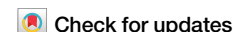


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Current inequality and future potential of US urban tree cover for reducing heat-related health impacts



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Excessive heat is a major and growing risk for urban residents. Here, we estimate the inequality in summertime heat-related mortality, morbidity, and electricity consumption across 5723 US municipalities and other places, housing 180 million people during the 2020 census. On average, trees in majority non-Hispanic white neighborhoods cool the air by 0.19 ± 0.05 °C more than in POC neighborhoods, leading annually to trees in white neighborhoods helping prevent 190 ± 139 more deaths, $30,131 \pm 10,406$ more doctors' visits, and 1.4 ± 0.5 terawatt-hours (TWhr) more electricity consumption than in POC neighborhoods. We estimate that an ambitious reforestation program would require 1.2 billion trees and reduce population-weighted average summer temperatures by an additional 0.38 ± 0.01 °C. This temperature reduction would reduce annual heat-related mortality by an additional 464 ± 89 people, annual heat-related morbidity by $80,785 \pm 6110$ cases, and annual electricity consumption by 4.3 ± 0.2 TWhr, while increasing annual carbon sequestration in trees by 23.7 ± 1.2 MtCO₂e yr⁻¹ and decreasing annual electricity-related GHG emissions by 2.1 ± 0.2 MtCO₂e yr⁻¹. The total economic value of these benefits, including the value of carbon sequestration and avoided emissions, would be USD 9.6 ± 0.5 billion, although in many neighborhoods the cost of planting and maintaining trees to achieve this increased tree cover would exceed these benefits. The exception is areas that currently have less tree cover, often the majority POC, which tend to have a relatively high return on investment from tree planting.

Climate change is already here, with myriad impacts on human health and society that are projected to increase over time as changes intensify^{1,2}. One important impact of climate change is increased risk from excessive heat, as climate change increases in average summer temperature as well as the frequency, intensity, and duration of heat waves. Already, in an average year, heat stress kills roughly 6100 Americans and 356,000 people globally³, as measured by epidemiological studies of excess deaths due to high temperatures. Note that the statistical estimate of excess deaths is considered more accurate than medical system records that often list another cause of death⁴ (e.g., the US Centers for Disease Control estimated an annual average of 1200 deaths from heat stress in the US based on medical records⁵). Higher

air temperatures increase mortality and morbidity by causing heat stroke and exhaustion and by exacerbating existing cardiovascular, pulmonary, and renal diseases^{6,7}. Summer temperatures in the United States (US), the focus of this paper, are increasing, and heat waves are becoming more frequent as climate change intensifies, with the average number of days with a dangerous heat index (high temperature and humidity) forecast to triple by 2050⁸.

Projected impacts on mortality are uncertain, varying among studies. One study projected that by 2090–2099, climate change in warmer regions of the world could increase annual heat-related mortality by 3.0% percentage points to 12.7%, depending on the region and the greenhouse gas

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(GHG) emissions scenario used. In the US specifically, annual heat-related mortality is forecast to increase by 3.5% percentage points under the high emissions scenario (RCP8.5)⁹. By contrast, another study in just the Eastern US projected an additional 11,562 annual deaths by 2050, which would represent a large increase in annual heat-related mortality¹⁰. While these two examples from the literature illustrate the wide range of projections of health impacts from increased heat waves, there is general agreement in the literature that climate change in the US will make heat waves more frequent and intense, increasing mortality and morbidity^{11,12}.

Trees can reduce solar radiation hitting surfaces such as asphalt and concrete, reducing temporary heat storage in these materials, which would later be emitted as thermal radiation. Trees also lose water to transpiration as they respire, and this phase change of water from liquid to gas increases latent heat flux¹³. The net effect of trees is, therefore, to reduce ambient air temperature, particularly during the daytime. The effect of trees is fairly local, reducing air temperatures primarily within a few hundred meters horizontal distance from the tree canopy, although this distance varies with factors such as the size of the canopy patch¹⁴, wind speed, and relative humidity⁷. It is important to note that while air temperature is correlated with health impacts, there are other heat stress metrics that take into account factors that are also important for thermal comfort, like humidity¹⁵ and direct solar radiation^{16,17}.

Heat action planning has been used by governments at many scales to reduce the risk to vulnerable populations. Common components of heat action planning include the creation of early warning systems, cooling centers, and response plans by medical institutions^{18,19}. One part of heat action planning can be actions to reduce ambient outdoor air temperature^{20,21}, and many city governments have begun to consider the additional role trees can play to reduce ambient outdoor air temperatures^{22–28}. Moreover, trees already provide significant heat-reduction benefits⁷. One study in the United States estimated that without urban tree canopy, annual mortality would have been 1200 deaths greater than at present²⁹.

Research on urban tree cover shows that its distribution is quite unequal. One way to measure this is to compare tree canopy across US Census blocks, for which we have associated socioeconomic data. In most US cities, low-income or people-of-color (POC) neighborhoods have less tree cover than high-income or non-Hispanic white (hereafter simply “white”) neighborhoods^{30–39}. One national survey of 5723 municipalities in the US (the same set of municipalities used in this study) found that in 92% of communities, low-income blocks have less tree cover than high-income blocks, with low-income blocks on average having 15.2% less tree cover and being 1.5 °C hotter (summer surface temperature) than high-income blocks⁴⁰. Multiple other studies show similar results using a variety of different methodologies, consistently finding that in most US cities, lower income and minority populations live in neighborhoods with higher summer surface temperatures^{41,42}.

Beyond the health impacts, heat has other impacts on society. For instance, Santamouris and others⁴³ found an average increase of 0.45–4.6% in peak electricity load for each 1 °C increase in air temperature. Trees near buildings can be one way to decrease electricity use, among other strategies such as implementing energy efficiency programs, reducing building albedo (“cool roofs”), and creating incentives to conserve electricity⁴⁴. Tree cover reduces ambient air temperature and shades buildings from solar insolation, reducing the energy demand for indoor cooling from 2.3% to 90%, depending on the study⁴⁵. This avoids electricity consumption and also avoids greenhouse gas emissions from electricity generation.

Urban trees also sequester and store carbon⁴⁶, among other ecosystem services⁴⁷. Urban trees are one kind of natural climate solution (NCS), defined as conservation, restoration, or management actions that increase carbon sequestration or avoid greenhouse gas emissions⁴⁸. In this study, we use estimates of net carbon sequestration by urban trees, accounting for both sequestration and emissions associated with tree mortality. Planting new trees in urban areas (afforestation or reforestation depending on site history, but for simplicity referred to as reforestation in this paper) will lead to net

carbon storage as the trees grow, even after accounting for GHG emissions associated with tree mortality^{49,50}.

Previous estimates of the urban reforestation potential in the United States were designed to estimate the maximum carbon sequestration potential. For instance, Fargione et al.⁴⁶ assumed that essentially all land in urban areas not currently developed (e.g., impervious surfaces, buildings) or under other land use (e.g., agriculture, sports fields, or golf courses) could be available for tree planting, estimating that (19.17–30.15 95% CI) 23.3 Mt CO₂ yr⁻¹ of carbon sequestration was possible, around 1.9% of the total NCS potential in the US⁴⁶. More recently, Cook-Patton et al.⁵¹ modeled fully planting all low-density open space in urban areas across the contiguous US where forest naturally occurs and estimated that 52.5 Mt CO₂ yr⁻¹ of carbon sequestration was possible.

However, only a fraction of the potentially available urban open area is likely to be plantable due to municipal codes and land-use regulations, landowner preferences, and conflicts with other land uses that require sparse vegetation like lawns. See Treglia et al. for an example of how these constraints may be considered in one municipality, New York City, with abundant geospatial data⁵². Moreover, past efforts at estimating the NCS potential of urban reforestation have often been based on 30 m Landsat-derived tree cover data. These coarser datasets miss many single tree canopies in urban areas and can significantly underestimate current tree cover⁵³, particularly in landscapes with <30% tree cover⁵⁴. Underestimation of the current urban forest canopy may lead to an overestimation of reforestation potential.

While there have been studies of individual cities or sets of cities^{22–27}, here we conduct a quantitative national prospective study for the US, of a large sample of thousands of cities, to estimate the potential that increases in urban tree cover have to reduce mortality, morbidity, and electricity consumption, examining how the potential of trees for heat-risk reduction varies across gradients of race/ethnicity. Understanding the potential of urban trees to serve as an adaptation to more frequent and intense heat waves is particularly important at this moment, when there is substantial investment in NCS as countries plan to achieve their Nationally Determined Contribution (NDC) commitments under the Paris Climate Accords⁵⁵, and the US has committed to increased funding for climate-related forestry programs as part of the Inflation Reduction Act⁵⁶. Similarly, substantial investment in climate adaptation is likely in the next decade by entities like the Green Climate Fund⁵⁷. Well-targeted, cost-effective investment in nature-based solutions for climate mitigation and adaptation is difficult without spatially detailed data on reforestation potential and need⁵⁸.

In this paper, we use a high-resolution (2 m) tree cover map for all 100 US urbanized areas >500 km² which contain 5723 municipalities or other Census-designated places that housed 180 million people in 2020 (68% of the people who live in urbanized areas in the United States or 55% of the national population)⁴⁰. For this large sample of 5723 municipalities (of which 50.6%, or 91 million people, represent majority white neighborhoods, 49.4%, or 89 million people, represent majority POC neighborhoods), we estimate reforestation potential at the Census block-level, accounting for variation in impervious cover among blocks and assuming that reforestation is only likely up to levels commonly seen in other blocks of similar impervious surface cover. We estimate the change in air temperature due to tree planting and the resultant reductions in human mortality, morbidity, and electricity consumption. In addition, we estimate the carbon mitigation potential achievable through this large-scale urban reforestation scenario. Across our analyses, we propagate statistical uncertainty to describe the precision of our estimates. The major goals of this paper are to:

- Quantify the inequality in the protective value trees currently provide by reducing mortality and morbidity across income and race/ethnicity.
- Estimate, for a variety of planting scenarios, the increase in urban tree canopy, the number of trees planted, the net carbon sequestration, and the costs. For each urban reforestation scenario, quantify the likely reduction in summer air temperatures, as well as the associated reduction in mortality, morbidity, and electricity consumption.

- Examine the return-on-investment (ROI) curve of urban reforestation's effect on avoided mortality, morbidity, and electricity consumption, to test whether ROI varies systematically with neighborhood income or race/ethnicity.

Results

Current national benefits

On average, across the country, neighborhoods with a majority of people of color (POC) have 11% less tree canopy cover and 14% more impervious surface than white neighborhoods (Table 1; unless otherwise stated, we present in this paper differences expressed as percentage points). We estimate that the current tree canopy, on average, reduces air temperatures by a population-weighted 1.01 ± 0.03 °C in white neighborhoods compared to 0.82 ± 0.03 °C in POC neighborhoods.

We estimate that in the majority of white neighborhoods, trees annually help avoid 632 ± 100 deaths. The annual economic value of that avoided mortality is USD 4.5 billion (Fig. 1). In contrast, we estimate that even though the total population in each race/ethnicity type is of relatively equal size (91 million in white neighborhoods vs. 89 million in POC neighborhoods), in majority POC neighborhoods trees help avoid 442 ± 97 deaths annually, an annual economic value of avoided mortality of USD 3.1 billion. This differential in benefits extends to other types of benefits. Morbidity is avoided because tree cover is $30,131 \pm 10,406$ greater in white neighborhoods than in POC neighborhoods (Table 1). Similarly, these trees reduce total electricity consumption in white neighborhoods by 1.4 ± 0.5 TWhr more than it does total consumption in POC neighborhoods (Table 1).

Patterns within urbanized areas

There is significant variation in current tree cover within urbanized areas, which leads to variation in the potential for tree cover increases to provide benefits. To demonstrate typical patterns, we provide a case study for Washington, DC, in Fig. 2. At a neighborhood scale, there is significant variation in tree cover, driven by differences in settlement density and urban form, as well as the existence of patches of forests within protected areas or otherwise undevelopable sites (Fig. 2a). Neighborhoods in DC that predominately house people of color have higher population density (average of 4828 people km^{-2}), and are more often centrally located, than neighborhoods that are predominately comprised of non-Hispanic white people, which are more often suburban or exurban (3962 people km^{-2}). On average, tree cover is 12% lower in POC neighborhoods than in white neighborhoods due to the correlation with population density (and hence impervious surface cover)⁴⁰ as well as other historical factors, such as redlining⁵⁹.

Across the entire Washington, DC urbanized area, there is an overall gradient in summer land surface temperature (Fig. 2b), with less densely populated suburbs and exurbs having lower land surface temperature than dense urban core neighborhoods, due to their lower impervious surface cover and greater tree cover. This pattern means that the greatest reduction in heat risk from additional planting, measured as annual avoided deaths per million people (M), occurs in denser, often POC, neighborhoods (Fig. 2c). However, the tree planting potential, measured in number of additional stems or in potential carbon sequestration, is greatest in suburban and exurban areas (Fig. 2d), which have low cover of impervious surfaces and hence more space for planting, even though those are the neighborhoods that already have disproportionately high tree cover. Thus, unless the total plantable area is increased in POC neighborhoods, benefits from increased tree cover are distributed unequally.

Patterns among urbanized areas

There is also variation among urbanized areas in the amount of tree cover and the protective benefits trees are providing from avoided heat-related mortality and morbidity. The largest benefit in terms of deaths avoided is in the urbanized areas with the greatest population, such as those centered around New York City and Los Angeles (Fig. 3). This is not surprising since there is a greater population potentially at risk from heat in the largest

Table 1 | Inequality in tree canopy cover, air temperature, heat-related mortality, morbidity, and electricity use

Race/ethnicity	Tree canopy cover (%)	Impervious surface (%)	Median reduction in summer air temperature due to trees (°C)	Reduction due to trees in annual mortality	Reduction due to trees in annual morbidity	Reduction due to trees in annual electricity (TWhr)
Majority non-Hispanic white	35	42	1.01 ± 0.03	632 ± 100	$114,936 \pm 7444$	6.2 ± 0.3
Majority POC	24	56	0.82 ± 0.03	442 ± 97	$84,805 \pm 7271$	4.8 ± 0.3

The median reduction in air temperature and total reduction in impacts is shown relative to a hypothetical case with no urban tree canopy cover to quantify the ecosystem service that urban tree canopy cover provides to heat-health. Neighborhoods are divided into those that are predominately non-Hispanic white or those that are predominately people of color (POC). Confidence intervals shown are calculated from regression analysis and error propagation; see "Methods" section for details. Tree cover and impervious surface cover are measured using remote sensing, and so the mean for our sample of cities is known with high precision (<0.1%), see the Methods for a discussion of the accuracy of classified remotely sensed imagery. The totals presented are for the 5723 municipalities in our sample.

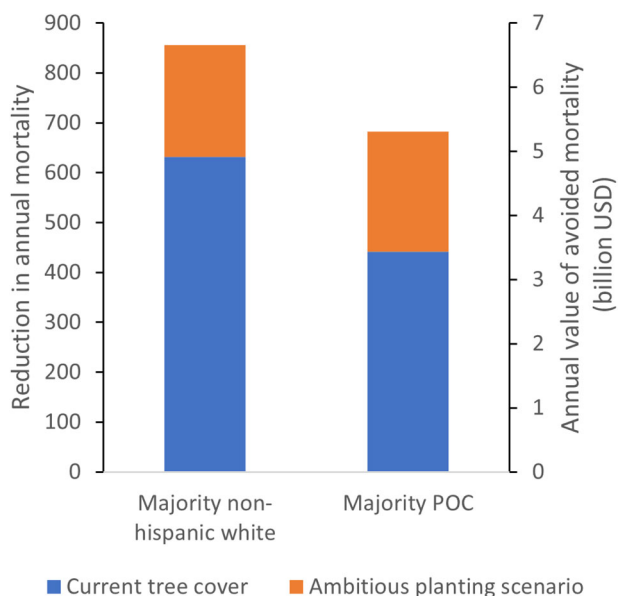


Fig. 1 | Mortality and urban tree canopy cover for our sample of 5723 US municipalities. Shown are the current annual reduction in mortality due to trees, as well as the additional reduction in mortality possible under the ambitious planting scenario. This quantity can be expressed not just in the annual lives saved (left axis) but also in the estimated annual value of avoiding this mortality (right axis).

urbanized areas, and so in absolute terms the number of avoided deaths due to trees is greatest in these urbanized areas. Other factors matter as well, however. Urbanized areas that are densely settled, with a lot of impervious surface cover, and yet have significant tree cover will have a relatively high number of avoided deaths due to trees, all else being equal. For instance, Boston (population 4.5 million) has both high impervious surface cover and relatively high population density, and trees currently help avoid an estimated 54 deaths annually. In comparison, Atlanta (population 5.1 million) has lower impervious surface cover and lower population density, and trees currently help avoid an estimated 32 deaths annually.

However, the protective benefits trees currently provide in terms of avoided mortality are unequally distributed with respect to race/ethnicity. To account for differences in population between majority POC and majority white neighborhoods, we calculated the protective rate, the number of heat-related deaths avoided annually due to trees per million people. The protective rate is generally lower in majority POC neighborhoods than in majority white neighborhoods (urbanized areas with yellow to red colors in Fig. 3). The inequality in protective rate is greatest in the Northeast of the US, in the so-called Northeast Corridor stretching from Washington (DC) to Boston (MA). These cities have substantial inequality in tree cover and surface temperature among neighborhoods, which leads to a substantial inequality in air temperature and the protective benefits of trees in reducing heat-related mortality⁴⁰. Northeastern US cities are characterized by dense city centers⁶⁰, often formed prior to the widespread availability of the automobile⁶¹, which often contain many of the POC neighborhoods and lower-density suburbs and exurbs that are often majority white⁴⁰. Conversely, there are urbanized regions where the protective rate is greater in POC than in white neighborhoods, such as Southeastern US cities like Atlanta⁴⁰. In these cities, most neighborhoods are at lower population densities and there is lower inequality in tree cover and surface temperature between neighborhoods⁴⁰.

National benefits of increased urban tree cover

Reforestation in our sample cities to an ambitious reforestation scenario (bringing each block up to the 90th percentile observed in each impervious surface category in each city; see methods section for details) could reduce population-weighted mean summer air temperatures by 0.38 ± 0.014 °C

(Table 2), with reductions up to 1.8 °C possible for specific neighborhoods. We estimate that this ambitious reforestation scenario would involve the addition of 1.2 billion trees and would reduce annual heat-related mortality by 464 ± 83 people, in addition to the current benefits that trees provide. There is roughly similar potential to reduce mortality in white and POC neighborhoods under the ambitious planting scenario (Fig. 1).

The ambitious reforestation scenario would deliver other benefits as well. It would reduce annual heat-related morbidity by an additional $80,785 \pm 6110$ cases and would increase net carbon sequestration in trees by 23.7 ± 0.2 MtCO₂e yr⁻¹ above the status quo (Table 2). It would also reduce annual electricity consumption by 4.3 ± 0.2 TWhr yr⁻¹, avoiding electricity-related GHG emissions annually by 2.1 ± 0.1 MtCO₂e yr⁻¹. Note, however, that even lower levels of tree canopy cover increases could still deliver substantial benefits. For instance, aiming for a nominal 5% increase in urban tree canopy cover where feasible would reduce annual morbidity by $23,614 \pm 1832$ cases (29% of the morbidity reduction achieved under the ambitious planting scenario).

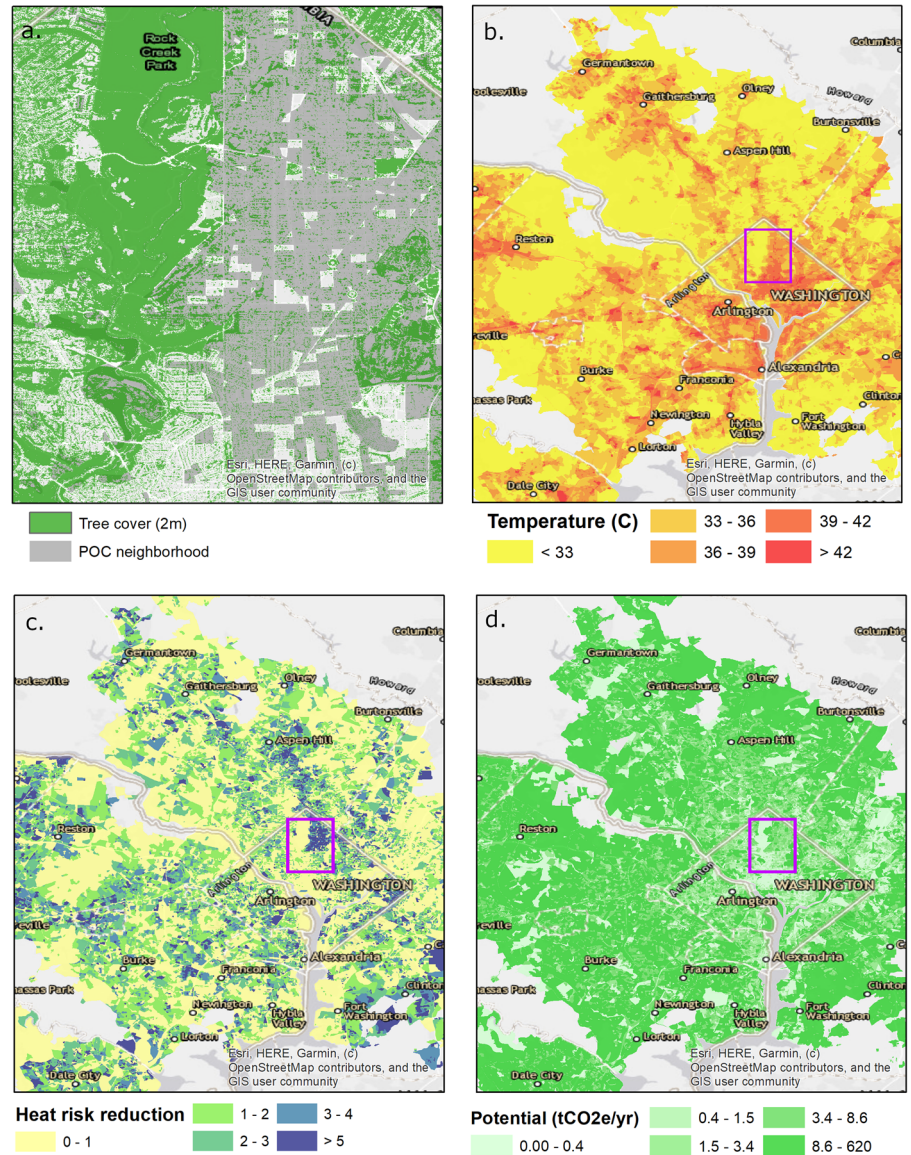
Spatial pattern of benefits of additional tree planting

Under the ambitious reforestation scenario, the largest reforestation potential, in terms of trees planted or additional net carbon sequestration, occurs in the urbanized areas with the largest geographic extent (Fig. 4). For instance, the Chicago and New York City urban areas are among the largest in extent in the United States, and both have an increase in net carbon sequestration of more than 1 MtCO₂e yr⁻¹ under the ambitious reforestation scenario. However, the potential additional net carbon sequestration varies by climate, with arid regions generally having lower feasible tree canopy targets due to natural limits on tree canopy in arid climates (see the “Methods” section for details), and humid regions in naturally forested biomes having higher feasible tree canopy targets. Similarly, the potential additional net carbon sequestration also varies by population density, with greater reforestation possible in lower population density areas, which have less impervious surface and hence higher proportions of plantable area. For the same reason, within urban areas, the greatest reforestation potential is often in suburban neighborhoods that are often majority white (e.g., Fig. 2, lower right). If reforestation in urbanized areas were to be prioritized solely based on potential additional carbon sequestration, then suburban neighborhoods would often have priority.

However, patterns are different with regard to tree canopy cover’s role in reducing mortality and morbidity. The greatest increase in protective rate (avoided annual deaths per million people) under the ambitious reforestation scenario occurs in the northeastern and western US (Fig. 4). These urbanized areas are relatively dense, with a high proportion of impervious surfaces. The addition of new tree canopy cover thus tends to shade impervious surfaces, reducing the urban heat island effect more substantially than if tree canopy shaded grass or other sparse vegetation. Moreover, these urbanized areas are in naturally forested biomes, so larger increases in tree cover are possible than in arid areas, where water limitations might limit tree canopy cover expansion.

For avoided mortality, we defined the return on investment (ROI) in tree planting as avoided annual heat-related mortality per tree planted. Within urbanized areas, the greatest increase in ROI under the Ambitious reforestation scenario is in dense neighborhoods, often located in city centers and often majority POC neighborhoods (e.g., Fig. 2, lower right). Thus, if reforestation in urbanized areas was to be prioritized solely based upon the potential protective health benefits of trees, then dense urban neighborhoods would have priority. For this reason, on average across the US, the ROI of tree planting is greater in majority POC neighborhoods than in majority white neighborhoods (Fig. 5, top panel). This is true for any level of planting ambition, from the 5% nominal target to the ambitious reforestation scenario. For instance, the 5% nominal target for majority POC neighborhoods would avoid more mortality than the 5% nominal target for majority white neighborhoods, with only half the number of trees as in white neighborhoods. It is worth stressing, however, that there is significant variation among neighborhoods in ROI. If we examine the mortality reduction

Fig. 2 | Inequality in the Washington, DC urbanized area. **a** Zoom-in of a purple rectangle shown in other panels. Tree cover varies significantly from block to block. Neighborhoods that are predominately people of color (POC) are shown in gray and are primarily east of Rock Creek Park, while the majority of non-Hispanic white neighborhoods are west of the park. Note that Rock Creek Park itself has no residents. **b** Land surface temperature in summer by census block, as observed by satellite imagery. For reference, the extent of the zoomed-in panel in the upper left is outlined in purple. **c** The potential reduction in heat risk due to additional tree planting (increase in protective rate, in avoided annual deaths per million people). **d** Potential additional carbon sequestered due to new tree planting within census blocks. While tree planting in the city center occurs at higher population densities and so benefits more people with heat reduction, the greatest number of potential trees can be planted in suburban areas.



benefits of the 5% of neighborhoods with the highest ROI (Fig. 5, bottom panel), we find the same general pattern of POC neighborhoods having higher ROI than white neighborhoods, but the number of deaths reduced per million trees planted is an order of magnitude greater in these high priority blocks than the overall national average.

Economic benefits of tree canopy increase

Total economic benefits of additional tree cover are shown in Table 3 for the 5% nominal target and the ambitious reforestation scenario. Benefits valued in this study are avoided mortality, avoided morbidity, avoided electricity consumption, and avoided damages resulting from higher atmospheric carbon dioxide concentrations, the latter due to avoided GHG emissions from avoided electricity generation and from increased carbon sequestration by the additional tree cover. Under the Ambitious tree planting scenario, USD 9.6 ± 0.4 billion in annual benefits would accrue. The 5% target tree planting scenario delivers fewer annual benefits, USD 2.5 ± 0.1 billion. The largest share of economic value is contributed by the carbon sequestered in the trees, followed closely by avoided heat-related mortality. Avoided electricity consumption, avoided GHG emissions from electricity consumption, and avoided heat-related morbidity all have meaningful but relatively smaller total economic values.

The economic benefits of the Ambitious tree canopy scenario are split relatively equally (Table 4) between POC neighborhoods (USD 3.9 ± 0.2 billion) and white neighborhoods (USD 5.0 ± 0.2 billion). Annual tree planting and maintenance costs would exceed annual benefits for both POC neighborhoods (costs of USD 19.5 ± 4.4 billion, Return on Investment, ROI = 0.20) and, especially, white neighborhoods (USD 40.5 ± 9.4 billion, ROI = 0.12). However, if tree canopy increases were targeted to the neighborhoods with the highest ROI, the situation looks different, with the annual economic benefits roughly equal to the costs of annual tree planting and maintenance. Indeed, a 5% nominal target for additional tree planting in High-ROI POC neighborhoods is estimated to provide USD 32 ± 4 million in benefits but to cost only USD 29 ± 7 million in planting and maintenance, an ROI of 1.12.

Discussion

Our results show that trees provide substantial benefits in terms of avoided heat-related mortality and morbidity in the US but that inequality in urban tree canopy cover leads to inequality in these protective benefits. In our sample of 5723 municipalities, we estimate that, annually, trees in white neighborhoods help avoid 190 more deaths, 30,131 more doctors' visits, and 1.4 TWh more electricity consumption than in POC neighborhoods, despite the nearly equal number of people in white and POC

Fig. 3 | Protective value of urban tree canopy for large US urbanized areas. The size of the circle is proportional to the avoided annual mortality due to urban tree canopy in the urbanized area. The color of the circle indicates the difference in the protective rate (annual deaths avoided due to urban tree canopy per million population) between people-of-color (POC) majority neighborhoods and non-Hispanic white majority neighborhoods. Negative values indicate that POC neighborhoods have a lower protective rate than white neighborhoods.

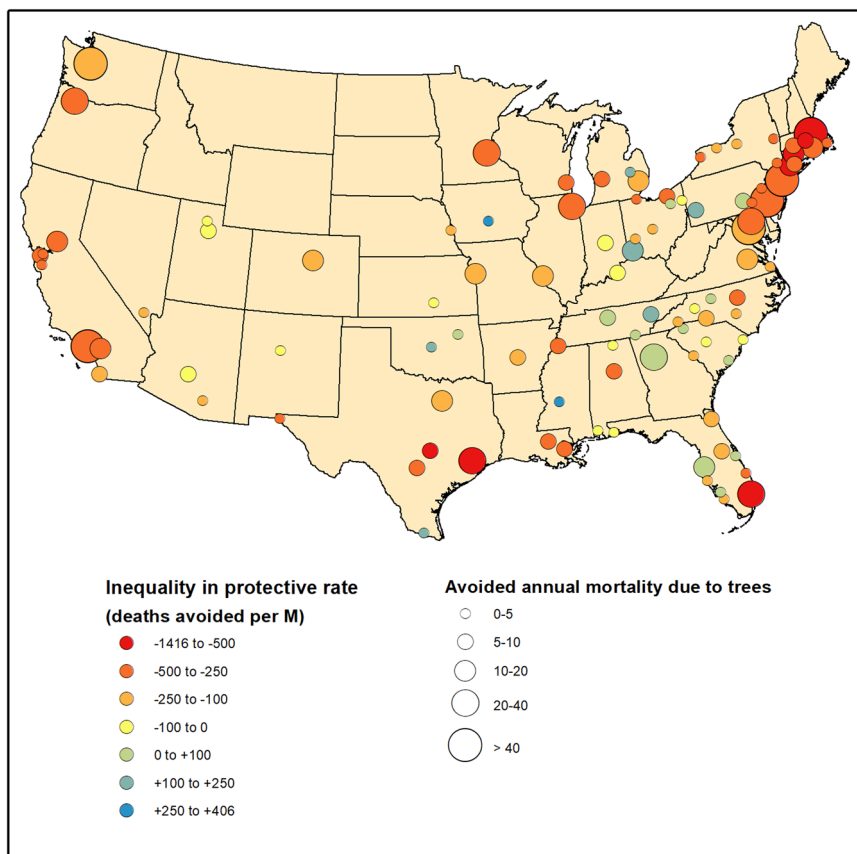


Table 2 | Estimated potential of reforestation in urbanized areas to provide benefits to human well-being for increases in tree canopy cover in 5% increments above current tree canopy

Target (%)	Reduction in median summer air temperature due to additional tree cover (°C)	Additional annual avoided mortality	Additional annual avoided morbidity	Additional annual avoided electricity consumption (TWhr)	Additional carbon storage (MtCO ₂ e)
5	0.11 ± 0.004	138 ± 25	23,614 ± 1832	1.2 ± 0.1	5.6 ± 0.1
10	0.19 ± 0.007	250 ± 44	42,855 ± 3280	2.2 ± 0.1	10.4 ± 0.1
15	0.26 ± 0.010	331 ± 59	56,993 ± 4340	3.0 ± 0.2	14.2 ± 0.2
20	0.31 ± 0.011	386 ± 69	66,535 ± 5064	3.5 ± 0.2	17.1 ± 0.2
25	0.34 ± 0.013	420 ± 75	72,626 ± 5524	3.8 ± 0.2	19.2 ± 0.2
30	0.36 ± 0.013	440 ± 79	76,260 ± 5792	4.0 ± 0.2	20.6 ± 0.2
35	0.37 ± 0.014	451 ± 81	78,326 ± 5938	4.1 ± 0.2	21.7 ± 0.2
40	0.37 ± 0.014	457 ± 82	79,468 ± 6017	4.2 ± 0.2	22.4 ± 0.2
Ambitious scenario	0.38 ± 0.014	464 ± 83	80,785 ± 6110	4.3 ± 0.2	23.7 ± 0.2

Shown are the annual reduction in mortality, morbidity, and electricity during heat waves, as well as the additional annual carbon storage. Error ranges show the 95% confidence interval of the estimate. The ambitious target scenario shows hitting the maximum possible planting, given our assumptions, across the 5723 municipalities in our sample. See text for details.

neighborhoods. While POC neighborhoods have less tree cover than white neighborhoods, their higher impervious surface area means that tree cover is more often shading impervious surfaces and thus provides relatively larger cooling benefits per unit canopy area. Climate change is expected to increase the frequency and intensity of heat waves, increasing mortality and morbidity⁹. This will likely elevate the public health importance of heat action planning in the coming decades. We believe that heat action planning should consider outdoor temperature, its public health impacts, the equity of these impacts, and strategies to mitigate these impacts and their inequity, such as increased investment in tree planting and maintenance.

We found that an ambitious reforestation scenario in these 5723 municipalities would annually save an additional 464 lives otherwise threatened by heat, equal to around 8% of current total heat-related deaths in the US³. It should be noted that this is just excess mortality associated with heat, and other studies that looked at health benefits from all pathways often show larger benefits. For instance, a study in Philadelphia estimated that an ambitious increase in tree canopy cover could avoid annually 298–618 premature adult deaths, due to all causes⁶². A similar study that looked at a sample of almost one thousand European cities estimated that an increase in NDVI to a level recommended by the World Health Organization could reduce mortality from all causes by 32,000–64,000 deaths annually⁶³.

Fig. 4 | Ambitious reforestation potential for large US urbanized areas. The size of the circles is proportional to the potential additional carbon storage under the ambitious reforestation scenario. The color of the circle indicates the increase in the protective rate (annual deaths avoided due to urban tree canopy per million population) under the same reforestation scenario.

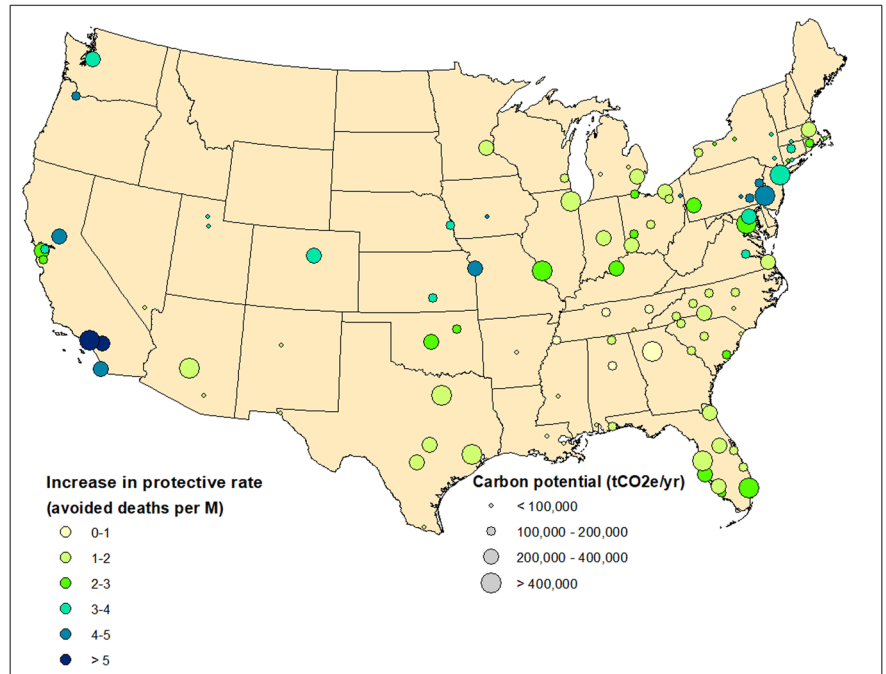
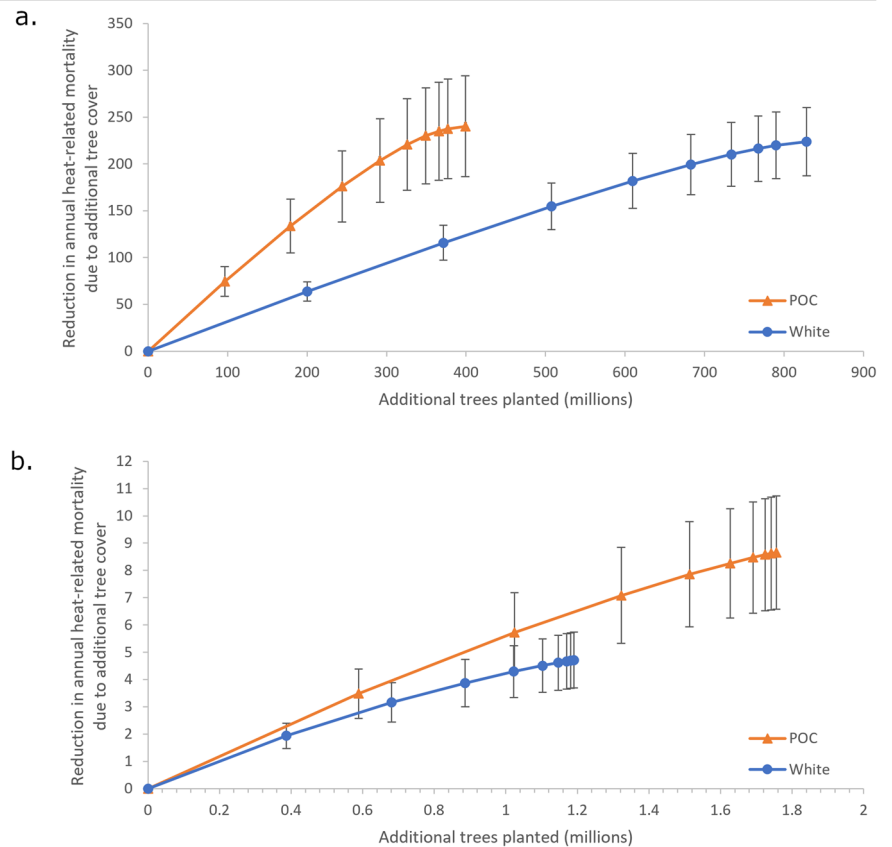


Fig. 5 | Mortality reductions as a function of planting ambition. Blocks are classified as either majority people of color (POC) or majority non-Hispanic white. For each census block, additions of tree cover of 5%, 10%, etc., up to an Ambitious Scenario, the maximum possible given our assumptions. Each point along the curve thus represents an additional 5% increase in tree cover, wherever this is possible. Error bars are the 95% confidence interval of reduction in annual heat-related mortality. **a** Results for all census blocks. For instance, planting 200 million additional trees in white blocks for a 5% increase in tree cover reduces annual heat-related mortality by an additional 62 lives. **b** Results for high ROI census blocks, defined as in the top 5% of ROI (see methods for details). Note the very different scales in the two plots. For instance, planting 0.4 million additional trees in white blocks for a 5% increase in tree cover reduces annual heat-related mortality by an additional 2 lives.



A more direct comparison to our work is a recent paper in Europe, which estimated that tree planting up to a 30% target in all neighborhoods would reduce European deaths from heat by around 33%⁶⁴. One potential reason for the difference between our study and this study is the differences in how targets were set. Our targets considered physical and social limitations in dense neighborhoods to tree planting while the European study did

not. Another potential reason is simply that European cities are, on average denser with more impervious surfaces than American cities, so tree cover is more likely to shade impervious surfaces, resulting in more significant heat reduction benefits.

Trees provide other benefits as well. We estimated that our ambitious tree restoration scenario could reduce annual heat-related morbidity by an

Table 3 | Economic benefits of tree planting for 5723 municipalities in the United States

Variable	Economic value (annual millions USD) at 5% target	Economic value (annual millions USD) at ambitious scenario target
Avoided mortality	982 ± 101	3299 ± 339
Avoided morbidity	32 ± 2	108 ± 7
Avoided electricity consumption	204 ± 14	703 ± 46
Carbon sequestration	1221 ± 65	5166 ± 287
Avoided GHG emissions from electricity	98 ± 6	344 ± 22
Total	2536 ± 121	9620 ± 447

Shown are the results for the 5% planting scenario and the ambitious planting scenario.

additional 80,785 cases, increase carbon sequestration in trees by 23.7 MtCO₂e yr⁻¹, and decrease electricity-related GHG emissions by 2.1 ± 0.1 MtCO₂e yr⁻¹. While expanding the urban forest by the additional 1.2 billion trees needed under this Ambitious Scenario would be a large financial investment, we want to emphasize that the heat-health benefits would likely offset a significant fraction of the costs. Indeed, targeted actions to increase tree canopy in high-ROI neighborhoods can result in benefits that equal or exceed tree planting and maintenance costs. Trees, of course, provide many other benefits not modeled in this paper, both to overall health⁶⁵ and to human well-being⁴⁷, and consideration of these other benefits would increase the total estimated benefits and ROI of increased urban tree canopy. Moreover, while our methods allowed for spatial variation in the impact of tree canopy on LST and air temperature by climate zone and region, as well as accounted for block-level variation in impervious surface cover, they do not allow for variation in model parameters with a city, potentially underestimating benefits at some sites within a city (see the Caveat and Limitations portion of the Methods section for a more detailed discussion).

There is greater return-on-investment in tree cover increases in majority POC neighborhoods for health benefits, relative to majority-white neighborhoods. That is, for a given number of trees planted, urban greening projects in POC neighborhoods will, on average, have a greater reduction in mortality and morbidity than projects in majority-white neighborhoods. Similarly, tree planting projects that target neighborhoods with disproportionately low tree cover will deliver disproportionate benefits to POC households because POC households tend to live in neighborhoods with less tree cover. Given the high tree cover inequality in the US with respect to race/ethnicity and income⁴⁰, programs such as the Inflation Reduction Act that aim to reduce heat-health impacts will have to address tree cover inequality, either explicitly or implicitly, if they are to target trees where they will have the greatest benefit. Of course, there are other reasons to consider race/ethnicity and socioeconomic status in heat action planning, as these populations are more vulnerable to heat hazards due to, among other things, lower access to air conditioning⁶⁶.

The estimated net carbon sequestration potential of reforestation in our sample of 5723 municipalities, under our Ambitious Scenario, is 23.7 MtCO₂e yr⁻¹. This is lower than Cook-Patton et al.'s estimate⁵¹ of 52.5 MtCO₂ yr⁻¹ and higher than Fargione et al.'s estimate⁴⁶ of 23.3 Mt CO₂ yr⁻¹, both of whose estimates cover all US urban areas (although the two studies used different definitions of what is urban). Another difference is that our definition of what could potentially be planted is more restrictive than in Cook-Patton et al.⁵¹ due to our consideration of both physical and social barriers to planting, which may further explain why our estimate is lower. Our estimation of reforestation potential in urbanized areas for sequestration is about 2.6% of the overall US potential for NCS across all natural climate solutions pathways in the US identified by Fargione et al.⁴⁶.

Table 4 | Economic benefits and costs of additional tree planting by race/ethnicity of census blocks

Target	Priority	Economic benefits (annual million USD) POC	Economic benefits (annual million USD) White	Cost of planting and maintenance (annual million USD) POC	Cost of planting and maintenance (annual million USD) White	ROI POC	ROI White
5% increase in tree cover	High ROI	32 ± 4	18 ± 2	29 ± 7	19 ± 4	1.12	0.95
5% increase in tree cover	Other blocks	1053 ± 64	1283 ± 49	4696 ± 1084	9794 ± 2261	0.22	0.13
Ambitious scenario	All blocks	1086 ± 64	1301 ± 49	4725 ± 1084	9813 ± 2261	0.23	0.13
Ambitious scenario	High ROI	81 ± 10	45 ± 5	86 ± 20	58 ± 13	0.94	0.77
Ambitious scenario	Other blocks	3805 ± 222	4967 ± 193	19,464 ± 4493	40,517 ± 9352	0.20	0.12
Ambitious scenario	All blocks	3886 ± 222	5012 ± 193	19,550 ± 4493	40,575 ± 9352	0.20	0.12

Shown is data for tree planting only in populated census blocks where human well-being benefits occur. Data are shown for neighborhoods that are majority people of color (POC) as well as majority non-Hispanic white (White). Census blocks are split into two priority categories, high return on investment (ROI) blocks and other blocks. High ROI is defined as neighborhoods in the top 5% of ROI.

For context, urbanized areas occupy about 2.8% of the total land area of the US⁶⁷. We also estimated that avoided electricity consumption due to additional trees would decrease electricity-related GHG emissions by 2.1 MtCO₂e yr⁻¹, for a total net climate mitigation potential of our ambitious reforestation scenario of 25.8 MtCO₂e yr⁻¹, a modest amount of carbon relative to the entire US carbon budget, but not insignificant, being the annual equivalent emissions of 5.7 million gasoline-powered cars⁶⁸.

We caution that there is, to some extent, a spatial disconnect between optimal sites for climate mitigation and climate adaptation. Although the carbon benefit per additional tree did not vary in our study and is expected to be the same from exurbs to downtown, the overall potential for carbon sequestration is greater in neighborhoods with more plantable areas (i.e., fewer impervious surfaces). This is more frequently the case in the suburbs or exurbs than in the city center. Patterns for avoided electricity consumption from space cooling (and hence avoided GHG emissions) are the opposite, being greater in densely populated blocks, but are an order of magnitude smaller than carbon sequestration in terms of MtCO₂ yr⁻¹. Heat-related health benefits also are greatest when trees are planted close to where people live and work, which is more frequently the case in city centers. We note that greater heat-related mitigation benefits in more densely populated neighborhoods would likely hold for other tree-provided ecosystem services that need to be generated close to people, such as air pollution mitigation, stormwater mitigation, and the benefits to physical and mental health from exposure to nature⁴⁷. The varying spatial scales of different ecosystem services lead to different optimal places for tree planting⁶⁹, with heat-reduction benefits needing to be provided within 100 m or so of people⁷. Carbon sequestration is, on the other hand, essentially global since the atmosphere is well-mixed and not restricted to locations near people. We stress, however, that this spatial disconnect between heat mitigation and carbon mitigation benefits is only partial, and sites can be found that have good returns for both. If both benefits are important, planners would do well to consider the joint return on investments from both benefits when making decisions about where to plant.

Realizing the climate mitigation and adaptation benefits of the reforestation scenarios considered in this paper requires overcoming the “wrong pocket problem”⁷⁰. This problem occurs when the person or institution that pays for an action is not the one benefiting from that action. Urban forestry agencies in municipalities do not generally have climate mitigation or adaptation as part of their mission, so while they must pay for increased tree planting and maintenance, they may not see a benefit in terms of their mission. Conversely, health agencies see heat action planning as part of their mission and would welcome the mortality and morbidity reductions of increased tree planting, but many have neither the capacity nor the budgetary authority to plant trees. Regulations, incentives, or investments created to increase the provision of ecosystem services can give value to these benefits and solve the wrong pocket problem by creating an incentive for different institutions to work together.

Investment at a higher level of government by agencies that have climate mitigation or climate adaptation as part of their mission can overcome the sometimes narrower goals and capacities of municipal forestry offices. To the extent that natural climate solutions are considered as part of federal policies to mitigate and adapt to climate change, reforestation in urbanized areas may be an investment that generates relatively modest carbon sequestration but delivers significant local climate adaptation benefits⁷¹. This may be particularly important in low-income neighborhoods, which generally have less tree cover and are hotter than high-income neighborhoods^{40,72}. Although there is a growing interest in reforestation in urbanized areas to meet climate mitigation goals, our work shows that a single-minded focus on carbon sequestration could further exacerbate inequities by shifting planting efforts outside of historically POC neighborhoods. Instead, putting equity first and making targeted investments in tree planting and maintenance in neighborhoods most at risk from heat could help correct some of the historic racial inequality in tree cover.

Methods

Our analysis proceeded in four phases. First, we assembled spatial data from multiple sources and compiled them into a common analysis unit. Second, we developed an algorithm that would set a plausible ambitious reforestation target, given other land-use constraints. Third, we estimated the heat mitigation-related benefits of the current tree canopy and of future planting scenarios up to the ambitious planting scenario. The benefits evaluated were avoided mortality, avoided morbidity, avoided electricity consumption, avoided release of greenhouse gases from avoided electricity consumption, and carbon sequestration in aboveground tree biomass. Fourth, we valued these benefits in monetary terms. In the following section, we discuss each of these phases in detail. We end the Methodology section with a broader conceptual discussion of some caveats and limitations of our analysis, discussing how they might affect our results and how future research might be able to improve upon our estimates.

Data sources

Our study focused on all US urbanized areas larger than 500 km² in extent⁴⁰. Urbanized area is defined by the US Census Bureau as census blocks that exceed a population density threshold (1000 people per square mile) as well as contiguous blocks with more than 500 people per square mile that link nearby blocks of high-density settlements^{67,73}. There are 100 urbanized areas that are >500 km² in extent, housing 180 million people during the 2020 census. Each urbanized area contains many municipalities or other census-designated places; in total, our study area contains 5723 such communities⁴⁰. These span the range of population sizes and densities, from a large central city like New York City (8.4 million people) to small communities at the edges of metro areas with just a few thousand people. These urbanized areas also span the range of biomes in the United States, from forests to deserts to grasslands.

The fundamental unit of analysis for our study is the census block, as defined by the US Census Bureau. These are the finest spatial resolution data on population and demography available in the United States, which makes them appropriate for an analysis of the cooling effects of trees for different demographic groups. The median census block in our cities (excluding census blocks with no population, such as parks) has 57 people in it, but this varies widely, with 80% of blocks having between 16 and 198 population. The average person lives in a census block of 4.5 ha (80% range: 1.2–50 ha). Importantly, census blocks are designed to be smaller in area in city centers and thus capture more fine-grained detail and to be larger in rural areas with lower population density.

Our tree cover maps are taken from McDonald et al.⁴⁰, which mapped tree cover for the same set of 100 urbanized areas, using the boundaries of the urbanized area set after the 2010 Census. For consistency with that dataset, we use the same boundary file for this analysis rather than the 2020 urbanized area boundaries. Aerial photos taken during the summer growing season at approximately 2 m resolution from the National Agricultural Imagery Program (NAIP) were classified into a forest/non-forest grid using Google Earth Engine’s cloud computing platform. Training data for the supervised classification came from Nowak and Greenfield⁷⁴, which examined tree cover at 10,000 control points throughout urban and community areas of the United States. After creating several texture variables and band indices (e.g., NDVI), this information, along with information from the original spectral bands, was classified using a random forests classifier built off the training data. Pixel-level classification accuracy varies by biome but averages 82%.

Importantly, however, our unit of analysis for this paper was the census block level, not the pixel level. Census blocks contain many 2 m pixels, so the estimate of tree cover at the census block level can be more accurate than at the pixel-level scale if any classification errors are uncorrelated. We validated our estimates of tree cover at the census block level against an independent dataset, the accurate high-resolution tree cover maps produced by Urban Tree Canopy assessments^{75,76}. At the block level, our estimates of tree cover were highly linearly correlated with those of the validation dataset ($R = 0.97$). On average, the median absolute block-level error of our tree

cover estimate, as compared to the validation dataset, was 6.0%. Thus, while the pixel-level accuracy of our classification was only moderate, our estimates of tree cover at the block level were highly correlated with an independent validation dataset. Much more information on our classification methodology is available in McDonald et al.⁴⁰

Our information on demography and socio-economic status comes from the US Census Bureau's 2020 decennial census, downloaded from the National Historical Geographic Information System (NHGIS)⁷⁷. Population and its breakdown by race and ethnicity were available at the Census block level. Details of the GIS analysis and processing of this data can be found in McDonald et al.⁴⁰, which used the 2010 Census but otherwise had similar processing of Census data.

Impervious surface data were taken from the National Land Cover Database 2019 product⁷⁸. This dataset was derived from Landsat imagery, and measures as a continuous variable the percent impervious surface in each pixel. While 30 m data on the impervious surface cover is coarser than our forest cover map, the fact that there is a continuous estimate of imperviousness helps address sub-pixel heterogeneity.

Land surface temperature (LST) was derived from the Collection 2 LST science product from Landsat 8 at 100 m resolution. Pixel level quality flags were used to remove cloud-contaminated pixels, following the methodology of Chakraborty et al.⁷⁹. All data between 2016 and 2020 were accessed through the Google Earth Engine platform⁸⁰ to create mean summer (June, July, August; JJA) LST composites. This 5-year period averages over year-to-year variability in LST while also being long enough to ensure that most regions have usable, cloud-free pixels for which LST can be estimated.

Reforestation scenarios

Next, we defined an algorithm to set an ambitious reforestation target, given other land-use and climatic constraints. Conceptually, we wanted to consider two constraints: a physical constraint (trees can generally only be planted on non-impervious surfaces, excluding rare landscape features such as planter boxes) and a social/political/climatic constraint (planting trees is constrained by numerous other considerations, including competing land uses, landowner preferences, zoning and building codes, and climatic conditions). For more conceptual discussion of these two constraints, see the "Defining plantable area" section below.

Tree cover is negatively correlated with impervious surface cover⁴⁰. We divided the landscape into five impervious surface categories (0–20%, 20–40%, 40–60%, 60–80%, 80–100%) to reflect the different landscape contexts from lightly settled suburbs to dense urban core. Our general strategy was to model different scenarios in each US Census block, where tree cover was increased by intervals of 5% (e.g., from 5% to 10%), potentially up to an Ambitious Scenario where all previous surface was greened. However, tree planting was stopped when there were likely to be other constraints. This likely constraint was defined at the 90th percentile of observed tree cover in each impervious surface category for each urbanized area. In other words, tree planting was halted at the 90th percentile of tree cover for blocks in that urbanized area with similar landscape contexts (imperviousness). This approach implicitly accounts for differences among cities (e.g., in climate), as well as urban form and zoning and building codes.

Once our ambitious reforestation scenario was estimated at the Census block level, we constructed a set of scenarios for all our sample cities, each aiming to hit a certain nominal increase in tree cover. Thus, for instance, the 5% increase planting scenario aimed to increase tree cover in each census block by 5%. If this nominal increase exceeded the Ambitious Scenario for a census block, then tree cover for that census block was held at the Ambitious Scenario tree cover amount instead. We constructed planting scenarios with increases of 5%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, and Ambitious (i.e., all census blocks set at the maximum possible reforestation amount, given our assumptions), respectively.

Note that an increase in tree canopy cover, as seen from directly overhead above the tree canopy, necessarily decreases other land covers since total land cover in a region must sum to 100%. To account for this in our planting scenarios, we made the simplest possible assumption that

additional tree cover occurs randomly over other land covers in proportion to their cover before planting. For instance, if in an impervious surface category in a particular city, 25% of the area not already in tree cover was impervious and 75% was in sparse vegetation, we assumed that any tree canopy increases would occur 25% over impervious surfaces and 75% over sparse vegetation, displacing these land cover types accordingly.

Finally, we calculated the number of new stems that would need to be planted to achieve this increase in the tree canopy based on the average canopy size of 19.6 m² stem⁻¹ derived from Nowak and Greenfield⁸¹. Note that planted trees grow their tree canopy over time, with some tree species in mesic environments taking 3–5 years to reach 5 m height and crown diameter and more than 10 years to reach 10 m height and crown diameter⁸². Our tree planting scenarios assume spacing appropriate for adult trees, and we are estimating benefits for the tree canopy associated with those adult trees.

Estimating benefits

We focused in our analysis on the most important heat-related benefits that trees provide, as identified in previous manuscripts^{7,29,83}, as well as on carbon sequestration⁴⁶.

Values of average annual carbon sequestration per m² of urban tree canopy were taken from Nowak et al.⁸⁴. They assembled data on tree growth rates and carbon accumulation in tree biomass using information from 28 cities and 6 states to estimate average gross carbon sequestration per m² of tree canopy. They then considered average mortality rates and associated release of stored carbon, estimating that there was 0.226 kg C annual average net carbon sequestration per m² of the canopy. We acknowledge that this estimate does not include greenhouse gas emissions from tree planting and management practices that result in greenhouse gas emissions, which can be significant, but we are not aware of national representative numbers that would account for this effect. For comparison, Kendall and McPherson⁸⁵ estimate that over the lifecycle of California-planted urban trees (note that many urban trees are not planted but spontaneously regenerate), carbon dioxide emissions from tree planting amount to a 20–50% reduction in mean annual net carbon dioxide storage rates.

To estimate the likely reduction in summer air temperature that would occur due to reforestation, we used a two-step regression approach, similar to that of Zhang et al.⁸⁶. Another recent paper in the *Lancet* by Lungman et al.⁶⁴ also uses a two-step approach, estimating as we do the effect of trees on LST, then the effect of LST on air temperature. This two-step regression approach allows us to set up two regressions that each relate observed information to observed values of predictor variables, allowing us greater interpretability for each regression and greater flexibility in functional form than if we tried to conduct a one-stage regression. Note also that the observed data for LST (derived from satellite imagery and available for all census blocks in our study area) and air temperature (measured at a smaller number of air temperature sensors) are at different spatial and temporal scales. By conducting two separate regressions, we avoid the loss of information that would occur from combining these two datasets.

In our first step, we statistically related impervious cover and urban tree cover to LST at the census block level. Urbanized areas were divided into two climatic groups, mesic and xeric, based on biomes (see McDonald et al.²⁹ for details). For each climatic group, a linear regression was conducted using PROC GLM in SAS, relating LST (the dependent variable) to both impervious cover and urban tree cover. A fixed effect for urbanized areas was also included. To avoid potential issues of spatial autocorrelation, we take a sparse sample of 10,000 census blocks out of the 2.3 million census blocks in our sample area. The sparse sample represents 0.4% of the total number of Census blocks and ensures that census blocks are, on average, quite far from one another and are thus more likely to be independent statistically in terms of the dependent variable, LST (i.e., any errors in the estimation of LST in one census block are likely to be spatially uncorrelated with errors in other census blocks). Five observations were dropped due to missing data. Results from our regression are shown in Table 5. The R^2 for xeric regions was 0.85, while that for mesic regions was 0.76.

Table 5 | Model parameters from regression relating LST to tree cover and impervious surface cover

	Type III SS	Mean SS	F value	P	Estimate	SE
MESIC. Tree cover (fraction)	1443	1443	310	<0.001	-2.88	0.16
MESIC. Impervious surface cover (fraction)	15,684	15,684	3367	<0.001	9.06	0.16
MESIC. NAME (N = 86)	68,869	810	174	<0.001	Multiple	
ARID. Tree cover (fraction)	1031	1031	212	<0.001	-8.06	0.55
ARID. Impervious surface cover (fraction)	327	327	67	<0.001	2.78	0.34
ARID. NAME (N = 14)	35,906	2762	567	<0.001	Multiple	

Separate regression analyses were undertaken for mesic and arid cities. A fixed effect for urbanized areas (NAME) was included. Shown is first the regression for mesic cities (N = 8498 with complete data), followed by the regression results for arid cities (N = 1497 with complete data).

Table 6 | Model parameters from regression relating air temperature to LST

Biomes	Estimate	SE
Temperate broadleaf and mixed forests	0.33	0.030
Temperate coniferous forests	0.35	0.030
Tropical and subtropical grasslands, savannas, and shrublands	0.40	0.033
Temperate grasslands, savannas, and shrublands	0.36	0.028
Flooded grasslands and savannas	0.46	0.034
Mediterranean forests, Woodlands, and scrub	0.25	0.026
Deserts and xeric shrublands	0.35	0.023

Regression slopes were allowed to vary by the biome in which an urbanized area is located. The overall regression also included an intercept term and was highly significant ($F = 57.8, P < 0.001$). Shown are the regression results for census blocks with air sensors (N = 423).

In our second step, we statistically related air temperature information with LST. The air temperature data came from the Global Historical Climatology Network⁸⁷ for summer (JJA) average daily mean (see McDonald et al.²⁹ for details on data handling and processing). There were 423 air temperature stations within our study area. A linear regression was conducted using PROC GLM in SAS, relating air temperature (the dependent variable) to LST. The fitted slope was allowed to vary by biome (i.e., biome is included as a fixed effect in interaction with LST in the model). A fixed effect for urbanized areas was also included. The number of air temperature sensors is relatively small, they are measured independently by different machines, and they are relatively far from one another, so we did not suspect there would be spatial autocorrelation in the dependent variable after accounting for LST. Results from our regression are shown in Table 6. The R^2 for this regression was 0.49, lower than for our statistical model explaining LST, perhaps reflecting the fact that there is a broad variety of factors that affect air temperature beyond the local surface temperature⁸⁸. Regardless, we can propagate any uncertainty in estimating air temperature in our analysis, which is an advantage of our statistical approach as opposed to more mechanistic models.

Note that, therefore, the air temperature impacts of our tree planting scenarios are a function of multiple factors: the amount of plantable area in a Census block; the fraction of impervious surface before planting, which determines how much impervious surface cover is reduced through planting; the aridity and biome of an urbanized area, and an urbanized area fixed effect. We summarize the effect of multiple factors in Supplementary Table 1, which lists (by urbanized area and impervious surface category) the realized change in tree cover and impervious surfaces for the 5% target scenario, as well as the estimated change in LST and air temperature. Not surprisingly, the greatest decline in impervious surface area with planting is generally in impervious surface category 5 (defined as neighborhoods with 80–100% impervious surface cover). The only exception is when there is not enough plantable area in impervious category 5 neighborhoods to approach the 5% target for tree canopy increase. Conversely, the smallest decline in

impervious surface area with planting is generally in impervious surface category 1 (defined as neighborhoods with 0–20% impervious surface cover). For this reason, the greatest decline in LST occurs in impervious category 5, while there are lesser declines in impervious category 1, with similar patterns across climate variables (aridity and biome). Asheville, NC, has the greatest average city-level decline in LST in impervious category 5 (0.49 °C). Patterns for air temperature declines are similarly generally greater in impervious category 5 and less in impervious category 1, with similar patterns across climate variables (aridity and biome). Bonita Spring, FL, has the greatest decline in air temperature in category 5 (0.21 °C). Finally, note that we estimate statistically the change in LST and air temperature at the scale of a US census block, which includes a variety of land-use types. This makes our estimates of temperature impact per unit increase in tree cover different from (and lower in magnitude than) the estimates of tree cooling efficiency of Zhao et al.⁸⁹, who used Landsat-based estimates of tree cover and LST to quantify change in LST for those pixels with tree canopy.

This study focuses on tree canopy and its benefits relative to the race/ethnicity of neighborhoods. Within our sample of cities, race/ethnicity is correlated to the impervious surface category (Table 7), with most neighborhoods in categories 4 and 5 being majority POC, while most neighborhoods in categories 1 and 2 are majority non-Hispanic white. This pattern is discussed extensively in McDonald et al.⁴⁰, results from low-income households, which are more likely to be POC, being more frequently located in US Census blocks with high population density and high impervious surface cover in city centers rather than less dense suburbs. Race/ethnicity is also correlated with aridity, as the arid southwest of the US has a larger fraction of POC in all impervious categories than does the mesic region of the country. This latter pattern is primarily caused by a higher share of people of Hispanic origin, who are counted in the POC category for our study. Since impervious surface category and aridity are two of the explanatory variables used to predict the impact of tree canopy increases on air temperature, the correlation of race/ethnicity with these variables necessarily implies that the impact of tree canopy increases on air temperature varies with respect to race/ethnicity.

To estimate the health impacts of an estimated change in air temperature due to tree canopy expansion, we follow the methodology of McDonald et al.²⁹. For estimating avoided mortality, we use published epidemiological studies that relate changes in air temperatures to changes in mortality over time. Specifically, we use Bobb et al.⁹⁰, who estimated the heat–mortality relationship for 105 US cities. In this study, we use Bobb et al.’s regional estimates of the heat–mortality response curve, listed in our Supplementary Table 2. For morbidity estimation, our analysis is based on Gronlund et al.⁹¹, who estimated heat-related hospitalizations as a function of air temperature for a large population in the US and then scaled from the Gronlund et al. numbers to estimate emergency department visits and doctor’s office visits²⁹.

We estimated avoided electricity consumption due to tree cover, following the methodology in McDonald et al.²⁹. We base our analysis on Santamouris et al.⁴³, a literature review that collected empirical estimates of

Table 7 | Race/ethnicity composition of our sample, relative to impervious surface and aridity

Impervious surface category	Arid population, millions (%) White	Arid population, millions (%) POC	Mesic population, millions (%) White	Mesic population, millions (%) POC	Total population, millions
1 (0–20%)	0.7 (54%)	0.6 (46%)	15.6 (79%)	4.1 (21%)	21.0
2 (20–40%)	2.0 (54%)	1.6 (46%)	25.9 (66%)	13.4 (34%)	42.9
3 (40–60%)	4.5 (36%)	8.1 (64%)	22.9 (52%)	20.7 (48%)	56.2
4 (60–80%)	3.0 (22%)	10.8 (78%)	10.6 (38%)	17.2 (62%)	41.8
5 (80–100%)	0.8 (22%)	2.7 (78%)	5.2 (36%)	9.2 (64%)	17.8
Overall categories	(32%)	(68%)	(55%)	(45%)	

Population totals, in millions, are shown. Percentage of the population within each aridity category and each impervious surface category is shown in parentheses. For instance, in arid urbanized areas, there are 2.7 million POC in impervious surface category 5, 78% of the total population of arid cities in this impervious surface category.

increases in electricity use during periods of high air temperature. We subset the results in Table 1 of their paper to just look at US studies, which gave a range of 2.9–8.5% increase in electricity consumption per 1 °C increase in air temperature. We assume that the shift in summer daily mean temperatures we modeled would only increase electricity consumption for space cooling during summer months (One quarter of the year). From this assumption, we calculated an estimated annual increase in electricity consumption, assuming no increase in other seasons. We then multiplied the percent increase in electricity consumption by city-level data on residential electricity use. To estimate avoided GHG emissions due to avoided electricity consumption, we multiplied avoided electricity consumption by the average carbon intensity of US electricity generation, taken from EPA data.

Finally, when calculating statistics at the level of urbanized areas or nationally, we used population-weighted statistics to give greater weight to Census Blocks with greater population.

Valuation and extrapolation

Our valuation methodology follows McDonald et al.²⁹ and is extensively described in the supplementary methods section of that paper. The costs of tree planting and maintenance costs (annualized) were assessed for a sample of US cities^{7,23}, and we use those values hereafter adjusting for inflation.

To briefly summarize, for avoided mortality, we use a value of a statistical life approach (VSL), adjusted for remaining life years (e.g. refs. ^{92,93}), using a range in the US of \$5.4–13.4M (2015\$)⁹⁴. Most heat-related deaths occur in people 55 years or older^{92,95}, and so we apply Murphy and Topel's⁹³ life cycle shape for the value of a life-year for 11 age classes to calculate an overall average, age-weighted VSL, accounting for the age distribution of mortality from heat-related events, of \$5.7M (2015\$, range: \$3.3–8.2M).

For morbidity, we use a cost-of-illness (COI) approach to assess the economic burden associated with heat-related illnesses (HRI) that were avoided due to tree cover. Economic calculations were done separately for avoided emergency department (ED) visits⁹⁶, avoided hospitalizations⁹⁷, and outpatient visits⁹⁸. We also estimated lost work productivity as the product of total work loss days (from HRI-related hospitalizations, ED visits, and outpatient visits) and the average US daily earnings rate (see McDonald et al.²⁹ for details).

For electricity consumption, we used the results of Santamouris and colleagues⁴³, which for US studies give a range of 2.9–8.5% increase in electricity consumption per 1 °C increase in air temperature. Data on average household residential electricity consumption and average cost per kWh, by electric utility were taken from the US Energy Information Administration (EIA, 2016) form EIA-861. See McDonald et al.²⁹ for details. While our methodology is an accurate estimate of the average relationship between changes in air temperature and electricity consumption, we acknowledge that for particular buildings or neighborhoods the relationship might have a greater or lesser slope. Note that we are accounting for different regional climates by the different regional regressions used to model LST and air temperature, as well as the information on local electricity consumption and cost by the electric utility.

For carbon sequestration and avoided GHG emissions due to avoided electricity consumption, we used the new EPA proposed Social Cost of Carbon (SCC) for 2020 of USD 190 expressed at 2020 prices, assuming a 2% discount rate⁹⁹. This estimate follows that of recent science by Rennert et al.¹⁰⁰. The SCC measures the total (global) estimated economic damages, expressed in monetary terms, that result from one additional ton of carbon dioxide in the atmosphere. These damages from increased atmospheric CO₂ concentrations are separate from and fully additional to, the local damages from health and electricity use impacts that increases in urban tree canopy avoid via their local cooling effects. Where necessary, all economic costs and benefits presented in this paper were standardized to USD in 2022, using the US Bureau of Labor Statistics Consumer Price Index¹⁰¹.

Caveats and limitations

In this section, we discuss conceptually some caveats and limitations of our analysis. We do not repeat the technical details of our methodology presented above. Rather, we discuss how these kinds of limitations, common and in some cases currently unavoidable in this kind of research, might affect our results. We also discuss how future research projects might overcome some of these limitations and improve the accuracy of our estimates.

As in many geospatial analyses of the linkage between land cover, temperature, and health, we had to deal with spatial and temporal differences in the underlying data. For instance, our tree cover data is high-resolution (2 m) binary data, while the best available impervious surface cover data for our sample of 5723 municipalities is at 30 m resolution but provides continuous estimates of the percent impervious. While the difference in spatial resolution between the two datasets will affect the accuracy of our results, it was unavoidable given the best available input datasets. One of the reasons we chose the census block as our unit of analysis, rather than the pixel level, was so that information from many pixels could be averaged, reducing the overall classification error rate. Similarly, the spatial boundaries for which 2016 forest cover was classified correspond with the 2010 US Census Bureau definition, which was altered for the 2020 US Census. The shifting of spatial boundaries is relatively minor, occurring generally at the edge of urbanized areas where population density is relatively low (Supplementary Fig. 1). We chose to minimize temporal differences, using our 2016 forest cover data and the 2020 census data on demography, rather than the alternative of using 2010 census data for demography.

Our general approach when dealing with spatial or temporal differences in input datasets is to avoid inconsistencies where possible but to choose methodologies that minimize their impact when not possible. The empirical regressions we used to link tree cover and impervious surface cover to land surface temperature (LST), as well as LST to air temperature, are one example of a methodology that corrects inconsistencies in input datasets. The regression parameters are chosen to maximally explain the predicted variables, and so linear transformations of explanatory variables alter the parameter but not the predicted variable. For instance, suppose with a high-resolution sensor, the impervious cover was measured at X%,

but with the 30 m resolution data we used the impervious surface cover was measured as some fraction of this, $fX\%$. If a regression relating impervious surface cover X to LST estimated a slope β , then a regression relating fX to LST would estimate a slope β/f , but the predicted values of LST would not change. If the relationship between impervious surface cover measured at different resolutions is not a linear function, the effect on the predicted values of LST is more complex to assess. In general, however, empirically relating measurable variables to one another helps account for small differences in spatial and temporal scale.

As with any analysis of the potential for increasing urban tree canopy cover, ours had to define decision criteria for what is plantable. There is some subjectivity in defining the maximum plantable area. In theory, an urban area could install green roofs on many buildings, depave substantial areas of impervious surfaces, and otherwise take expensive but feasible steps to increase urban tree canopy cover and vegetative area. What is easier to objectively define is how a certain percentage point increase in tree canopy cover will affect temperatures. In our study, we consider a range of tree cover increases (5%, 10%, 15%, etc.), plus an “Ambitious” scenario where tree cover is maximized subject to two constraints, discussed below. We acknowledge that other studies could define a more or less ambitious scenario of tree planting by making different assumptions about constraints.

Our first constraint, as in other studies^{7,23}, is to consider the fraction impervious as unplantable. Note that this constraint is implemented at the census block level, not the pixel level. We acknowledge that there are very detailed studies, such as Treglia et al.⁵², that use fine spatial resolution data at the pixel level that consider how new trees might overhang impervious surfaces in pixels adjacent to where the stem was planted. Note, however, that at the US Census Block scale, it is rare that the amount of tree cover exceeds the previous fraction (i.e., 1—impervious cover). Supplementary Fig. 2 shows the relationship between tree cover and the impervious fraction for the New York City urbanized area. In only 5.5% of the census blocks, does the tree cover exceed the previous fraction (i.e., 1—impervious), and in those cases where it does, tree cover exceeds the previous by a median of 3.7%p. For almost all census blocks, tree cover does not substantially exceed the previous fraction.

Our second constraint tries to account for many other factors that vary among urban areas, such as differences in aridity, regulations, urban form, and landowner preferences. We acknowledge that a detailed study in one municipality⁵² may have spatial information on many of these factors. Such an approach becomes infeasible, however when dealing with thousands of municipalities, as is the case in this study. Following other published studies^{7,23}, we set a target at the 90th percentile of tree cover observed in neighborhoods of similar impervious surface cover. Our way of setting an Ambitious target using the observed distribution within an impervious category within an urban area implicitly accounts for factors that vary among urban areas, such as climate, urban form, and regulations. It is also an ambitious target implying, for example, that the Charlotte urbanized area (mesic climate) could raise population-weighted tree cover from 50% to 67% percent, while the Phoenix urbanized area (arid climate) could go from 10% to 22%. By definition, however, there are 10% of neighborhoods that exceed our 90th percentile target, and we acknowledge our “Ambitious Scenario” is not the maximum imaginable.

One important innovation in our methodology is to calculate tree cover and its benefits at the local (census block) level when possible. When we present averages or use them in calculations, we use the population-weighted average rather than the simple average to better represent the tree cover the typical person experiences. To see why the type of average matters, consider our Ambitious Scenario, where the simple average increase in the New York City urbanized area was from 26% to 44%, while the population-weighted average increase was from 22% to 35%. Focusing on the highest impervious surface category used in setting our targets (80–100% impervious), where 7.4 million people lived in the New York urbanized area in 2020, the population-weighted average increase in tree cover under the Ambitious Scenario was from 6.8% to 12%. In other words, a disproportionate part of the tree cover increase in the urbanized area would occur in

relatively sparsely populated census blocks, while dense census blocks in Manhattan would have relatively small increases. Contrast our methodology with the assumption made in some studies that a city might hit a certain tree cover target (e.g., 30%) at a simple average level, essentially assuming all neighborhoods hit that goal and then estimating health benefits using that simple average change calculation. Such an approach would potentially overstate the tree cover increases that are possible in more densely populated neighborhoods, which in the US are often predominately people of color⁴⁰.

Finally, another challenge for any study of many municipalities is deciding when to use a national average, perhaps relatively precisely estimated, versus when to account for regional variation. Our approach has been to use regional estimates where they can be consistently estimated for our 5723 municipalities and to otherwise use the best available national estimates. For instance, our empirical regressions relating tree cover and impervious cover to LST (Supplementary Fig. 3) and LST to air temperature (Supplementary Fig. 4) allow for regional variation in the parameters of the model. The amount of regional variation allowed (i.e., the regional boundaries) depended on the patterns in our dataset, as described above in the subsection “Estimating benefits” section. Our estimate of mortality impacts comes from Bobb et al.⁹⁰, who also allowed their regression parameters to vary by region (Supplementary Table 2). Readers should note, however, that there are many other studies of heat/mortality relationships, using different indices of thermal comfort and showing various response curves^{102–104}.

Sometimes, however, national averages were the best available. For instance, we used data on average planting and maintenance costs from a sample of US cities^{7,23}. These were estimates for municipal staff planting and maintenance, and we acknowledge other groups that use volunteer labor, such as non-profit organizations might have lower costs. While this dataset of costs is sufficient to calculate a national average, we do not have information for each of the 5723 municipalities in our database, and we acknowledge that individual municipalities might have quite different planting costs. Similarly, we use the US national average for canopy size from the US Forest Service but do not have access to information on the average canopy size for each municipality. Undoubtedly, tree canopy size varies by municipality due to the species planted, planting age, and climate, among other factors. In general, the use of accurate national averages means our national estimates are correct but we cannot map regional or local variability in these factors. Future US national studies would benefit from more spatially resolved data on planting costs and canopy size.

Reporting summary

Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The datasets generated during the current study are available in the Data Dryad repository, <https://doi.org/10.5061/dryad.zgmsbckkf>.

Code availability

The underlying code for this study is available in Zenodo and can be accessed via the linked Data Dryad repository, <https://doi.org/10.5061/dryad.zgmsbckkf>.

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Author contributions

R.I.M. designed and led the analysis. T.B. calculated tree cover for the municipalities in our sample. T.C.C. calculated land-surface temperatures. T.K. designed the economic valuation analysis. S.C.C.-P. helped design the rules for where reforestation was feasible, and with J.E.F. helped design the calculation of carbon sequestration. All co-authors helped write the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s42949-024-00150-3>.

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