Landscape and Urban Planning 242 (2024) 104947

Contents lists available at ScienceDirect

Landscape and Urban Planning

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

Leafy localities, longer lives: A cross-sectional and spatial analysis

Gweneth Leigh [a], Andrew Leigh [b,*]

[a] University of Canberra, Australia
[b] Parliament of Australia, Australia

HIGHLIGHT

- We study tree cover and mortality using Australian area-level data from 2015 to 2020.
- One standard deviation more tree cover is associated with 0.1 SD fewer deaths.
- The relationship between tree cover and health holds for most major causes of death.
- The association between tree cover and health is larger for men than women.
- Value of life estimates suggest the mortality benefit of trees exceeds planting costs.

ARTICLE INFO

Keywords:
Mortality
Morbidity
Health
Tree canopy cover
Forests
Nature

ABSTRACT

Are trees good for your health? Using detailed satellite imagery, we estimate the extent of tree coverage at a fine neighborhood level across urban Australia. We then look at the neighborhood-level association between tree canopy cover and mortality. Holding constant socioeconomic status, we find evidence of a strong beneficial relationship. Neighborhoods with more trees have lower levels of mortality, with a 10 percentage point increase in tree cover (about one standard deviation) associated with a reduction in mortality of 11 deaths per 100,000 people (about one eighth of a standard deviation). This association holds for most major causes of death, and is larger for men than for women. Health morbidity is better in areas with more trees, although this relationship is not statistically significant. Analysis of sub-samples does not support the critique that our results are merely driven by short-term selection effects in which healthier people move to tree-lined suburbs. Using standard estimates of the value of a statistical life, the mortality benefit of additional trees substantially exceeds the cost of planting and maintenance. Our findings support the protection and restoration of tree canopy in urban neighborhoods as a means of promoting public health and reducing health inequalities.

1. Introduction

Cities differ dramatically in the extent of their tree canopy cover. While some of this variation can be explained by soil quality and climatic factors, differences also depend on how planners and policy makers prioritize the inclusion and availability of green space to city dwellers. Once considered an exclusive amenity for the wealthy, parks and open spaces are now recognized as critical infrastructure to be accessed by all city dwellers (Zhao et al., 2023). This includes the urban tree canopy.

There are a range of ways that trees may affect cities and their residents (Roy, Byrne and Pickering, 2012; Pearlmutter et al., 2017). Trees can make a city more beautiful. Their foliage and form can enhance the aesthetic value of neighborhoods in ways that provide pleasant spaces for recreation. Trees reduce environmental harm by absorbing stormwater, filtering pollutants and sequestering carbon. However, trees can also cause harm. They can block sunlight, damage footpaths, and drop limbs in storms. In public areas, planting and maintaining trees places pressure on stretched government budgets.

The accessibility of the urban forest can impact the health of communities (Wolf et al., 2020). Tree-lined streets can create more enjoyable places for physical activity that may improve longevity (Knobel et al., 2021). By providing shelter from the sun, trees may also ameliorate the health impact of extreme heat. These characteristics are most often found in more affluent communities, epitomized by the phrase 'leafy neighborhood'. If trees improve health, then improving tree

* Corresponding author.
E-mail addresses: gweneth.leigh@canberra.edu.au (G. Leigh), andrew.leigh.mp@aph.gov.au (A. Leigh).

https://doi.org/10.1016/j.landurbplan.2023.104947
Received 12 December 2022; Received in revised form 24 October 2023; Accepted 27 October 2023
Available online 2 November 2023

coverage in disadvantaged areas may also help reduce life expectancy gaps across socioeconomic groups (Mitchell et al., 2015). Understanding this relationship between foliage and human health therefore has immediate implications for policymakers.

Our study builds on the existing literature by exploring whether urban tree canopy is related to neighborhood mortality. We do this by analyzing detailed tree data from Australia, an advanced nation with a temperate climate that is conducive to outdoor activities. Using new data on tree coverage, we precisely estimate the share of a given neighborhood that is covered by trees, and then match this to existing neighborhood-level data on mortality and socioeconomic characteristics. This allows us to regress mortality on tree cover and socioeconomic characteristics, which provides an estimate of the neighborhood-level association between tree canopy cover and mortality, holding constant the socioeconomic mix of the local community.

The remainder of our paper is structured as follows. In Section 2, we outline the theoretical pathways through which tree cover might affect population health, and summarize the existing evidence. In Section 3, we discuss our data and methodology. Section 4 presents and discusses our findings and robustness checks. Section 5 discusses how the magnitude of our estimates compares with those in the literature, and compares the costs of tree planting to the mortality benefits. The final section concludes.

2. Background

Multiple studies find a positive association between urban greenspace and health outcomes (Hartig, 2021, Markevych, 2017). Exposure to greenspaces have been associated with a reduced risk of high blood pressure (Tamosiunas et al., 2014), being overweight (Knobel et al., 2021) or having Type 2 diabetes (Mazumdar et al., 2021) – all risk factors linked to cardiovascular disease, the leading cause of mortality worldwide (Nowbar et al., 2019).

The relationship between greenspace and health is not uniformly positive. In the case of air pollution, trees have a beneficial impact by absorbing pollutants, but may also have a detrimental effect by emitting allergenic pollens and reducing the dispersion of car exhaust. A review of the literature finds that the relationship between urban vegetation, air quality and asthma is inconclusive (Eisenman et al., 2019). However, the net effect of greenspace on health appears to be positive. In a meta-analysis, Rojas-Rueda et al. (2019) found the risk of all-cause mortality was significantly lower with increased exposure to residential greenspace.

Some studies have sought to differentiate between trees and greenspace more broadly. Astell-Burt and Feng (2019a) found that tree canopy was associated with lower rates of diabetes, hypertension and cardiovascular disease, while total greenspace was associated with lower rates of diabetes only. Similarly, Reid et al. (2017) found significantly higher rates of self-reported health among those living near high tree cover, but no association between self-reported health and grass cover. A systematic review reaches a similar conclusion: the relationship between tree canopy and health does not appear to hold for grasslands and health (Nguyen et al., 2021).

In a scoping review looking at the relationship between urban trees and human health by Wolf et al (2020), the preponderance of evidence points to a negative relationship between trees and unhealthy factors including excess heat, air pollution, ultraviolet radiation, and crime. One of the factors that has been most carefully studied is the urban heat island effect, where higher temperatures lead to heat related fatalities, particularly in those with cardiovascular disease or respiratory illness (Basu, 2009; Brown et al., 2018). Temperatures tend to be lower in areas with trees, with a meta-analysis estimating that daytime temperatures in urban parks are around 1°C cooler than in the surrounding streets (Bowler et al., 2010).

Focusing on Australia, a series of recent papers have identified relationships between greenspace and mental health (Astell-Burt and Feng 2019b), cardiovascular health (Astell-Burt et al. 2021), sleep (Astell-Burt and Feng 2020a), dementia (Astell-Burt, Navakatikyan and Feng 2020), memory (Astell-Burt and Feng 2020b), loneliness (Astell-Burt et al. 2022) and physical activity (Feng, Toms and Astell-Burt 2021). A systematic review finds that most of those studies which disaggregate effects by gender have found that greenspace has a stronger protective effect for women than men (Sillman et al. 2022).

Other studies have explored the equity implications the relationship between greenspace and health. Studies have shown that low-income areas have lower rates of vegetation and higher temperatures, exposing residents to a larger mortality burden (Kondo et al., 2020; Schwarz et al., 2015). Growing scientific evidence suggests that greenspace serves an important preventative health measure within urban environments that could also help reduce the health gap between rich and poor people (Kondo et al., 2020; Mitchell et al., 2015; Wolch et al., 2014).

Although most of the foregoing literature is cross-sectional (Wolf et al., 2020), several papers have used experiments or natural experiments to measure the relationship between trees and health. A systematic review of multiple randomized experiments concluded that treatment groups who walked in nature ('forest bathing') had better mental wellbeing than control groups who walked in urban areas (Kotera, Richardson and Sheffield, 2022).

In a natural experiment, Donovan et al. (2013) studied the impact of the emerald ash borer, an invasive forest pest that caused the loss of 100 million trees across the United States. In counties where trees were lost, deaths from cardiovascular and lower-respiratory-tract illness rose. Like the randomized trials of forest bathing, the natural experiment approach addresses one of the potentially confounding factors in this literature: if healthier people choose to live in neighborhoods with more trees, then the association between tree coverage and health may not reflect the causal impact of trees on health.

Our research builds on this prior literature in three ways. First, we present evidence on the most important health outcome: mortality. Although we recognize the interest in studying proximate health outcomes (and indeed, our study also looks at obesity and inactivity), longevity is of central importance to health researchers. Focusing on mortality also makes it possible to use estimates of the value of a statistical life to carry out a cost-benefit analysis of additional tree plantings. Second, while some research on tree cover and health has used small and potentially unrepresentative samples (such as a single city), our analysis uses all available data from Australia, a geographically large country whose neighborhoods exhibit considerable variation in tree cover. Third, we address the issue of neighborhood sorting through a robustness check in which we re-analyze the relationship between tree cover and mortality, progressively excluding the areas with the highest levels of population mobility.

3. Methodology

3.1. Tree coverage data

Historically, the main limitation on large-scale studies of tree cover has been the low resolution of satellite imagery and aerial photography (see eg. Smith et al., 2010; Browning and Locke, 2020). Using imagery with large pixel sizes (eg. 30 m) makes it difficult to ascertain the true extent of tree cover in an area. When coding such imagery, it is difficult to distinguish between trees and other features, such as agricultural fields, or buildings with green painted roofs.

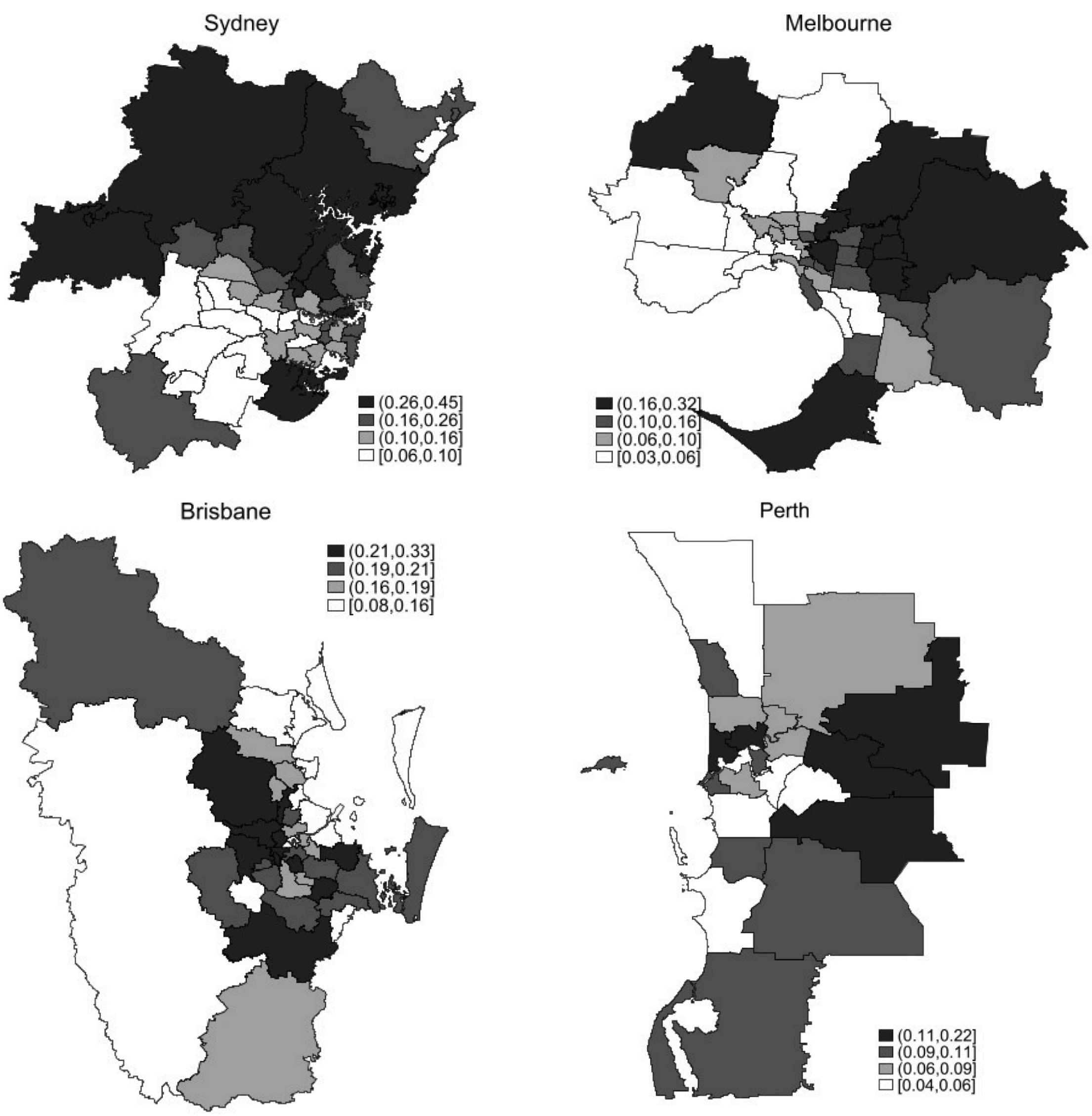
After reviewing all available tree datasets in Australia, we opted to purchase a proprietary dataset compiled by Geoscape Australia, a provider of national location data. Geoscape tree coverage data is generated from a pixel-level analysis of tree coverage derived from satellite imagery taken in June 2020 (Geoscape, 2020). The Geoscape data was chosen in preference to other alternatives such as the National Vegetation Information System dataset due to the high resolution. For example, the Geoscape data has a pixel size of 2 m by 2 m, while National Vegetation Information System dataset has a pixel size of 100 m by 100 m. If the typical urban tree has a canopy of 10 m diameter, it will be captured by the Geoscape data, but missed by the National Vegetation Information System data unless it is surrounded by other trees.

The Geoscape source imagery identifies for each pixel whether or not tree cover is present. Within each neighborhood, we then count the number of pixels with tree cover and divide this by the total number of pixels to estimate the percentage of tree cover. To calculate the percentage tree cover by census area using the Geoscape tree cover dataset (version 1.6), we followed these steps, using ESRI ArcGIS Pro and the open source QGIS desktop software:

1. Append all tree cover raster data to a single dataset in GDA2020 GA LCC projection.
2. Convert pixel values to either 1 (trees present in pixel) or 0 (no trees present in pixel). The source data also includes tree height per pixel, but we do not use this information.
3. Determine which SA1 areas are fully covered by the Geoscape tree data.
4. Analyze tree cover data for SA1 areas which are fully covered by the Geoscape tree data.
5. Calculate percentage tree cover for each SA1 area as the sum of pixel values with tree cover divided by the total number of pixels.

To follow these steps in the two software programs requires the graphical interface, rather than code. Screenshots of the relevant graphical interface choices are available to anyone having difficulty in replicating our work based on the description above.

Fig. 1 provides a sample of the data, depicting tree canopy coverage in Australia's four most populous cities: Sydney, Melbourne, Brisbane and Perth.



Note: Boundaries are at the Australian Bureau of Statistics Statistical Area 3 level. Legend shows tree cover range (eg. '0.26,0.45' denotes tree cover ranging from 26 percent to 45 percent).

Fig. 1. Tree Canopy Coverage in Four Australian Cities. Note: Boundaries are at the Australian Bureau of Statistics Statistical Area 3 level. Legend shows tree cover range (eg. '0.26,0.45′ denotes tree cover ranging from 26 percent to 45 percent).

Our tree cover data are based on imagery that focuses on urban areas with a population of 200 or more people. The tree cover dataset covers less than 1 percent of the total land area of Australia (we estimate the total Geoscape tree data dataset coverage as 51,109 km^2, and the Geoscape tree data coverage of areas fully within an SA1 boundary as 22,739 km^2, while according to the website of Geoscience Australia, the total land area of Australia including islands is 7,688,287 km^2). However, the dataset provides us with accurate tree coverage for 90 percent of the Australian population (based on the 2016 Census, 20,964,733 people were in an SA1 area for which we were able to calculate tree coverage using the Geoscape dataset, out of a total of 23,401,461 people covered by the 2016 Census and assigned to an SA1 area).

For the purposes of our analysis, we aggregate tree canopy coverage data to the same level as the available mortality and morbidity statistics. For mortality statistics, data are only available at an SA3 level, so we aggregate tree coverage to that level, averaging across SA1s on a population-weighted basis. For morbidity statistics, data are only available at a PHN level, so we aggregate tree coverage to that level, averaging across SA1s on a population-weighted basis.

Those areas for which we do not have tree coverage data tend to have lower rents, lower incomes, lower levels of education, lower shares of people who do not speak English at home, and higher shares of Indigenous people. This is consistent with these omitted areas being more disadvantaged, remote communities.

Our data correlate closely with other studies of tree coverage. For example, the Australian Capital Territory Government used LiDAR remote sensing to estimate urban tree canopy cover at a suburb level (ACT Government, 2021). To compare our data against this source, we aggregated our tree coverage estimates to a suburb level. Across 94 ACT suburbs for which tree cover estimates exist in both datasets, the average tree cover is higher in the ACT Government data (25 percent) than in our dataset (14 percent). However, the two datasets closely correspond in terms of which suburbs have more tree coverage. Across suburbs, the correlation between the ACT government's estimates and ours is 0.9. This provides us with some reassurance as to the accuracy of our tree coverage estimates.

3.2. Health data and socioeconomic controls

The main health measures we use are mortality figures from the Mortality Over Regions and Time (MORT) books. These aggregate deaths over a five-year period, 2015–2019, and at the geographic level of a Statistical Area 3 (SA3). SA3 units are an aggregate of SA1 units, and generally have a population of between 30,000 and 130,000 people. In major cities, SA3 areas represent the areas served by a major commercial or transport hub. In regional areas, SA3s cover the areas served by regional cities with a population of 20,000 or more, often aligning to Local Government Areas. The MORT books cover the full universe of deaths, and are based on the Cause of Death Unit Record File data, maintained by the Australian Institute of Health and Welfare (AIHW) in the National Mortality Database.

Mortality figures are represented as annual deaths per 100,000 people. Naturally, areas with a higher average age tend to have higher mortality rates, so all mortality figures are adjusted to account for the age structure in the local area (Kleinman 1977). In effect, this converts the local area mortality rate to what it would be if its age structure matched that of the full Australian population at a common point in time (by convention, the Australian Bureau of Statistics uses the national age structure in 2001). Where m_i is the mortality rate for age group i and W_i is that age group's population share in 2001, the age-adjusted mortality rate is equal to $\sum m_i W_i / \sum W_i$. In addition to all-cause mortality, we present age-adjusted mortality rates from some of the most common causes of death, including cancer, heart conditions, kidney failure and suicide.

For the purposes of our analysis, it is necessary to make some minor adjustments to the causes of death dataset. The MORT books show, for each SA3 region, the number of deaths that occurred in the period 2015–2019. Figures are presented for each of the top 20 causes of death on a national level. Where a cause of death is one of the top 20 causes for a particular SA3, the AIHW data shows the age-adjusted mortality rate. For example, the age-adjusted rate of death for coronary heart disease is shown for every SA3, since it is always one of the top 20 causes of death in each region. However, where a cause of death is not one of the top 20 causes of death in a region, the AIHW dataset shows the number of deaths, but not the age-adjusted rate. For example, we know the number of deaths due to accidental falls in all SA3 areas, but in some cases the AIHW does not report the age-adjusted rate of death due to accidental falls.

To account for this, we therefore estimate the mean age-adjusted population denominator for all reported deaths (we calculate this figure for each SA3 and cause of death, and then average it across the SA3, weighting by the number of deaths in each cause). We use this age-adjusted population denominator to estimate the age-adjusted death rate where it is not reported. Note that this will necessarily be imprecise, since the age profile differs across causes of death. However, the advantage of this approach is that it allows us to compare causes of death across all SA3 areas, without needing to contend with issues of sample selection. In general, our results are not particularly sensitive to excluding cases where we cannot precisely calculate the age-adjusted mortality rate for particular causes of death. There are a handful of SA3 areas for which the AIHW data report all-cause mortality for persons, but do not provide a breakdown by gender or cause of death. Since these are a tiny fraction of the total sample, we drop them in the interests of comparability.

For ease of exposition, we do not present results for the top 20 causes of death. Instead, we aggregate mortality statistics, following the International Statistical Classification of Diseases and Related Health Problems 10th revision (ICD-10). We create a category of major cancers, which is the sum of deaths due to Lung cancer (C33, C34), Colorectal cancer (C18–C20, C26.0), Prostate cancer (C61), Breast cancer (C50), Pancreatic cancer (C25), Cancer of unknown or ill-defined primary site (C26, C39, C76–C80 excl. C26.0), and Liver cancer (C22), which are all classified as 'Neoplasms', ICD-10 codes C00-D48. We also create a category of heart conditions, which is the sum of deaths due to Coronary heart disease (I20–I25), Cerebrovascular disease (I60–I69), Heart failure and complications and ill-defined heart disease (I50–I51), Cardiac arrhythmias (I47–I49), and Hypertensive disease (I10–I15), which are all classified as 'Diseases of the circulatory system', ICD-10 codes I00-I99. This reduces the 20 top causes of death in Australia to 10 major causes.

To shed further light on our mortality results, we explore how tree cover relates to three health measures: overweight, exercise and blood pressure. To this end, we use data collected in the 2017–18 National Health Survey, a survey conducted by the Australian Bureau of Statistics covering approximately 21,300 people in 16,400 private dwellings across Australia. Although the National Health Survey excludes Very Remote areas of Australia and discrete Aboriginal and Torres Strait Islander communities, this makes little difference to our analysis, since our tree data covers urban areas. National Health Survey data are available only at the level of the Primary Health Network (PHN). PHNs connect health services across a specific geographic area, as defined by the Australian Government Department of Health. There are 31 PHNs, covering the entirety of Australia.

Unlike tree cover data and mortality data, measures from the National Health Survey are affected by sampling error. The specific measures we use are:

- **The proportion of adults with high blood pressure.** High blood pressure is defined as the share of people with a systolic reading of 140 or higher and/or a diastolic reading of 90 or above, plus people who reported they were taking hypertension medication (regardless of their blood pressure reading).

- **The share of people who are overweight or obese.** Overweight is defined as a body mass index of 25 or above, while obesity is defined as a body mass index of 30 or above.
- **The percentage of people who do not meet the recommended physical activity guidelines.** Respondents aged 18 to 64 met the physical activity guidelines if they completed 150 min of physical activity (where vigorous activity is multiplied by 2) on 5 days or more in the prior week. Respondents aged 65 over met the guidelines if they completed 30 min or more of physical activity on at least 5 days in the last week. Physical activity includes exercise at work, walking for fitness, recreation, or sport; walking to get to or from places; moderate exercise; and vigorous exercise recorded in the week prior to interview.

As with mortality data, each of these health measures is age-standardized to the Australian population. These are all risk factors, so the interpretation of their coefficients is the same as that for mortality, with negative coefficients representing lower risk levels (and therefore better population health).

What controls should be included? Ideally, our regression specification should hold constant baseline socioeconomic differences. By doing so, we are effectively comparing health outcomes in areas with similar levels of affluence, racial diversity and education. These socioeconomic variables are not pathways through which greenspace affects health, and they may confound the relationship between tree cover and health if they are correlated with both metrics. For example, if richer areas have more trees and better health, then failing to include a control for affluence could lead to us mistakenly concluding that trees affect health, when in fact both are driven by affluence.

However, we deliberately do not include control variables that may capture the pathways through which trees could affect health. As Wooldridge (2013, 205-206) points out, including additional variables in an attempt to maximize the goodness-of-fit (R^2) can lead to the problem of overcontrolling. Overcontrolling occurs when the researcher controls for the mechanisms through which the key independent variable affects the dependent variable. For example, if trees improve the air quality, noise levels or temperature in local neighborhoods, then controlling for these variables would capture part of the causal effect of trees on health. Mistakenly including an air quality, noise level or temperature control would then us to underestimate the true impact of trees on health. The same is true of controlling for health behaviors. For example, if trees cause people spend more time outdoors or with friends, then controlling for outdoor time or socializing would lead us to underestimate the true impact of trees on health. Admittedly, data constraints make this a hypothetical point in some cases. Since our analysis requires finely disaggregated geographic data across Australia, detailed data on some of these metrics would not be available, even if we wished to include them.

Our socioeconomic controls are drawn from the 2016 Census, which provides precise neighborhood-level measures across the nation. We include five socioeconomic controls: median rent, median household income, the share of the population who have a year 12 education, the share of the population who are Indigenous, and the share of the population who speak a language other than English at home. We include rent as a proxy for housing wealth, since the Census does not include home values, and rent is more closely related to housing values than average mortgage repayments (which vary significantly with the timing of house purchase). In our analysis (though not in the summary statistics table) the rent and income variables are logged, reflecting the fact that we expect health to be affected by a given percentage change in rents and incomes, not a given dollar change. The other variables are shares, which range from zero to one. Table 1 presents population-weighted summary statistics.

Note: All summary statistics are population-weighted.

Table 1
Summary Statistics.

	Mean	Standard deviation
Tree cover	0.139	0.082
Mortality per 100,000 people		
All deaths	539.393	90.128
Cancer	96.195	16.687
Heart conditions	117.022	22.415
Dementia	40.919	13.545
Chronic obstructive pulmonary disease	25.03	10.347
Diabetes	16.677	8.706
Influenza/Pneumonia	10.739	3.925
Kidney failure	6.847	2.763
Liver disease	7.102	3.058
Suicide	13.542	4.996
Accidental falls	8.616	3.712
Morbidity measures		
High blood pressure	0.318	0.032
Overweight or obese	0.671	0.045
Did not meet physical activity guidelines	0.543	0.049
Socioeconomic controls		
Median weekly rent ($A)	353.853	105.803
Median household income ($A)	1553.459	424.85
Share who have completed high school	0.407	0.123
Share Indigenous	0.034	0.047
Share speaking a language other than English	0.173	0.155

3.3. Regression specification

Our regression specifications take the form:

$$H_j = \alpha T_j + \beta X_j + \varepsilon_j \tag{1}$$

where H is a health outcome in geographic area j, T is the share of that area covered in trees, X represents a vector of socioeconomic controls, ε is a normally distributed error term, and α and β are coefficients.

Since mortality only varies at the SA3 level, we average tree coverage and socioeconomic controls to that level. Likewise, because morbidity only varies at the PHN level, we average tree coverage and socioeconomic controls to that level. Results are qualitatively similar if we run the regressions at the SA1 level but cluster our standard errors at the SA3 level (as per Abadie et al. 2023). All regressions are population weighted.

4. Results

4.1. Graphing simple bivariate relationships

Before presenting regression results, it is useful to observe the simple bivariate relationships between tree cover, affluence and mortality. We begin in Figs. 2 and 3 by plotting average tree cover against median weekly rent and median weekly household income, with each dot representing a local neighborhood. In each chart, we show the line of best fit, weighted by the population in each neighborhood.

In both figures, there is an upwards slope. Areas with weekly rent around A$300 had on average about 10 percent tree cover, while areas with weekly rent around A$500 had approximately 40 percent tree cover. Likewise, areas with weekly household income around A$1500 had on average about 10 percent tree cover, while areas with weekly incomes around A$2000 had approximately 40 percent tree cover.

In Fig. 4, we plot the bivariate relationship between mortality and tree cover, showing on the vertical axis the number of deaths for every 100,000 people. We observe a strong negative relationship between mortality and tree cover, with the number of age-adjusted deaths averaging around 500 per 100,000 people in areas with 10 percent tree cover, but falling to almost 400 in areas with over 40 percent tree cover.

In Fig. 5, we show the bivariate association between overweight and tree cover. Since we only observe overweight data at a PHN level, we average tree cover to that level. At this higher level of aggregation, the

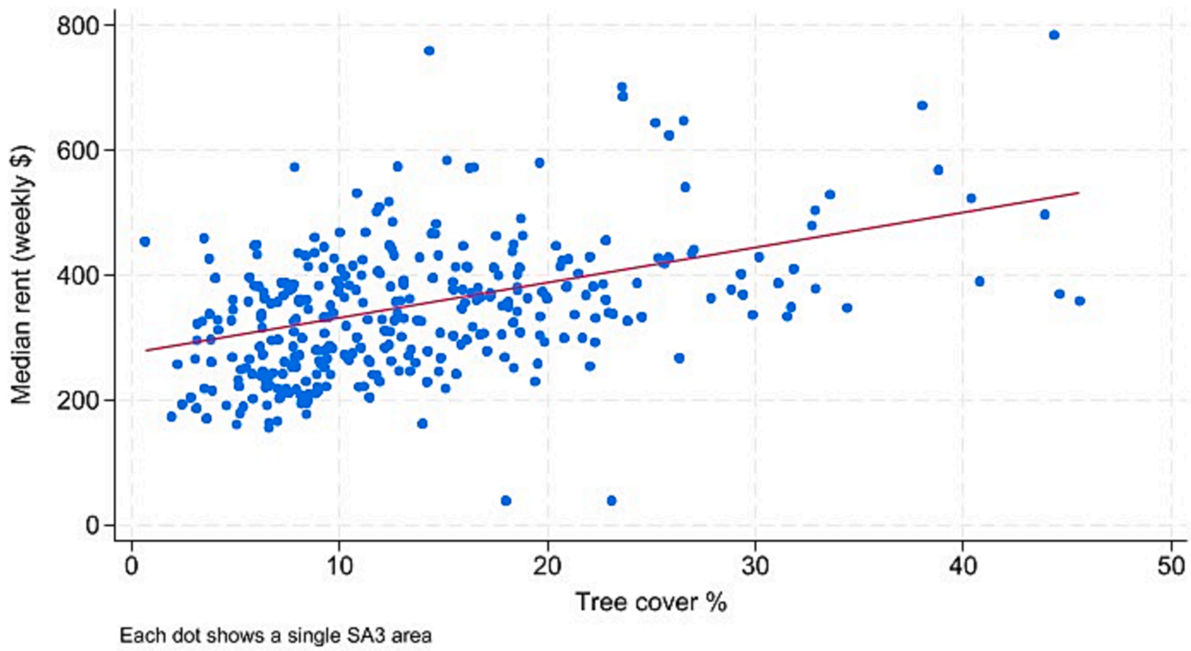


Fig. 2. Median Rent and Tree Cover.

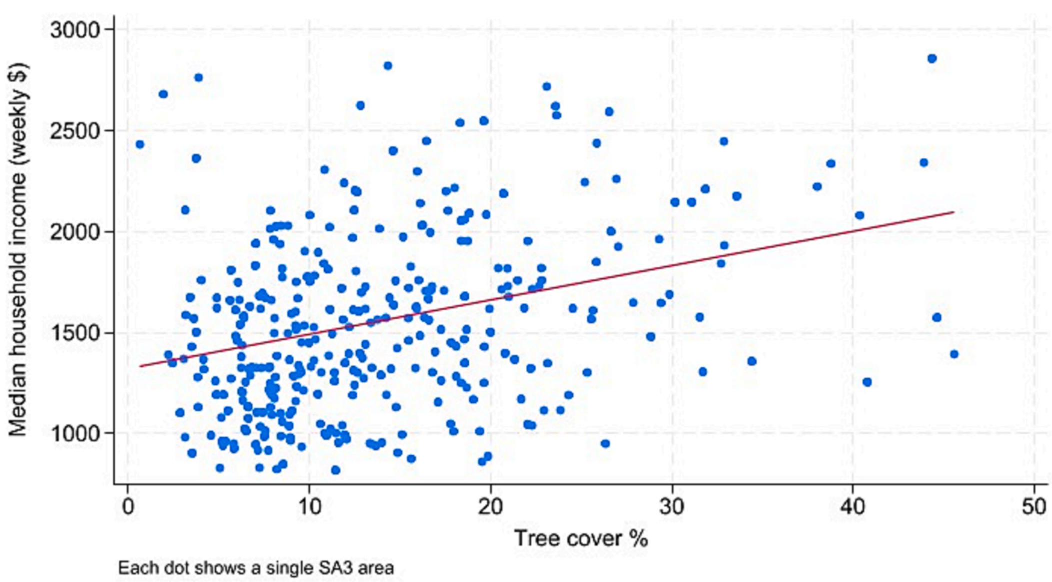


Fig. 3. Median Income and Tree Cover.

range of tree cover falls, with the highest rate being 29 percent. We observe that in areas with 10 percent tree cover, age-adjusted rates of overweight and obesity average around 70 percent, while in areas with 20 percent tree cover, overweight and obesity averages around 65 percent.

It is difficult, however, to discern from these scatterplots the extent to which the positive relationship between health and tree cover is merely an artefact of the positive relationship between affluence and tree cover. To discern this, it is necessary to regress health outcomes on tree cover, holding constant measures of socioeconomic status.

4.2. *Mortality regression results*

Table 2 shows regression results for mortality, beginning with all-cause mortality, and then analyzing particular causes of death. Controlling for socioeconomic status, the coefficient on all deaths is −110, which is statistically significant at the 5 percent level. This implies that a 10 percentage point increase in tree cover (approximately one standard deviation) reduces the annual mortality rate by 11 deaths per 100,000 people. Across ten causes of death, the coefficients are negative and statistically significant at the 1 percent level for influenza/pneumonia, kidney failure, liver disease, and accidental falls; at the 5 percent level for suicide, and at the 10 percent level for diabetes. It is worth noting that these six causes of death include both communicable and non-communicable conditions.

The other control variables in Table 2 largely take the expected sign. As Figs. 2 and 3 show, both rent and income are negatively related to overall mortality, but the relationship is stronger for rent than income. When both are included in the regression, the coefficient on rent remains negative and significant, while the coefficient on income is negative but

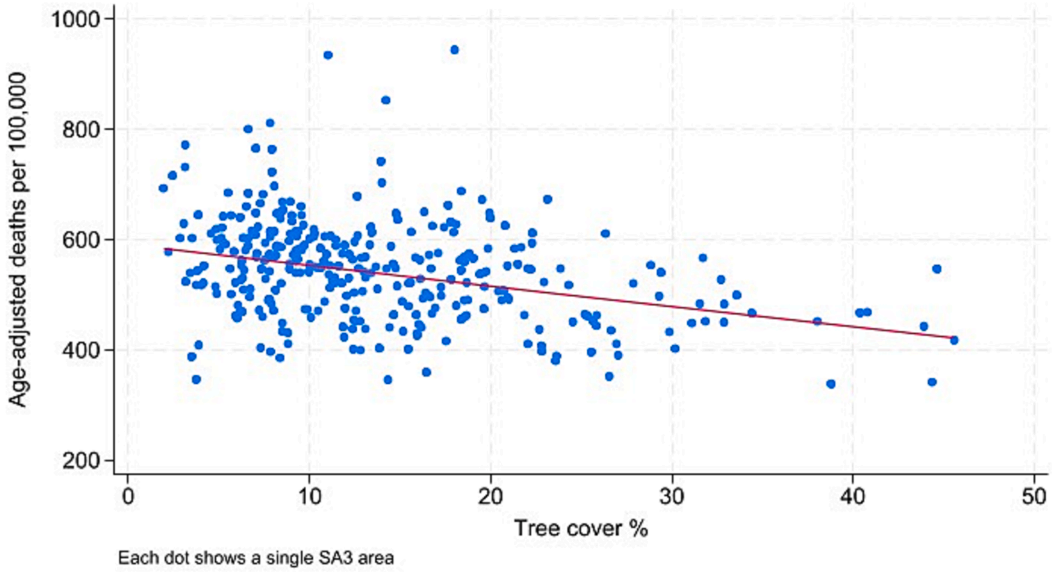


Fig. 4. Mortality and Tree Cover.

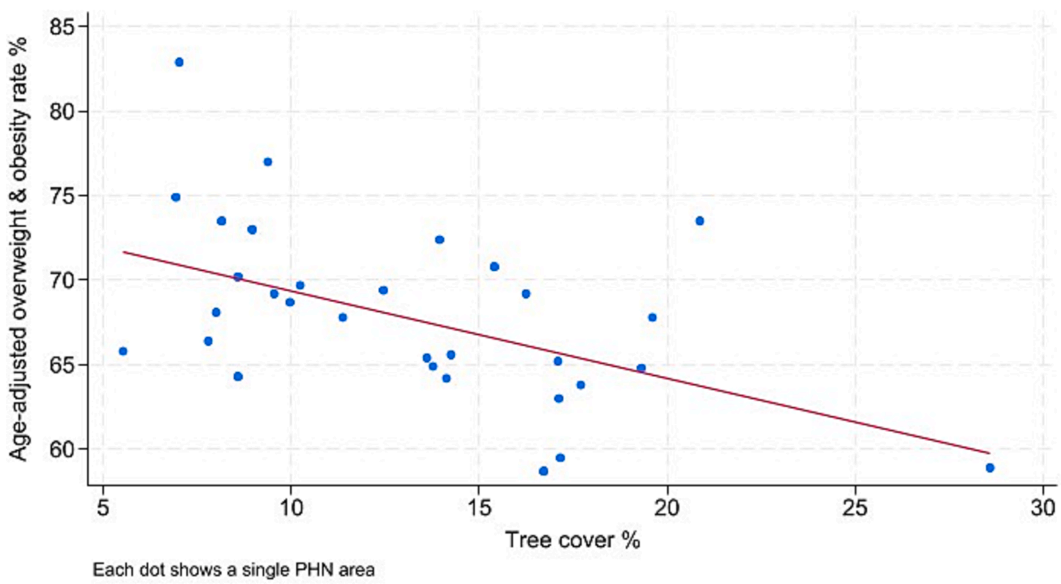


Fig. 5. Overweight and Tree Cover.

statistically insignificant. In the overall deaths specification, the log rent coefficient is −61, indicating that a 10 percent increase in rent prices is associated with 6 fewer deaths per 100,000 people.

Reflecting the established association between education and health, the schooling coefficient of −171 suggests that a 10 percentage point increase in the share of people who have completed high school is associated with 17 fewer deaths per 100,000 people. Education is negatively related to most of the specific causes of death.

The Indigenous coefficient is 782, suggesting that a neighborhood with only Indigenous people would have a death rate that was 782 deaths per 100,000 higher than a neighborhood with no Indigenous people. This is more than three times larger than the racial Indigenous gap (212 deaths per 100,000: AIHW 2020), indicating that in areas with a larger share of Indigenous people, non-Indigenous residents also have higher rates of mortality. The Indigenous share is positively related to mortality across specific causes of death (except accidental falls), and is statistically significant in most instances.

The share of people in an area who speak a language other than English at home does not have a consistent relationship with mortality, either for all-cause mortality or for particular causes of death. Finally, the R^2 indicates that our model explains around 62 percent of variation in overall mortality across areas. In regressions where the dependent variable is a specific cause of death, the R^2 is lower. Taken together, tree cover and socioeconomic status are strongly predictive of cancer, chronic obstructive pulmonary disease, diabetes and suicide, but explain little of the regional variation in dementia and influenza/pneumonia.

4.3. Mortality effects by sex

Since neighborhood-level mortality statistics are available by sex, we run the analysis separately for male mortality and female mortality, reporting the results in Table 3. We find that tree cover has seven times as large an impact on reducing male mortality as on reducing female mortality. The coefficients are –209 for men and –30 for women, implying that a 10 percentage point increase in tree cover reduces the annual mortality rate by 21 men per 100,000, but only by 3 women per

Table 2
Tree Cover and Mortality.

Variable	All deaths	Cancer	Heart conditions	Dementia	Chronic obstructive pulmonary disease	Diabetes	Influenza/ Pneumonia	Kidney failure	Liver disease	Suicide	Accidental falls
Tree cover	−109.638**	−11.164	−2.692	8.913	−5.581	−8.771*	−14.200***	−6.745***	−5.946***	−6.743**	−13.836***
	(46.012)	(9.180)	(14.311)	(10.935)	(5.598)	(4.734)	(3.055)	(2.028)	(1.972)	(3.098)	(2.639)
Log rent	−60.543***	8.584**	−13.851**	8.195*	−10.178***	−5.958***	0.238	−1.707**	−0.646	−0.321	−3.970***
	(18.106)	(3.612)	(5.631)	(4.303)	(2.203)	(1.863)	(1.202)	(0.798)	(0.776)	(1.219)	(1.038)
Log household income	−25.504	−15.087***	−19.892***	−13.745***	1.517	3.758**	−0.426	0.844	−1.026	−1.476	−0.796
	(18.057)	(3.602)	(5.616)	(4.291)	(2.197)	(1.858)	(1.199)	(0.796)	(0.774)	(1.216)	(1.036)
Share who have completed high school	−170.637***	−65.835***	−24.084*	14.667	−23.629***	−11.141**	1.011	−3.081	−0.290	0.155	10.647***
	(46.921)	(9.361)	(14.593)	(11.151)	(5.709)	(4.827)	(3.115)	(2.068)	(2.011)	(3.159)	(2.691)
Share Indigenous	782.085***	117.995***	129.965***	19.369	72.337***	110.017***	9.779*	10.121***	31.708***	34.263***	−28.171***
	(84.333)	(16.825)	(26.229)	(20.042)	(10.261)	(8.677)	(5.599)	(3.717)	(3.615)	(5.678)	(4.836)
Share speaking a language other than English	12.810	3.802	9.367	0.448	1.401	15.990***	−1.776	3.043**	0.198	−13.479***	−2.975*
	(27.640)	(5.514)	(8.597)	(6.569)	(3.363)	(2.844)	(1.835)	(1.218)	(1.185)	(1.861)	(1.585)
R squared	0.618	0.557	0.406	0.040	0.570	0.565	0.108	0.205	0.386	0.433	0.254
Sample size	328	328	328	328	328	328	328	328	328	328	328

Note: ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % levels respectively. Standard errors in parentheses. All regressions are population-weighted.

Table 3
Tree Cover and Mortality by Sex.

	Men	Women
Tree cover	−209.480***	−29.740
	(58.639)	(44.977)
Log rent	−29.604	−87.616***
	(23.075)	(17.699)
Log household income	−80.810***	25.209
	(23.012)	(17.651)
Share who have completed high school	−165.384***	−151.067***
	(59.797)	(45.865)
Share Indigenous	926.347***	637.842***
	(107.477)	(82.436)
Share speaking a language other than English	−16.701	35.769
	(35.225)	(27.018)
R squared	0.579	0.537
Sample size	328	328
Test for equality of tree cover coefficients across male and female specifications	χ^2(1 DF) = 18.91 (P < 0.001)	

Note: ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % levels respectively. Standard errors in parentheses. All regressions are population-weighted.

100,000. A Chi^2 test shows that the relationship between tree cover and mortality differs significantly between men and women.

Our finding that the health benefits of greenspace are greater for men contrasts with the bulk of the literature, which has tended to find that the benefits are greater for women (Sillman et al., 2022). The available data do not allow us to investigate the causal pathways more thoroughly, but we can speculate on possible explanations. Safety concerns have been identified as a barrier in promoting access and use of urban greenspace by women, reducing their likelihood to walk in local neighborhoods compared to men (Ward Thompson et al., 2005). This may help explain why additional tree canopy would benefit men significantly more, as concerns around safety would make women more reluctant to access urban open space regardless of canopy density and extent. Further study around the relationship of greenspace and women's health is warranted, particularly if women are to experience the full benefits of increased tree planting programs in urban areas.

4.4. *Morbidity regression results*

Table 4 analyses three morbidity metrics, drawn from the National

Table 4
Tree Cover and Morbidity.

Dependent Variable:	High blood pressure	Overweight or obese	Did not meet physical activity guidelines
Tree cover	−0.290	−0.080	−0.311
	(0.221)	(0.227)	(0.408)
Log rent	−0.010	−0.110	0.102
	(0.078)	(0.080)	(0.143)
Log household income	−0.119	−0.030	−0.129
	(0.101)	(0.104)	(0.187)
Share who have completed high school	0.224	−0.054	−0.056
	(0.228)	(0.233)	(0.420)
Share Indigenous	0.184	−0.120	0.371
	(0.269)	(0.276)	(0.497)
Share speaking a language other than English	−0.040	0.018	0.086
	(0.091)	(0.093)	(0.167)
R squared	0.349	0.588	0.110
Sample size	31	31	31

Note: ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % levels respectively. Standard errors in parentheses. All regressions are population-weighted.

Health Survey. High blood pressure, overweight and failing to meet exercise guidelines are all negatively related to tree cover, but not statistically significant at conventional levels. The coefficients suggests that a 10 percentage point increase in tree cover is associated with a 2.9 percent drop in the share with high blood pressure, a 0.8 percent fall in the share of people who are overweight or obese, and a 3.1 percent fall in the share of people who fail to meet exercise guidelines.

The other controls in the morbidity regressions largely follow the pattern of the mortality regressions reported in Table 2, but are not statistically significant at conventional levels. This likely reflects the high levels of aggregation in the morbidity analysis, which is done at a Primary Health Network level (of which there are only 31 in Australia) rather than at an SA3 level (of which there are over 300 in Australia). Together, tree cover and our socioeconomic measures explain 35 percent of the area-level variation in high blood pressure, 59 percent of the variation in obesity, and 11 percent of the variation in physical activity.

4.5. Specification checks

Neighborhood-level analysis is inherently necessary when considering tree cover, since the theoretical pathways through which urban trees affect human health – which fall into the categories of reducing harm, restoring capacity and building capabilities (Markevych et al., 2017) – all posit that it is the trees in a person's neighborhood that matter, not just the trees in their own backyard. Therefore, even if it were technically possible to obtain household-level data on mortality and morbidity, it would not be desirable to regress this on the tree cover in that person's backyard. When considering factors such as neighborhood walkability, our interpretation of the literature suggests that tree coverage in an area covering one's nearest 400 neighbors is likely to correspond to the local area that matters most to a person's health.

Another concern is that the impacts of urban trees on health will occur with some delay. Conditions such as diabetes, cancer and obesity typically take years to manifest. To the extent that population mobility is uncorrelated with health or tree coverage, migration between regions with different levels of tree cover will attenuate our estimated effects. To get some sense of the potential magnitude of this attenuation bias, the share of Australians who make a long-distance move is around 3 percent per year (Productivity Commission 2014, 104). This potential attenuation should be borne in mind when interpreting our results. For example, it is possible that our failure to find a significant negative relationship between tree coverage and dementia contrasts with Astell-Burt, Navakatikyan and Feng (2020) (who do find such a negative relationship) because their study uses longitudinal data spanning an 11-year period, while ours uses cross-sectional data.

A further consideration is whether our results are driven by spatial autocorrelation. To test this, we apply a Moran test for spatial dependence to the main specification (the first result shown in Table 2). This test is unable to reject the hypothesis that the error terms are independent and identically distributed. We therefore estimated a spatial autoregressive model, which shows that the relationship between tree cover and mortality is large and negative, as in the results of Table 2. Because spatial autoregressive models do not accommodate weighting (and therefore place the same weight on areas with low and high populations), our preferred estimate remains that from the linear model.

An additional potential concern is that our results reflect sorting. For argument's sake, suppose that trees have zero impact on health, but people who are already healthy (for lifestyle or genetic reasons) prefer to live in neighborhoods with more trees. If healthier homebuyers are willing to pay more for homes in leafy suburbs, then we will observe a positive relationship between health and tree cover, even if no causal effect exists.

To the extent that selection effects are driving our results, they should lead the relationship between mortality and tree cover to be largest in the areas with the highest level of mobility, since these will be the areas where healthy people are moving into tree-lined suburbs. To test this, we identified for every neighborhood the share of the population who did not live in the same house five years ago. We then rank all neighborhoods according to the level of mobility, and re-run the first regression specification shown in Table 2 (with the dependent variable being all-cause mortality). We do this 81 times, each time dropping 1 percent of the sample until we are left with only the 20 percent of the sample with the lowest level of mobility.

The results of this exercise are shown in Fig. 6. The line shows the coefficient on tree cover, and the shaded area depicts the 95 percent confidence interval. With 100 percent of the sample, the coefficient on tree cover is –110, corresponding to the first specification shown in Table 2. When the sample is restricted to the least mobile 75 percent of the areas, the coefficient on tree cover is –98. With the least mobile 50 percent, the coefficient on tree cover is –87. As we move to the least mobile 25 percent, the coefficient grows in magnitude to –122. Naturally, the standard error increases as the sample shrinks (as reflected by the widening of the shaded bars as we move to the right).

While the results of this exercise are not conclusive, they do provide suggestive evidence that our results are not driven by selective mobility. The line in Fig. 6 does not show a marked trend upwards or downwards, suggesting that restricting the sample to less mobile neighborhoods does not tangibly affect the relationship between tree cover and mortality.

5. Discussion

How do our results compare with estimates in the literature? Rojas-Rueda et al. (2019) use the Normalized Difference Vegetation Index (NDVI), a measure of vegetation density based on the difference between visible red and near-infrared surface reflectance in Land Remote-Sensing Satellite (Landsat) imagery. To convert NDVI to urban tree canopy (UTC), we use a formula set out in Kondo et al. (2020), which is that NDVI = -0.03 + (0.51 × UTC$^{0.5}$). At our mean value of tree cover of 13.9 percent, a 10 percentage point increase in tree cover is equivalent to a 0.06 increase in the NDVI. Our estimates suggest that a 0.06 increase in NDVI would result in a mortality hazard rate of 0.980 [(539–11.0)/539], and that a 0.1 increase in the NDVI results in a mortality hazard rate of 0.966. By comparison, the nine studies summarized in Rojas-Rueda et al. (2019) estimate a mean pooled mortality hazard ratio of 0.96 from a 0.1 increase in NDVI, with a 95 percent confidence interval of 0.94 to 0.97. Thus our point estimate is quite close to the average of the nine studies on greenspace and mortality summarized by Rojas-Rueda et al. (2019). Note however that this is an imprecise comparison, since the NDVI-to-UTC formula was not derived from Australian data, and our comparison is with studies in a range of different international contexts.

How should we think about the magnitudes in our study? Our central result is that a 1 percentage point increase in tree cover reduces mortality by 1.10 deaths per 100,000 people. Recall that in total, our analysis covers 21 million people and an area of 20,000 square kilometers. A 1 percentage point increase in tree cover would therefore require an additional 200 square kilometers of trees, and would be associated with around 230 fewer deaths.

One way to compare these figures is to carry out a cost-benefit analysis. The cost of urban tree planting varies considerably, but one estimate places the cost at between A$50 and A$100 per tree per year (Moore 2021). If we assume that the typical urban tree has a canopy that is 10 m in diameter, then 2.5 million trees have a combined canopy of 200 square kilometers (the number of trees is calculated as (200 × 1,000,000)/(π × 5^2)). This implies an annual cost of A$125 million to A$250 million to increase tree canopy by 200 square kilometers.

To convert the mortality estimate to monetary terms, we use the Australian Government's estimate for the value of a statistical life, which is A$5 million (Department of Prime Minister and Cabinet 2021). Multiplying this figure by 230 lives per year, this suggests an annual benefit of A$1.15 billion, which is more than four times larger than our

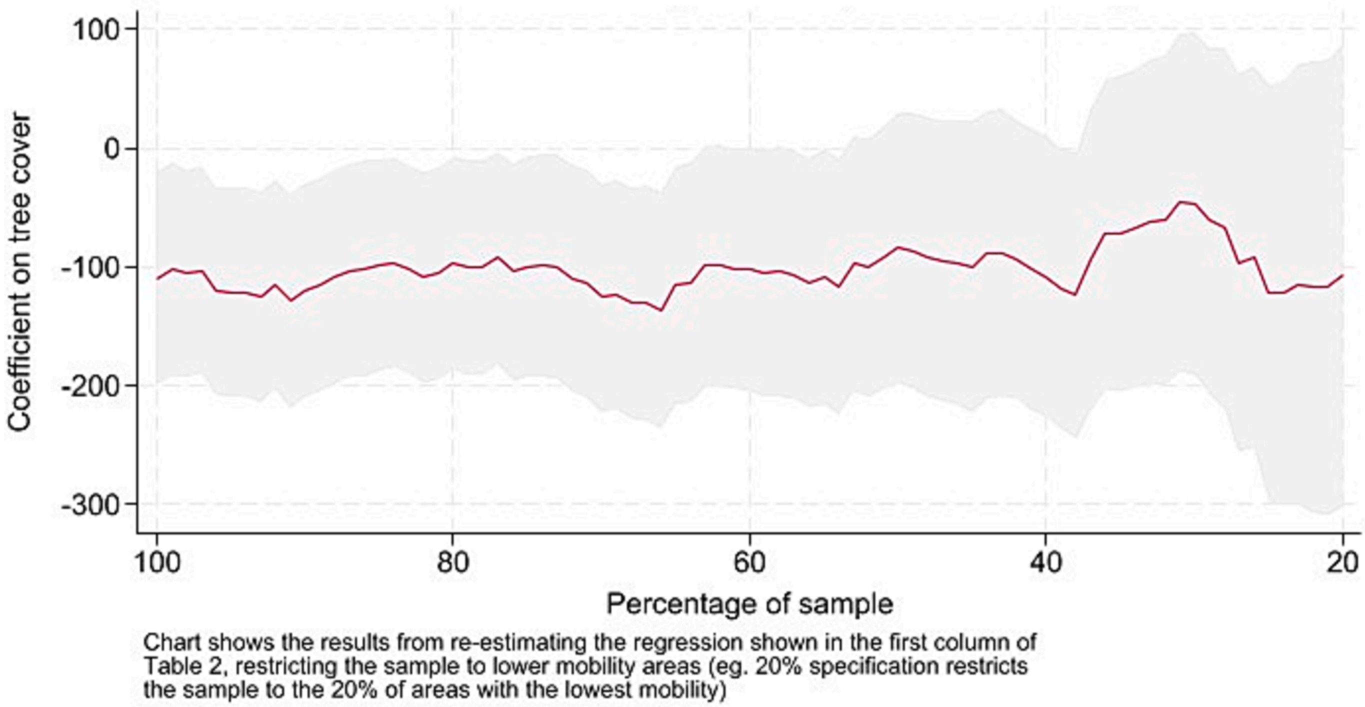


Fig. 6. Re-Estimating Mortality Regression in Areas with Progressively Lower Mobility.

upper estimate of the annual cost of planting and maintaining an additional 200 square kilometers of tree canopy. Note that our findings consider only mortality, and do not take account of the fact that trees also have positive benefits as carbon sinks, as well as improving the quality of life of residents. Therefore, another way of regarding our result is that it provides a preventive health lens to urban greening strategies: if urban tree planting can be carried out at a reasonable cost, it may be justified solely terms of the benefits of reduced mortality.

These results also show the potential risk of urban development that replaces trees with buildings. To the extent that urban infill reduces total tree coverage, it may adversely affect population health. From a health perspective, a development that increases the residential density of an existing block should be preferred to a development that converts a tree-filled public park into an apartment complex.

Our findings also have equity implications. As Figs. 2 and 3 show, tree cover is more prevalent in affluent neighborhoods. Given the health benefits outlined above, establishing more equitable tree cover targets within urban areas could help reduce the health gap between rich and poor people. A tree planting program could in principle be focused on neighborhoods with low tree canopy and high levels of chronic disease.

Using only aerial geospatial data to calculate canopy density does present limitations. Since our data cover only 90 percent of the Australian population, it is not perfectly nationally representative. Another limitation is that we do not have data on the types of trees in a neighborhood. Being able to distinguish tree species would allow us to investigate whether different types of trees produce different health effects. More detailed data would also allow us to contrast the health benefits provided by tree canopy against the health impacts of other vegetation types such as grass and understory. In future research, street-level images could complement aerial imagery and provide a more precise understanding of which types of greenspace have the greatest impact on population health.

6. Conclusion

Analyzing high-quality tree cover data for Australia, we find a strong association between the percentage of tree cover and the health of a neighborhood, holding constant several socio-economic variables. This relationship is strongest for mortality, with clear evidence that neighborhoods with more trees have fewer deaths.

Focusing on specific causes of death, we find a significant negative association between mortality and tree cover for six out of ten broad causes of death: influenza/pneumonia, kidney failure, liver disease, accidental falls (all at the 1 percent level), suicide (at the 5 percent level), and diabetes (at the 10 percent level). This is consistent with prior Australian studies showing that greenspace is associated with better physical and mental health outcomes (eg. Astell-Burt and Feng, 2019b; Astell-Burt et al., 2021; Astell-Burt and Feng, 2020a; Astell-Burt, Navakatikyan and Feng, 2020).

Contrary to much of the literature (as reviewed in Sillman et al., 2022), we find that the relationship between tree cover and mortality is substantially larger for men than for women. Using data from the National Health Survey, we also observe suggestive (but not statistically significant) evidence of a negative association between measures of morbidity and tree cover.

As a way of testing whether our findings might be driven by sample selection, we re-analyze the data on neighborhoods where a lower share of people have moved house in the previous five years. Our mortality findings do not weaken when we restrict the sample to the neighborhoods with the least population mobility, suggesting that the results may not be driven entirely by sample selection.

Traditional economic approaches to planning and development sometimes neglect to quantify the benefits of urban forest on city livability. Our findings suggest that trees are associated with lower rates of mortality. We also uncover key disparities, with trees tending to be concentrated in advantaged areas, and the association between urban tree cover and health being larger for men than for women. These findings suggest the planning and management of the urban forest can be one way to promote public health and reduce health inequalities. Cities of the future should ensure all residents can harness the health benefits of seeing the urban forest and its street trees.

Declaration of Competing Interest

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

Data availability

The tree cover data used in our paper are confidential, and cannot be freely shared online. All other data and code are available on request.

Acknowledgements

Our thanks to Associate Editor Jason Byrne and three anonymous referees for valuable comments. This paper would not have been possible without the data-crunching prowess of Tim Leigh, who ran the algorithms that aggregated tree mapping data to the neighborhood level. Tim humbly declined our invitation to co-author this paper, but should be regarded as our third collaborator. We are grateful to him for his indispensable work on this study. Since our study did not involve collecting any new data on human subjects and does not identify any individuals, it falls outside the category of research that would require approval from a human research ethics committee or institutional review board.

References

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. M. (2023). When should you adjust standard errors for clustering? *Quarterly Journal of Economics, 138*(1), 1–35.
ACT Government. (2021). *Report to the Legislative Assembly of the Australian Capital Territory: Urban Tree Canopy Coverage*. Canberra, November: Transport Canberra and City Services Directorate.
Astell-Burt, T., & Feng, X. (2019a). Urban green space, tree canopy and prevention of cardiometabolic diseases: A multilevel longitudinal study of 46 786 Australians. *International Journal of Epidemiology, 49*(3), 926–933.
Astell-Burt, T., & Feng, X. (2019b). Association of urban green space with mental health and general health among adults in Australia. *JAMA Network Open, 2*(7), e198209–e.
Astell-Burt, T., & Feng, X. (2020a). Does sleep grow on trees? A longitudinal study to investigate potential prevention of insufficient sleep with different types of urban green space. *SSM – Population Health, 10*, Article 100497.
Astell-Burt, T., & Feng, X. (2020b). Greener neighbourhoods, better memory? A longitudinal study. *Health and Place, 65*, Article 102393.
Astell-Burt, T., Hartig, T., Eckermann, S., Nieuwenhuijsen, M., McMunn, A., Frumkin, H., & Feng, X. (2022). More green, less lonely? A longitudinal cohort study. *International Journal of Epidemiology., 51*(1), 99–110.
Astell-Burt, T., Navakatikyan, M. A., & Feng, X. (2020). Urban green space, tree canopy and 11-year risk of dementia in a cohort of 109,688 Australians. *Environment International, 145*, Article 106102.
Astell-Burt, T., Navakatikyan, M. A., Walsan, R., Davis, W., Figtree, G., Arnolda, L., & Feng, X. (2021). Green space and cardiovascular health in people with type 2 diabetes. *Health and Place, 69*, Article 102554.
Australian Institute of Health and Welfare. (2020). *Indigenous Life Expectancy and Deaths*. Canberra: AIHW.
Basu, R. (2009). High ambient temperature and mortality: A review of epidemiologic studies from 2001 to 2008. *Environmental Health, 8*(1), 1–13.
Bowler, D. E., Buyung-Ali, L., Knight, T. M., & Pullin, A. S. (2010). Urban greening to cool towns and cities: A systematic review of the empirical evidence. *Landscape and Urban Planning, 97*(3), 147–155.
Brown, H., Proust, K., Newell, B., Spickett, J., Capon, T., & Bartholomew, L. (2018). Cool Communities—Urban Density, Trees, and Health. *International Journal of Environmental Research and Public Health, 15*(7), 1547.
Browning, M. H., & Locke, D. H. (2020). The greenspace-academic performance link varies by remote sensing measure and urbanicity around Maryland public schools. *Landscape and Urban Planning, 195*, Article 103706.
Department of Prime Minister and Cabinet. (2021). 'Best Practice Regulation Guidance Note: Value of statistical life, August 2021', Office of Best Practice Regulation, Department of Prime Minister and Cabinet.
Donovan, G. H., Butry, D. T., Michael, Y. L., Prestemon, J. P., Liebhold, A. M., Gatziolis, D., & Mao, M. Y. (2013). The relationship between trees and human health: Evidence from the spread of the emerald ash borer. *American Journal of Preventive Medicine, 44*(2), 139–145.
Eisenman, T. S., Churkina, G., Jariwala, S. P., Kumar, P., Lovasi, G. S., Pataki, D. E., … Whitlow, T. H. (2019). Urban trees, air quality, and asthma: An interdisciplinary review. *Landscape and Urban Planning, 187*, 47–59.
Feng, X., Toms, R., & Astell-Burt, T. (2021). Association between green space, outdoor leisure time and physical activity. *Urban Forestry and Urban Greening, 66*, Article 127349.
Geoscape (2020). *Trees. Product Description. Version 1.6*. PSMA Australia, Griffith ACT.
Hartig, T. (2021). Restoration in Nature: Beyond the Conventional Narrative. In: Schutte, A.R., Torquati, J.C., Stevens, J.R. (eds) *Nature and Psychology*. Nebraska Symposium on Motivation, vol 67. Springer, Cham, 89-151.
Kleinman, J. C. (1977). Age-adjusted mortality indexes for small areas: Applications to health planning. *American Journal of Public Health, 67*(9), 834–840.
Knobel, P., Maneja, R., Bartoll, X., Alonso, L., Bauwelinck, M., Valentin, A., … Dadvand, P. (2021). Quality of urban green spaces influences residents' use of these spaces, physical activity, and overweight/obesity. *Environmental Pollution, 271*, Article 116393.
Kondo, M. C., Mueller, N., Locke, D. H., Roman, L. A., Rojas-Rueda, D., Schinasi, L. H., … Nieuwenhuijsen, M. J. (2020). Health impact assessment of Philadelphia's 2025 tree canopy cover goals. *Lancet Planetary Health, 4*(4), e149–e157.
Kotera, Y., Richardson, M., & Sheffield, D. (2022). Effects of shinrin-yoku (forest bathing) and nature therapy on mental health: A systematic review and meta-analysis. *International Journal of Mental Health and Addiction, 20*, 337–361.
Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., … Nieuwenhuijsen, M. J. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research, 158*, 301–317.
Mazumdar, S., Chong, S., Astell-Burt, T., Feng, X., Morgan, G., & Jalaludin, B. (2021). Which Green Space Metric Best Predicts a Lowered Odds of Type 2 Diabetes? *International Journal of Environmental Research and Public Health, 18*(8), 4088.
Mitchell, R. J., Richardson, E. A., Shortt, N. K., & Pearce, J. R. (2015). Neighborhood environments and socioeconomic inequalities in mental well-being. *American Journal of Preventive Medicine, 49*(1), 80–84.
Moore, G. (2021). 'Street Tree Cost Models for Australia', available at treenet.org.
Nguyen, P. Y., Astell-Burt, T., Rahimi-Ardabili, H., & Feng, X. (2021). Green space quality and health: A systematic review. *International Journal of Environmental Research and Public Health, 18*(21), 11028.
Nowbar, A. N., Gitto, M., Howard, J. P., Francis, D. P., & Al-Lamee, R. (2019). Mortality from Ischemic Heart Disease. *Circulation: Cardiovascular Quality and Outcomes, 12*(6), e005375.
Pearlmutter, D., Calfapietra, C., Samson, R., O'Brien, L., Ostoić, S. K., Sanesi, G., and del Amo, R. A. (2017). *The urban forest. Cultivating green infrastructure for people and the environment*, Future City, vol. 7, Springer, Cham.
Productivity Commission (2014). *Geographic Labour Mobility*, Research Report, Canberra.
Reid, C. E., Clougherty, J. E., Shmool, J. L., & Kubzansky, L. D. (2017). Is all urban green space the same? A comparison of the health benefits of trees and grass in New York City. *International Journal of Environmental Research and Public Health, 14*(11), 1411.
Rojas-Rueda, D., Nieuwenhuijsen, M. J., Gascon, M., Perez-Leon, D., & Mudu, P. (2019). Green spaces and mortality: A systematic review and meta-analysis of cohort studies. *Lancet Planetary Health, 3*(11), e469–e477.
Roy, S., Byrne, J., & Pickering, C. (2012). A systematic quantitative review of urban tree benefits, costs, and assessment methods across cities in different climatic zones. *Urban Forestry and Urban Greening, 11*(4), 351–363.
Schwarz, K., Fragkias, M., Boone, C. G., Zhou, W., McHale, M., Grove, J. M., … Childers, D. (2015). Trees grow on money: Urban tree canopy cover and environmental justice. *PLoS One1, 10*(4), e0122051.
Sillman, D., Rigolon, A., Browning, M. H., & McAnirlin, O. (2022). Do sex and gender modify the association between green space and physical health? A systematic review. *Environmental Research, 209*, Article 112869.
Smith, M. L., Zhou, W., Cadenasso, M., Grove, M., & Band, L. E. (2010). Evaluation of the national land cover database for hydrologic applications in urban and suburban Baltimore, Maryland. *JAWRA Journal of the American Water Resources Association, 46*(2), 429–442.
Tamosiunas, A., Grazuleviciene, R., Luksiene, D., Dedele, A., Reklaitiene, R., Baceviciene, M., … Nieuwenhuijsen, M. J. (2014). Accessibility and use of urban green spaces, and cardiovascular health: Findings from a Kaunas cohort study. *Environmental Health, 13*(1), 20.
Ward Thompson, C., Aspinall, P., Bell, S., & Findlay, C. (2005). "It gets you away from everyday life": Local woodlands and community use—what makes a difference? *Landscape Research, 30*(1), 109–146.
Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landscape and Urban Planning, 125*, 234–244.
Wolf, K. L., Lam, S. T., McKeen, J. K., Richardson, G. R., van den Bosch, M., & Bardekjian, A. C. (2020). Urban trees and human health: A scoping review. *International Journal of Environmental Research and Public Health, 17*(12), 4371.
Wooldridge, J. M. (2013). *Introductory Econometrics: A Modern Approach* (5th ed.). Mason, OH: South Western.
Zhao, J., Zhao, X., Wu, D., Meili, N., & Fatichi, S. (2023). Satellite-based evidence highlights a considerable increase of urban tree cooling benefits from 2000 to 2015. *Global Change Biology, 29*(11), 3085–3097.