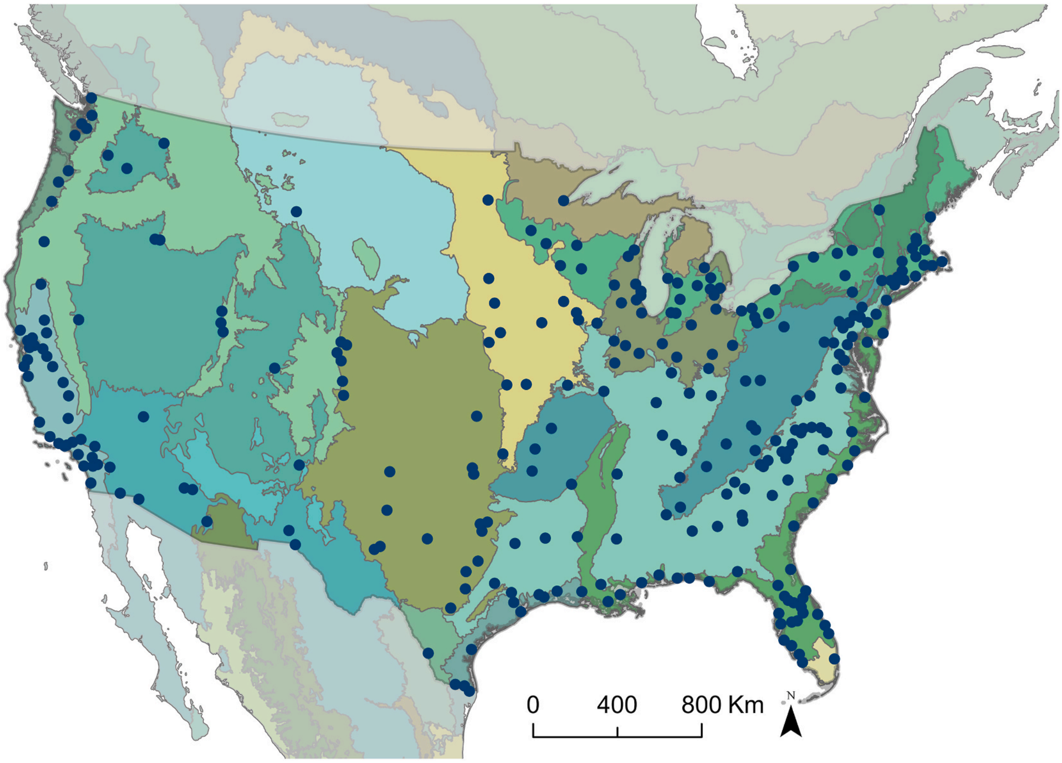

Fig. 1. Urban area locations with level III ecoregions

We masked out waterbodies and excluded tracts (n = 6) with negative mean NDVI values. We then calculated tract-level summer mean NDVI value.

The finest scale that mortality counts are publicly available in the US is the county, which is larger than the census tract. We obtained county-level all-cause mortality counts for 2019 from the US Centers for Disease Control and Prevention (CDC) via the CDC WONDER (Wide-ranging ONline Data for Epidemiologic Research) database (Centers for Disease Control and Prevention, 2024). We excluded deaths due to "external causes" such as accidents and injuries, which the CDC defines using ICD-10 codes (Centers for Disease Control and Prevention, 2019). We then calculated the proportion of natural deaths by adult age group (aged 20+ in 5-year age categories ranging from ages 20-24 to ages 85+) at the county level and applied these proportions to census tract populations, resulting in an estimated 1,102,053 natural deaths across all adult age groups. We also used the 2019 Social Vulnerability Index (SVI) as an indicator of socioeconomic conditions (Supplement 1 p 5) (Flanagan et al., 2011). SVI is scaled from 0 to 1, and indicates the ranking of each census tract relative to census tracts in the country, with higher values indicating higher vulnerability.

Mean TCC, NDVI, population density and Social Vulnerability Index values for one urban area of moderate population density are shown in Fig. 2. Maps of two additional urban areas, one with relatively lower population density located in an arid ecoregion, and one with higher population density in a temperate climate, are shown in Figs. S2 and S3 (Supplement 1 pp 6-7).

2.3. TCC to NDVI translation

Since HIA for green space typically applies NDVI-based ERFs, we translated TCC targets into corresponding NDVI values, following a similar approach used in previous studies (Barboza et al., 2021; Yañez et al., 2023; Iungman et al., 2025), and adjusting it specifically to the TCC-NDVI relationship. Because the relationship between TCC and summertime mean NDVI is typically non-linear (Supplement 1 p 9), we modeled the relationship between baseline (2019) tract-level TCC and NDVI within each urban area using generalized additive models (GAM): NDVI ~ s(TCC) (Supplement 1 p 8). This urban area-specific non-linear approach accounts for geographic differences in the TCC-NDVI relationship due to variation in climate, vegetation types and urban form. We further conducted sensitivity analyses adjusting the GAM for census tract area, population density, or both. We then used these models to predict the NDVI value corresponding to each urban area's TCC target.

To ensure the validity and robustness of the urban area-specific GAMs, we applied a set of exclusion criteria before using the models for counterfactual estimation. We excluded 31 urban areas with NDVI point predictions that were out of range [−1,1], 83 that exceeded an optimal ratio of sample size to model complexity, and 19 showed poor model fit, leaving 144 urban areas in the final analytic sample (specifications defined in detail in Supplement 1 pp 9-10). Table S1 (Supplement 1 p 11) shows excluded urban areas. Table S2 (Supplement 1 p 12) shows descriptive differences in total population TCC and ecoregion between included and excluded areas.

2.4. Health impact assessment methodology

We used a comparative risk assessment (CRA) approach using a counterfactual (policy-based scenario) (Murray et al., 2003), as it has been widely used in HIA for urban and transport planning studies. All HIA procedures are described in Supplement 1 (pp 12-14). We applied the mortality-green space exposure-response function (ERF) from the meta-analyses conducted by Rojas-Rueda et al. (2019) to all cities, which estimated a hazard ratio of 0.96 (95% Confidence Interval (CI): 0.94−0.97) for all-cause mortality per 0.1 unit increase in NDVI, to estimate the relative risk (RR) associated with the exposure level difference for each age group within each census tract. Rojas-Rueda et al. (2019) provides the most recent and robust known meta-estimate for continuous ERF using data only from longitudinal cohort studies. While an ERF derived from US-specific studies would be preferred, at the time of this study no such function exists for a representative population or

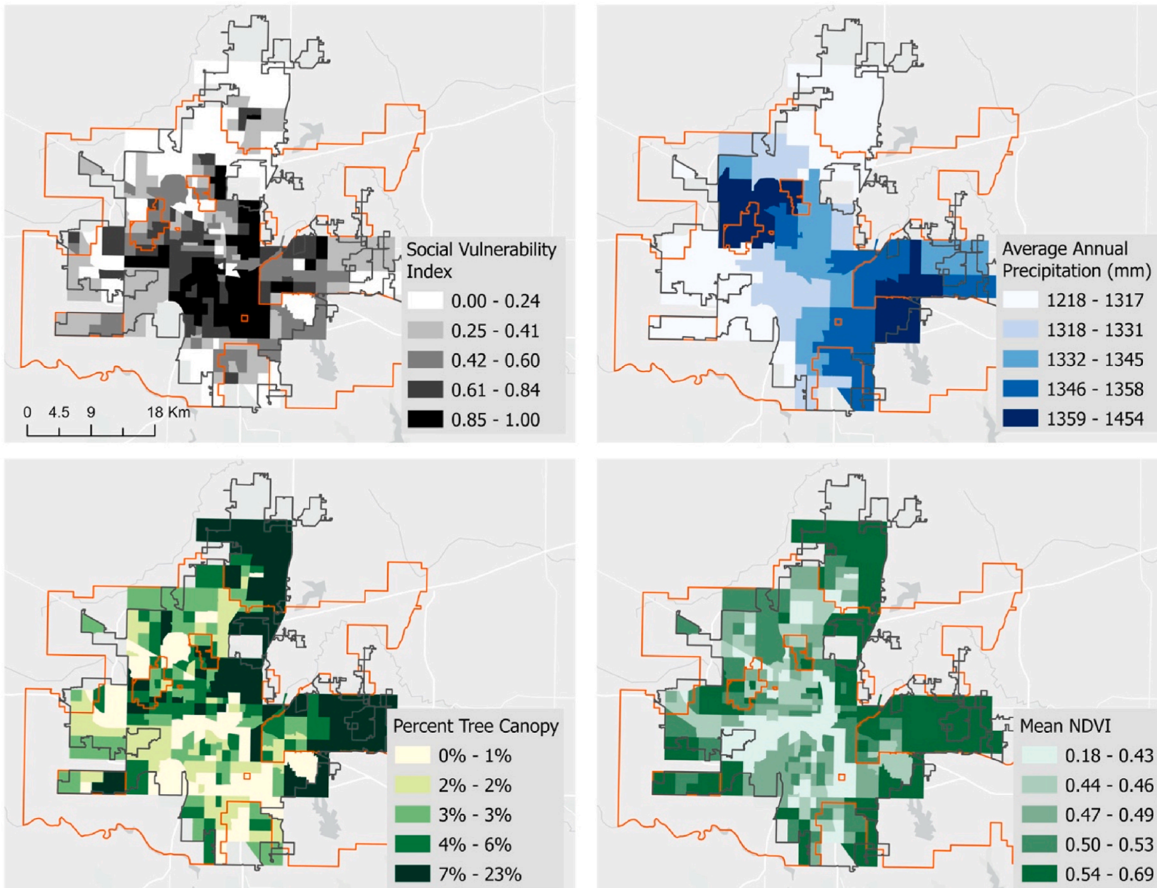

Fig. 2. Social Vulnerability Index, mean Social Vulnerability Index (SVI) values, annual precipitation (mm), mean NDVI and percent tree canopy cover for census tracts in Oklahoma City, OK, located within the plains ecoregion. (Municipal boundary is shown in orange and Census-designated urban area boundary is shown in dark grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

geographies. Next, we calculated the population attributable fraction (PAF) associated with an increase in TCC (reaching the counterfactual NDVI values) for each age group within each census tract. We then calculated the mortality burden of TCC levels below targets. In our calculations, we incorporated Monte Carlo iterations, considering the range of uncertainty for the NDVI counterfactual (Supplement 1 p 14). We estimated years of life lost (YLL) associated with the estimated mortality burden by first calculating the average age of death as the mean age within each age group, then multiplying the attributable deaths for each age group by the life expectancy at the age of death. We obtained census tract-level life expectancy from the National Center for Health Statistics at the US Centers for Disease Control and Prevention (Centers for Disease Control and Prevention, 2024).

Finally, we estimated the associated economic burden by assigning each attributable death with the Value of a Statistical Life (VSL) in 2019 of US$ 8.0 million (90% CI: $2.4–$14.0 million) (Banzhaf, 2022). The VSL is frequently used to compare policies, reflecting healthcare costs associated with mortality-driving disease and society's willingness to pay for marginal reductions in population mortality risk. We conducted all analyses using R and Stata v15.

2.5. Primary policy and benchmark scenarios

We set two scenarios for primary analyses: 1) a stated and imputed policy scenario (“Primary Policy Scenario”), for which we assigned the TCC target based on the overlapping city's stated target (and based on other targets in respective ecoregions, when no city target could be found); and 2) a policy-neutral benchmark scenario (“Primary Benchmark Scenario”), for which we assigned a NDVI counterfactual associated with a 5% increase from baseline TCC levels (year 2019).

We stratified our Primary Policy Scenario estimates of attributable deaths by urban area and by categories relevant to the population and geographies within the US, including urban area population total (by quartiles: <144,273; 144,274–273,795; 273,796–743,704; 743,705+), age group (in four categories: ages 20-34; 35–49; 50–64; 65+), and Social Vulnerability Index (by quartiles: <0–0.19; 0.19–0.45; 0.45–0.75; 0.75+).

2.6. Sensitivity analyses

The TCC targets for the Primary Policy Scenario may be viewed as ambitious, and given the multiple barriers to establishing new tree canopy (Roman et al., 2018), as a sensitivity analysis, we also calculated attributable mortality burden for a more conservative policy scenario (shown in Table 1). For Sensitivity Analysis 1 (SA-1), we assigned the NDVI counterfactual associated with 50% of TCC targets in the Primary Policy Scenario. At the same time, the Primary Benchmark Scenario may be viewed as conservative for some cities. For Sensitivity Analysis 2 (SA-2), we assigned a NDVI counterfactual associated with a 10% increase from baseline. For example, for a city with a TCC of 10%, a 10% increase would be 11%. Because the policy targets are set by cities or municipalities, we calculated attributable mortality burden for the study area within (SA-3a) and outside (SA-3b) of formal city boundaries. We also calculated attributable mortality burden for only urban areas with stated TCC targets (SA-4a), versus those with imputed goals (SA-4b).

We performed six additional sensitivity analyses to assess the effects

Table 1
List of models and specifications.

Model	Specification
Primary Policy Scenario	Stated and imputed tree canopy goal by city
Primary Policy-Neutral Benchmark Scenario	5% increase from baseline % tree canopy
Sensitivity Analysis 1	50% main tree canopy goal by city
Sensitivity Analysis 2	10% increase from baseline % tree canopy
Sensitivity Analysis 3a	Within city boundaries
Sensitivity Analysis 3b	Outside city boundaries
Sensitivity Analysis 4a	Original TCC goal
Sensitivity Analysis 4b	Imputed TCC goal
Sensitivity Analysis 5	Annual mean NDVI
Sensitivity Analysis 6a	50% ERF
Sensitivity Analysis 6b	150% ERF
Sensitivity Analysis 7a	GAM adjusted for tract area
Sensitivity Analysis 7b	GAM adjusted for population density
Sensitivity Analysis 7c	GAM adjusted for tract area + population density

NDVI = normalized difference vegetation index.
GAM = generalized additive model.
ERF = exposure response function.

of changes in the input variables for the HIA on the magnitude of our mortality estimates. Using the main TCC target for each urban area, we: 1) generated NDVI counterfactuals using the annual mean NDVI value (instead of summertime mean) for 2019 (SA-5); 2) applied half of (SA-6a) and double (SA-6b) the Rojas-Rueda et al. (2019) ERF, respectively, to give a range of estimates; and 3) adjusted the GAM using average census tract area (SA-7a), population density (SA-7b), and both (SA-7c).

Our funders played no role in data collection, analysis, interpretation, writing of the manuscript or the decision to submit.

3. Results

Our final study population included 121,156,788 adults (20+ years). Urban areas were on average 1211 km^2 in area (range: 98–9755 km^2), and contained 261 tracts on average (range: 17–4354). Within urban areas, mean tract population was 3068 people (range: 1886 to 4669), and mean tract size was 6.9 km^2 (range: 1.7–20.9 km^2). Sixty-nine percent of included urban areas were located within the Eastern Temperate Forest ecoregion, and the remainder were located within plains and other primarily forested ecoregions (Table S2; Supplement 1 p 12). Of the 144 urban areas, 58 had original TCC targets, and we assigned the remaining using level III ecoregion (n = 72), level II ecoregion (n = 13), or level I ecoregion (n = 1). TCC targets are shown in Supplement 2.

There were 1,102,636 deaths in our study area in 2019. The average TCC within tracts was 19.1% (standard deviation (sd): 15.2%), and ranged from 0 to 77%. Tract-level TCC averages across urban areas ranged from 3% (Corpus Christi, TX) to 51.6% (Danbury, CT). The tract-level average mean (annual) NDVI was 0.43 (sd: 0.14), and for urban areas was 0.45 (sd: 0.08). The tract-level average mean (summertime) NDVI value was 0.50 (sd: 0.17), and for urban areas was 0.56 (sd: 0.1). Descriptions for each urban area are shown in Supplement 2.

As shown in Table 2, for the Primary Policy Scenario, 85% of the population lived below the TCC target. The mortality burden of 2019 TCC levels compared to urban areas reaching their specific TCC target levels was 67,377 (95% confidence interval (CI): 41,209−95,150) deaths annually, representing 6.1% (95% CI: 3.7%−8.6%) of all natural-cause deaths and an associated 487,234 (95% CI: 262,743−761,925) YLL. In stratified analyses comparing estimates by geographical and socio-demographic characteristics, the highest proportional mortality burdens due to lack of green space were among individuals aged 20-34 (8.1%; 95% CI: 4.6%−11.4%), and among the most vulnerable populations (SVI 4th quartile; 9.4%; 95% CI: 5.7%−13.5%). Applying the Value of a Statistical Life (VSL) to the mortality burden of our Primary Policy Scenario translated to an associated economic burden of $539.0 billion (90% CI: $329.7−$761.2 billion) annually (based on Value of a Statistical Life; 90% CI).

Under the Primary Benchmark Scenario (TCC target of 5% increase over baseline), the mortality burden of 2019 TCC levels was approximately one third of the Primary Policy Scenario, with an estimated 22,894 (95% CI: 14,119−32,095) deaths, or 2.1% (95% CI: 1.3%−2.9%), and 167,193 (95% CI: 101,183−240,144) YLL.

By applying sensitivity analyses, we found that reducing the policy goal to 50% of the Primary Policy Scenario (SA1) reduced the burden to 26,391 (95% CI: 15,997−36,631) deaths, or 2.4% (95% CI: 1.5%−3.3%) of deaths. Similarly, applying the scenario of a 10% increase in the baseline TCC (SA2) changed the burden to 24,789 (95% CI: 15,284−34,759) deaths.

SA3a and SA3b showed that most attributable mortality burden (81.6%) was associated with TCC below the target within city boundaries compared to outside of city boundaries (but within urban areas). In addition, SA4a and SA4b showed that approximately 55% of our study population (66,460,753) lived in urban areas with stated policy goals, and approximately 60% of the attributable mortality burden (42,152 deaths; 95% CI: 25,523−59,512) was derived from these 86 urban areas.

Sensitivity analyses, in which we applied varying specifications in our counterfactuals, also revealed some relevant differences. SA-5 employed the annual mean instead of summertime mean NDVI in the TCC-NDVI translation. Annual mean NDVI in most locations is lower than the summertime mean because the annual mean includes measurements during leaf-off season (when vegetation is often less green). Therefore, for this scenario, the counterfactual values were slightly lower than those for the Primary Policy Scenario, resulting in a slightly lower mortality burden of 62,838 (95% CI: 39,262−88,173) deaths. SA-6a, which applied the ERF reduced by 50%, estimated a mortality burden of 32,384 (95% CI: 20,203−45,105) attributable deaths, and SA-6b which applied the ERF increased by 50%, estimated 146,499 (95% CI: 85,724−213,366) attributable deaths. Remaining sensitivity analyses, where the GAM was adjusted for census tract area (SA-7a; 63,934 deaths; 95% CI: 39,411−89,609), population density (SA-7b; 64,633 deaths; 95% CI: 39,192−91,082), or both (SA-7c; 62,770 deaths; 95% CI: 37,217−89,688), produced slightly lower estimates of mortality burden compared to the Primary Policy Scenario. Adjusting for census tract area *and* population density in the GAM resulted in an attributable mortality burden of 62,770 (95% CI: 37,217−89,688) deaths. Comparing model fit, the mean adjusted R^2 values for the Primary Policy Scenario (0.654; see Table 2) was only slightly lower than it was for SA-7a (0.663), SA-7b (0.659) and SA-7c (0.658).

4. Discussion

This study applied a quantitative health impact assessment approach, drawing on existing epidemiological evidence of the relationship between green space exposure and mortality established in longitudinal cohort studies (Rojas-Rueda et al., 2019), to provide a comprehensive estimate of the potential health consequences of having tree canopy cover below targets in 144 of the largest urban areas across the US, where a population of over 121 million adults resides. Our estimates show an annual mortality burden just over 67,000 (6.1%) deaths, and approximately 487,000 years of life lost, associated with TCC levels in 2019, compared to TCC target levels, with an estimated annual economic burden of $539 billion. Our approach advances the small body of work modeling mortality burden attributable to canopy cover below TCC targets by modeling this burden using specific city targets, where available, by using a relatively finer exposure resolution of 30m, at a national scale. Our results align closely with those of Giannico et al. (2024), who estimated a mortality burden of up to 5.2% of deaths annually, for 2022 TCC levels compared a 30% target in cities across Italy.

Table 2
Estimated mortality and related economic burden under the Primary Policy and Benchmark scenarios and sensitivity analyses.

Scenario	Mean TCC	Mean NDVI (summer, annual)	TCC Target (min, max)	NDVI Counterfactual (min, max)	Mean GAM Adj-R^2	Total Population	Mean SVI	% Population below Target	2019 Deaths	Annual Mortality Burden (n; 95% CI)	Annual Attributable Age-Standardized Mortality Rate (per 100,000; 95% CI)	Annual Mortality Burden % (95% CI)	Years of Life Lost (per 10,000; 95% CI)
Primary Policy	22%	(0.55, 0.50)	(10%, 60%)	(0.45, 0.90)	0.654	12,11,56,788	0.49	85%	11,02,636	67,377 (41,209–95,150)	56 (34-79)	6.1% (3.7%, 8.6%)	48.7 (26.3-76.2)
Primary Benchmark	22%	(0.55, 0.50)	(3%, 54%)	(0.27, 0.75)	0.654	12,11,56,788	0.49	56%	11,02,636	22,894 (14,119–32,095)	19 (12-26)	2.1% (1.3%, 2.9%)	16.7 (10.1-24)
SA-1	23%	(0.56, 0.50)	(5%, 30%)	(0.39, 0.65)	0.654	12,11,56,788	0.49	56%	11,02,636	26,391 (15,997–36,631)	22 (13-30)	2.4% (1.5%, 3.3%)	20 (12.1-28.8)
SA-2	22%	(0.55, 0.50)	(3%, 57%)	(0.27, 0.76)	0.654	12,11,56,788	0.49	59%	11,02,636	24,789 (15,284–34,759)	20 (13-29)	2.2% (1.4%, 3.2%)	18 (10.9-25.9)
SA-3a	20%	(0.52, 0.47)	(10%, 60%)	(0.45, 0.9)	0.654	7,91,43,655	0.55	93%	6,90,910	54,991 (32,681–79,023)	69 (41-100)	8.0% (4.7%, 11.4%)	4.1 (2.2-6.3)
SA-3b	27%	(0.61, 0.54)	(10%, 60%)	(0.45, 0.9)	0.654	4,20,13,132	0.40	69%	4,11,726	12,934 (8077–18,149)	31 (19-43)	3.1% (2%, 4.4%)	0.8 (0.4-1.3)
SA-4a	21%	(0.54, 0.48)	(10%, 60%)	(0.45, 0.9)	0.654	6,64,60,753	0.49	85%	5,91,191	42,152 (25,523–59,512)	63 (38-90)	7.1% (4.3%, 10.1%)	3.1 (1.6-4.8)
SA-4b	23%	(0.56, 0.50)	(10%, 60%)	(0.45, 0.9)	0.654	5,46,96,035	0.49	84%	5,11,445	26,154 (16,468–36,748)	48 (30-67)	5.1% (3.2%, 7.2%)	1.8 (1.0-2.8)
SA-5	22%	(0.55, 0.49)	(10%, 60%)	(0.25, 0.83)	0.627	12,20,44,251	0.49	84%	11,12,314	62,838 (39,262–88,173)	51 (32-72)	5.6% (3.5%, 7.9%)	44.9 (23.6-71.1)
SA-6a	22%	(0.55, 0.50)	(10%, 60%)	(0.45, 0.90)	0.654	12,11,56,788	0.49	85%	11,02,636	32,384 (20,203–45,105)	27 (17-37)	2.9% (1.8%, 4.1%)	23.4 (12.9-36)
SA-6b	22%	(0.55, 0.50)	(10%, 60%)	(0.45, 0.90)	0.654	12,11,56,788	0.49	85%	11,02,636	146,499 (85,724–213,366)	121 (71-176)	13.3% (7.8%, 19.4%)	106.4 (54.8-172.2)
SA-7a	21%	(0.55, 0.49)	(10%, 60%)	(0.16, 0.84)	0.663	12,25,39,735	0.49	84%	11,13,908	63,934 (39,411–89,609)	52 (32-73)	5.7% (3.5%, 8.0%)	46.3 (24.8-73.3)
SA-7b	21%	(0.55, 0.49)	(10%, 60%)	(0.24, 0.88)	0.659	12,15,57,152	0.49	83%	11,02,534	64,633 (39,192–91,082)	53 (32-75)	5.9% (3.6%, 8.3%)	46.6 (25.1-73.4)
SA-7c	21%	(0.55, 0.49)	(10%, 60%)	(0.17, 0.79)	0.658	12,21,46,913	0.49	83%	11,09,133	62,770 (37,217–89,688)	51 (30-73)	5.7% (3.4%, 8.1%)	45.3 (24.2-71.9)
Scenario 1 Estimates Stratified by Urban Area Size (per 1000)													
<144	23%	(0.58, 0.52)	(38%, 55%)	(0.68, 0.90)		33,25,185	0.50	82%	34,296	1761 (1053–2460)	55 (33-77)	5.1% (3.1%, 7.2%)	1 (0.5-1.8)
144-273	24%	(0.57, 0.51)	(41%, 55%)	(0.67, 0.77)		72,48,307	0.44	86%	80,486	3193 (1939–4428)	47 (28-65)	4.0% (2.4%, 5.5%)	2 (0.9-3.5)
273-744	24%	(0.57, 0.51)	(39%, 60%)	(0.67, 0.77)		1,70,23,349	0.45	80%	1,76,984	6759 (4075–9348)	40 (24-56)	3.8% (2.3%, 5.3%)	4.4 (2.2-7.4)
744+	19%	(0.50, 0.45)	(37%, 60%)	(0.65, 0.79)		9,35,59,946	0.51	86%	8,10,870	56,180 (34,094–78,580)	60 (36-83)	6.9% (4.2%, 9.7%)	41.3 (22.7-63.6)
Scenario 1 Estimates Stratified by Age Group													
20-34	17%	(0.47, 0.42)	(10%, 60%)	(0.45, 0.90)		3,55,60,703	0.47	88%	9690	780 (444-1106)	2 (1-3)	8.1% (4.6%, 11.4%)	3.8 (2.1-5.9)
35-49	19%	(0.49, 0.43)	(10%, 60%)	(0.45, 0.90)		3,17,71,532	0.48	85%	41,423	2808 (1601–3981)	9 (5-13)	6.8% (3.9%, 9.6%)	9.7 (5.3-15.1)
50-64	20%	(0.51, 0.45)	(10%, 60%)	(0.45, 0.90)		3,05,36,210	0.50	83%	1,77,565	11,223 (6400–15,886)	37 (21-52)	6.3% (3.6%, 8.9%)	22.4 (12.1-35)
65+	21%	(0.51, 0.45)	(10%, 60%)	(0.45, 0.90)		2,32,88,343	0.50	82%	8,73,957	53,053 (31,626–73,917)	228 (136-317)	6.1% (3.6%, 8.5%)	12.8 (6.9-20.1)
Scenario 1 Estimates Stratified by Quartile of Social Vulnerability Index													
quartile 1	26%	(0.56, 0.49)	(10%, 60%)	(0.45, 0.90)		3,16,67,154	0.45	73%	3,16,772	12,289 (7317–17,169)	38 (23-53)	3.9% (2.3%, 5.4%)	8.4 (4.3-13.6)
quartile 2	21%	(0.52, 0.46)	(10%, 60%)	(0.45, 0.90)		3,24,05,655	0.48	85%	3,17,530	16,739 (9792–23,802)	51 (30-73)	5.3% (3.1%, 7.5%)	11.1 (5.8-17.8)

(*continued on next page*)

Table 2 (*continued*)

Scenario	Mean TCC	Mean NDVI (summer, annual)	TCC Target (min, max)	NDVI Counterfactual (min, max)	Mean GAM Adj-R^2	Total Population	Mean SVI	% Population below Target	2019 Deaths	Annual Mortality Burden (n; 95% CI)	Annual Attributable Age-Standardized Mortality Rate (per 100,000; 95% CI)	Annual Mortality Burden % (95% CI)	Years of Life Lost (per 10,000; 95% CI)
quartile 3	17%	(0.47, 0.42)	(10%, 60%)	(0.45, 0.90)		3,09,97,682	0.43	94%	2,70,793	19,688 (12,278–27,541)	64 (40-89)	7.3% (4.5%, 10.2%)	13.9 (7.6-21.6)
quartile 4	12%	(0.42, 0.37)	(10%, 60%)	(0.45, 0.90)		2,59,57,785	0.54	97%	1,97,346	18,619 (11,167–26,607)	74 (44-106)	9.4% (5.7%, 13.5%)	15.3 (8.6-23.2)

TCC = tree canopy cover.
NDVI = normalized difference vegetation index.
SVI = social vulnerability index.
Adj-R^2 = adjusted-R^2.

While TCC targets are increasingly common in US cities, our study provides the first national estimates of the health impacts of meeting TCC targets. In comparison to previous studies, Kondo et al. (2020) estimated a mortality burden of nearly 400 deaths per year (or approximately 3% of total mortality) in Philadelphia associated with 2014 TCC levels compared to a 30% tree canopy cover goal, which is comparable to our finding of 3.9% attributable mortality burden in that city. Our estimate of mortality burden of TCC levels below Denver's target of 20% was about two times higher than that of Dean et al. (2024), likely because their estimate was specific to at-risk populations and because our study area was the urban area rather than the city boundary.

We found some variation in estimates by urban area size and sociodemographic group. First, TCC is lower in both larger and denser urban areas and while meeting TCC targets can be more challenging in these contexts, the estimated annual mortality burden is much higher in the largest quartile (25,338 deaths; 10.3%) than the smallest quartile of urban areas (12,123 deaths; 4.2%). Similar to other studies (Anguelovski et al., 2022; Kondo et al., 2020), we found proportionally higher attributable mortality burden in lower socioeconomic status areas. We also found a higher attributable mortality burden among people ages 20-34. These findings are expected, as these populations tend to be represented disproportionately in more urbanized, and lower tree canopy cover, areas.

These numbers should be interpreted with caution. First, common TCC targets are often found to be ambitious due to a number of restraints related to financing, climate, and development, among others (Morgenroth et al., 2025). The Primary Benchmark Scenario which compared 2019 TCC levels to a modest TCC increase of 5% showed a mortality burden of nearly 23,000 deaths, or just over 167,000 YLL. Second, the Primary Policy Scenario estimates are based on imputed goals in more than half of the 144 urban areas (stated targets for 58 urban areas, and imputed based on ecological region for the remaining urban areas), and therefore should be understood as reflecting many approximations of appropriate canopy goals. Yet, 55% of our study population (nearly 66.5 million residents) were located in urban areas with stated TCC targets, and an estimated mortality burden of approximately 42,000 deaths were associated with TCC below target levels.

There are some additional considerations necessary when interpreting our results particularly regarding our use of NDVI as a proxy for conducting a HIA of a green space policy goal measured by land cover rather than NDVI. At the time of this study, the only existing ERF generalizable beyond specific localized areas or specific sub-populations was that developed by Rojas-Rueda et al. (2019). Our approach to estimating an NDVI counterfactual corresponding to a policy-relevant green space metric has been used and validated in numerous other studies (Barboza et al., 2021; Giannico et al., 2024; Iungman et al., 2025; Kondo et al., 2020; Opbroek et al., 2024; Yañez et al., 2023). As described in Supplement 1 (pp 8-11), we applied an urban area-specific function, assessing each urban area's adjustment and robustness individually, and included sensitivity analyses adjusting the GAM for census tract area and population density. We also applied rigorous exclusion criteria, retaining only 144 out of 289 original urban areas; for the eight retained urban areas with a relatively low adjusted R^2 ($0.3<R^2<0.4$; Supplement 2 p 11), TCC targets and estimated mortality burdens should be interpreted cautiously.

Applying an ERF derived from NDVI (a composite greenness index) to a policy target defined solely by TCC (a subset of greenness) warrants consideration. Trees are understood to be a primary driver through which green space reduces morbidity and mortality, particularly by mitigating heat, air pollution and noise, and TCC is a widely accepted, actionable policy goal tangible to city managers, policymakers, and the public. Yet little evidence exists to help policymakers weigh TCC investments against potential mortality benefits. In the absence of direct evidence, we assume – as have previous studies – that the proportion of the NDVI-attributable mortality risk due specifically to TCC is constant and transferable across urban areas.

This assumption introduces directional uncertainty. Because NDVI captures multiple forms of vegetation beyond TCC, applying an NDVI-based exposure-response function to a policy target defined solely by TCC may either underestimate or overestimate the true mortality burden. In areas where TCC contributes strongly to NDVI, the NDVI-based approach may underestimate exposure gains associated with increasing TCC, particularly where the NDVI–TCC relationship begins to plateau (Huemmrich et al., 2021; Ju et al., 2024). Conversely, because NDVI reflects a broader range of vegetated environments and associated pathways than TCC alone, applying the full NDVI-based association to canopy interventions may overestimate health benefits if part of the observed mortality reduction is attributable to other forms of greenness. The net direction and magnitude of this bias remain uncertain and are likely to vary across urban contexts.

Use of a single ERF does not capture heterogeneity of effect across sub-populations with differing health behaviors or pre-existing conditions. However, the ERF pools estimates from nine studies encompassing over 8 million individuals across seven countries and a wide range of population and environmental characteristics; all nine studies adjusted for sociodemographic factors, three for air pollution exposures, and five for behaviors such as smoking. The ERF is therefore broadly generalizable at the population level, though estimates should not be interpreted as reflective of specific subpopulations or local contexts. Age distributions were unavailable at the census tract level, so we applied county-level distributions, which may introduce inaccuracies in age-adjusted (but not overall) estimates. In addition, ERF exposure measurements were based on residential location, which may not capture variation due to time-activity patterns.

The ERF employed is based upon population-level associations, and the studies included in the NDVI-based meta-analysis did not consistently adjust for major environmental pathways through which green space may affect health: only four adjusted for air pollution, only one considered transport noise, and none accounted for heat-related exposures (Rojas-Rueda et al., 2019). As a result, the ERF likely reflects the combined effects of multiple correlated features of greener environments, including pathways related to air pollution reduction, noise attenuation, heat mitigation, physical activity, and restoration. The direction of bias introduced by combining multiple modeled relationships in a single ERF supports interpreting the estimates as approximate and directionally informative rather than precise measures of canopy-attributable mortality impacts.

Experts have concluded that research on mechanisms – particularly for tailored health impact assessment modeling – needs significant development (Williams et al., 2025). ERFs accounting for more specific aspects of exposure (e.g., green space quality and accessibility), and response (e.g., among specific sociodemographic groups) would make context-specific HIAs possible (Williams et al., 2025). Research on neighborhood TCC and health associations is emerging (James et al., 2024), and could eventually yield a TCC-specific ERF.

Several additional limitations warrant consideration. Mortality data were at the county level, with age group proportions applied to census tracts, which may introduce small inaccuracies in within-city estimates. We used Census-designated urban areas rather than cities as our unit of analysis because urban area boundaries reflect development patterns and population density rather than the inconsistent administrative boundaries of municipalities. We found that approximately 19% of attributable mortality burden was derived from urban areas outside of formal city boundaries, indicating presence of a considerable population living in areas with canopy cover below target levels. However, since these boundaries may not necessarily align with geographic scope of tree canopy targets, estimates in more arid regions – where meeting canopy target outside of city boundaries may be less feasible – should be interpreted cautiously. In addition, our economic valuation should be interpreted with caution, application of a uniform VSL across all age groups may not reflect age-specific willingness to pay.

We estimated TCC from 2019 NLCD data, which at the time were the only source allowing for consistent baseline estimates across the US. However, NLCD data have been found to underestimate tree canopy cover on average (Pourpeikari Heris et al., 2022), which could inflate our mortality burden estimates. Emerging research also suggests that blue space and non-green nature exposures (e.g., desert or ice/snow landscapes) may reduce mortality (Li et al., 2023); since we did not include these, attributable mortality may be overestimated in landscapes with other forms of nature exposure.

Existing literature indicates that urban forest management and tree planting are important public health amenities with sizable benefits. We are unable to provide benefit-cost estimates, as costs of achieving tree canopy targets vary widely and no generalizable estimates have been published to-date. Several important caveats also apply to our findings. Our analysis assumes immediate benefits upon target achievement, though trees require decades to mature and provide full canopy coverage. Further, despite widespread tree planting initiatives, most US cities are losing tree canopy cover due to climate-related pests, diseases and disasters, real estate development, and inadequate preservation policies and enforcement. Meeting ambitious targets is especially challenging and costly in high density and arid areas, and prioritizing quantity over socioecological priorities carries drawbacks in any city (Morgenroth et al., 2025). Nevertheless, integrating health evidence into urban forestry and climate adaptation policies – alongside sustainable long-term planning, adequate maintenance, and community engagement – can help cities set achievable, equitable, and resilient greening goals that ensure lasting health, social, and environmental benefits.

5. Conclusions

The mortality and economic burden of tree canopy cover below city-specific target levels is significant, especially in denser areas and among younger and socially vulnerable populations. These results can be used to consider estimated benefits to health, as one among many other ecosystem services, that result from growing and maintaining urban tree canopy.

CRediT authorship contribution statement

Michelle C. Kondo: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Tamara Iungman:** Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Evelise Pereira Barboza:** Formal analysis, Methodology, Validation, Visualization, Writing – review & editing. **Dexter H. Locke:** Investigation, Methodology, Writing – original draft, Writing – review & editing. **Ray Yeager:** Data curation, Investigation, Resources, Visualization, Writing – original draft, Writing – review & editing. **Dustin Fry:** Data curation, Resources, Writing – review & editing. **Ava-Clare Steed:** Data curation, Writing – original draft, Writing – review & editing. **Marcia Pescador Jiménez:** Methodology, Writing – review & editing. **David Rojas-Rueda:** Methodology, Writing – review & editing. **Mark Nieuwenhuijsen:** Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mark Nieuwenhuijsen reports financial support was provided by Spain Ministry of Science Innovation and Universities. Mark Nieuwenhuijsen reports financial support was provided by Generalitat de Catalunya. Mark Nieuwenhuijsen reports financial support was provided by Centro de Investigación Biomédica en Red. If there are other authors, they 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.envres.2026.125205.

Data availability

Data will be made available on request.

References

Anguelovski, I., et al., 2022. Green gentrification in European and North American cities. Nature Comm 13 (1), 3816.
Astell-Burt, T., Feng, X., 2019a. Association of urban green space with mental health and general health among adults in Australia. JAMA Netw. Open 2 (7), e198209.
Astell-Burt, T., Feng, X., 2019b. Urban green space, tree canopy, and prevention of heart disease, hypertension, and diabetes: a longitudinal study. Lancet Planet. Health 3, S16.
Banzhaf, H.S., 2022. The value of statistical life: a meta-analysis of meta-analyses. J. Benefit-Cost Anal. 13 (2), 182–197.
Barboza, E.P., et al., 2021. Green space and mortality in European cities: a health impact assessment study. Lancet Planet. Health 5 (10), e718–e730.
Bowler, D.E., et al., 2010. Urban greening to cool towns and cities: a systematic review of the empirical evidence. Landsc. Urban Plann. 97 (3), 147–155.
Brochu, P., et al., 2022. Benefits of increasing greenness on all-cause mortality in the largest metropolitan areas of the United States within the past two decades. Front. Public Health 10, 841936.
Browning, M., et al., 2024. Measuring the 3-30-300 rule to help cities meet nature access thresholds. Sci. Total Environ. 907, 167739.
Burford, K.G., et al., 2025. Tree canopy cover and injurious pedestrian falls: a location-based case-control study. Am. J. Epidemiol. 194 (12), 3529–3536.
Centers for Disease Control and Prevention, 2019. The international classification of diseases (10th revision) clinical modification (ICD–10–CM) external cause-of-injury framework for categorizing mechanism and intent of. Injury.
Centers for Disease Control and Prevention, 2024. National Vital Statistics System, Mortality 2018-2022 on CDC WONDER Online Database.
Corro, L.M., et al., 2025. An enhanced national-scale urban tree canopy cover dataset for the United States. Sci. Data 12 (1), 490.
Dean, D., et al., 2024. Health implications of urban tree canopy policy scenarios in Denver and Phoenix: a quantitative health impact assessment. Environ. Res. 241, 117610.
Donovan, G.H., et al., 2013. The relationship between trees and human health: evidence from the spread of the emerald ash borer. Am. J. Prev. Med. 44 (2), 139–145.
Donovan, G.H., et al., 2022a. Shortcomings of the normalized difference vegetation index as an exposure metric. Nat. Plants 8 (6), 617–622.
Donovan, G.H., et al., 2022b. The association between tree planting and mortality: a natural experiment and cost-benefit analysis. Environ. Int. 170, 107609.
Donovan, G.H., et al., 2022c. The natural environment and social cohesion: tree planting is associated with increased voter turnout in Portland, Oregon. Trees For. People 7 100215.
Donovan, G.H., et al., 2025. The association between tree planting and birth outcomes. Sci. Total Environ. 975, 179229.
Flanagan, B.E., et al., 2011. A social vulnerability index for disaster management. J. Homel. Secur. Emerg. Manag. 8 (1), 0000102202154773551792.
Giannico, O.V., et al., 2024. The mortality impacts of greening Italy. Nature Comm. 15 (1), 10452.
Huemmrich, K.F., et al., 2021. Canopy reflectance models illustrate varying NDVI responses to change in high latitude ecosystems. Ecol. Appl. 31 (8), e02435.
Iungman, T., et al., 2025. Co-benefits of nature-based solutions: a health impact assessment of the Barcelona Green Corridor (Eixos Verds) plan. Environ. Int. 196, 109313.
James, P., et al., 2016. Exposure to greenness and mortality in a nationwide prospective cohort study of women. Environ. Health Perspect. 124 (9), 1344.
James, P., et al., 2024. Assessing greenspace and cardiovascular disease risk through deep learning analysis of street-view imagery in the Us-Based nationwide nurses' health study. SSRN.
Ju, Y., et al., 2024. Assessing normalized difference vegetation index as a proxy of urban greenspace exposure. Urban For. Urban Green. 99, 128454.
Kondo, M.C., et al., 2017. The association between urban tree cover and gun assault: a case-control and case-crossover study. Am. J. Epidemiol. 186 (3), 289–296.
Kondo, M.C., et al., 2020. Health impact assessment of Philadelphia's 2025 tree canopy cover goals. Lancet Planet. Health 4 (4), e149–e157.
Li, H., et al., 2023. Beyond "bluespace" and "greenspace": a narrative review of possible health benefits from exposure to other natural landscapes. Sci. Total Environ. 856, 159292.
Locke, D.H., et al., 2021. Residential housing segregation and urban tree canopy in 37 US Cities. NPJ Urban Sustain. 1 (1), 15.
Lovasi, G.S., et al., 2013. Urban tree canopy and asthma, wheeze, rhinitis, and allergic sensitization to tree pollen in a New York City birth cohort. Environ. Health Perspect. 121 (4), 494.
Markevych, I., et al., 2017. Exploring pathways linking greenspace to health: theoretical and methodological guidance. Environ. Res. 158, 301–317.
Martin, G.K., et al., 2025. A health impact assessment of progress towards urban nature targets in the 96 C40 cities. Lancet Planet. Health 9 (4), e284–e293.
Martínez Pastur, G., et al., 2018. Ecosystem services from forest landscapes: an overview. Ecosystem Services from Forest Landscapes: Broadscale Considerations, pp. 1–10.
McDonald, R.I., et al., 2020. The value of US urban tree cover for reducing heat-related health impacts and electricity consumption. Ecosystems 23, 137–150.
Morgenroth, J., et al., 2025. Urban tree cover targets: the good, the bad and the SMART. Urban For. Urban Green., 128979
Multi-Resolution Land Characteristics Consortium, 2019. National Land Cover Database (NLCD) 2019 Tree Canopy Cover.
Murray, C.J., et al., 2003. Comparative quantification of health risks: conceptual framework and methodological issues. Popul. Health Metr. 1, 1–20.
Nowak, D.J., et al., 2006. Air pollution removal by urban trees and shrubs in the United States. Urban For. Urban Green. 4 (3–4), 115–123.
Nowak, D.J., et al., 2014. Tree and forest effects on air quality and human health in the United States. Environ. Pollut. 193, 119–129.
Opbroek, J., et al., 2024. Urban green spaces and behavioral and cognitive development in children: a health impact assessment of the Barcelona "Eixos Verds" Plan (Green Axis Plan). Environ. Res. 244, 117909.
Pettorelli, N., et al., 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. Trends Ecol. Evol. 20 (9), 503–510.
Pourpeikari Heris, M., et al., 2022. Assessing the accuracy and potential for improvement of the national land cover database's tree canopy cover dataset in urban areas of the conterminous United States. Remote Sens. 14 (5), 1219.
Qiu, H.-L., et al., 2025. Green spaces and preventable disease and economic burdens in China from 2000 to 2020: a health impact assessment study. Landsc. Urban Plann. 261, 105393.
Rojas-Rueda, D., et al., 2019. Green spaces and mortality: a systematic review and meta-analysis of cohort studies. Lancet Planet. Health 3 (11), e469–e477.
Roman, L.A., et al., 2018. Human and biophysical legacies shape contemporary urban forests: a literature synthesis. Urban For. Urban Green. 31, 157–168.
United Nations, 2015. Transforming our World: the 2030 Agenda for Sustainable Development.
U.S. Environmental Protection Agency, 2025. Ecoregions of North America.
Wang, J., Banzhaf, E., 2018. Towards a better understanding of Green Infrastructure: a critical review. Ecol. Indic. 85, 758–772.
Williams, H., et al., 2025. Expert perspectives on exposure-response functions for urban health policy: lessons from a UBDPolicy workshop. Environ. Res., 123150
Wolf, K.L., et al., 2020. Urban trees and human health: a scoping review. Int. J. Environ. Res. Publ. Health 17 (12), 4371.
Yanez, D.V., et al., 2023. An urban green space intervention with benefits for mental health: a health impact assessment of the Barcelona "Eixos Verds" plan. Environ. Int. 174, 107880.
Zhao, N., et al., 2021. Tree characteristics and environmental noise in complex urban settings–A case study from Montreal, Canada. Environ. Res. 202, 111887.