

ACCEPTED MANUSCRIPT • OPEN ACCESS

The potential of urban trees to reduce heat-related mortality in London

To cite this article before publication: Jonathon Taylor *et al* 2024 *Environ. Res. Lett.* in press <https://doi.org/10.1088/1748-9326/ad3a7e>

Manuscript version: Accepted Manuscript

Accepted Manuscript is “the version of the article accepted for publication including all changes made as a result of the peer review process, and which may also include the addition to the article by IOP Publishing of a header, an article ID, a cover sheet and/or an ‘Accepted Manuscript’ watermark, but excluding any other editing, typesetting or other changes made by IOP Publishing and/or its licensors”

This Accepted Manuscript is © 2024 The Author(s). Published by IOP Publishing Ltd.



As the Version of Record of this article is going to be / has been published on a gold open access basis under a CC BY 4.0 licence, this Accepted Manuscript is available for reuse under a CC BY 4.0 licence immediately.

Everyone is permitted to use all or part of the original content in this article, provided that they adhere to all the terms of the licence <https://creativecommons.org/licenses/by/4.0>

Although reasonable endeavours have been taken to obtain all necessary permissions from third parties to include their copyrighted content within this article, their full citation and copyright line may not be present in this Accepted Manuscript version. Before using any content from this article, please refer to the Version of Record on IOPscience once published for full citation and copyright details, as permissions may be required. All third party content is fully copyright protected and is not published on a gold open access basis under a CC BY licence, unless that is specifically stated in the figure caption in the Version of Record.

View the [article online](#) for updates and enhancements.

The potential of urban trees to reduce heat-related mortality in London

Jonathon Taylor^{1*}

Charles Simpson²

Oscar Brousse²

Anna-Kaisa Viitanen¹

Clare Heaviside²

¹Department of Civil Engineering, Tampere University, Tampere, Finland

²UCL Institute for Environmental Design and Engineering, UCL, London, UK

*Corresponding Author: jonathon.taylor@tuni.fi

Abstract

Increasing temperatures and more frequent heatwave events pose threats to population health, particularly in urban environments due to the Urban Heat Island (UHI) effect. Greening, in particular planting trees, is widely discussed as a means of reducing heat exposure and associated mortality in cities. This study aims to use data from Personal Weather Stations (PWS) across the Greater London Authority to understand how urban temperatures vary according to tree canopy coverage and estimate the heat-health impacts of London's urban trees. Data from Netatmo PWS from 2015 – 2022 were cleaned, combined with official Met Office temperatures, and spatially linked to tree canopy coverage and built environment data. A Generalized Additive Model was used to predict daily average urban temperatures under different tree canopy coverage scenarios for historical and projected future summers, and subsequent health impacts estimated. Results show areas of London with higher canopy coverage have lower urban temperatures, with average maximum daytime temperatures 0.8 °C and minimum temperatures 2.0 °C lower in the top decile versus bottom decile canopy coverage during the 2022 heatwaves. We estimate that London's urban forest helped avoid 153 heat attributable deaths from 2015-2022 (including 16 excess deaths during the 2022 heatwaves), representing around 16% of Urban Heat Island-related mortality. Increasing tree coverage 10% in-line with the London Strategy would have reduced UHI-related mortality by a further 10%, while a maximal tree coverage would have reduced it 55%. By 2061-2080, under RCP8.5, we estimate that London's current tree planting strategy can help avoid an additional 23 heat-attributable deaths a year, with maximal coverage increasing this to 131. Substantial benefits would also be seen for carbon storage and sequestration. Results of this study support increasing urban tree coverage as part of a wider public health effort to mitigate high urban temperatures.

Keywords: Urban Heat Island; Personal Weather Stations; Climate Change; Heat Mortality; Tree Canopy

1. Introduction

Climate change is leading to elevated global average temperatures and increased frequency and severity of heatwave events [1]. London is already experiencing extreme heat episodes, for example in 2022 when heatwave temperatures exceeded a record 40 °C, an event estimated 160 times more likely because of climate change [2]. Heat exposure may be exacerbated by the Urban Heat Island (UHI) effect, where urban centers are typically hotter than surrounding rural areas. UHIs are primarily caused by human modification of land surfaces, replacing natural vegetation with materials like concrete and asphalt that have different thermal and surface radiative properties and which absorb and retain heat during the day [3]. In London, the difference between the urban monthly mean maximum urban and surrounding rural temperature has been observed around 1.4–2.9 °C [4,5], with lower intensities found in more vegetated areas.

Heat exposure can lead to several negative physical health effects, with older people, the socially isolated, very young children, and those with chronic illnesses the most vulnerable [6]. It can lead to cardiovascular strain, respiratory distress, dehydration, and heat stroke, and exposure to excess heat is associated with all-cause and cardiorespiratory mortality, adverse pregnancy outcomes, and mental health problems [1,6,7]. During the 2022 heatwaves, 2,985 all-cause excess deaths were observed in England, 387 of which were in London [8]. While rates of heat-attributable deaths are greatest during extreme weather, many deaths occur during the more frequent warm and hot days [9].

Therefore, focus on urban heat mitigation and climate adaptation is growing. Increasing vegetation is one way to decrease near-surface air temperatures [3,10] due to changes in surface material properties, shading, and evapotranspiration, where plants absorb water and release it as water vapour. Trees, in particular, have been widely studied to assess their potential for mitigating heat in urban environments [11–15] because their leaves and branches provide shading and they have higher transpiration rates than low vegetation. However, the relationship is complex, as increased surface roughness from trees can reduce windflow and heat dissipation [14], and recent evidence suggests that in many European cities, trees have a small or negligible effect on daytime air temperature [15]. Estimating any heat-health benefits provided by trees can be complicated due to meteorological data scarcity in urban environments, meaning many studies rely on remotely-sensed Land Surface Temperature (LST). A recent study using LST showed that 25% of UHI-attributable deaths could have been avoided in 2015 if tree coverage was increased by 30 % in London [16]. However, LST can be a poor predictor of urban-canopy air-temperature [15,17,18], and further work is required to disentangle how trees are associated with higher or lower heat-related mortality locally.

The recent growth of personal weather stations (PWS) has provided opportunities to use crowd-sourced meteorological data in urban climate studies [19–23] that have typically relied on limited numbers of official meteorological stations, researcher-measured conditions, or climate models. PWS popularity has led to increased density of PWS networks in cities and improved geographical coverage of monitored data. While PWS have greater uncertainty than official monitoring stations and data may be noisy [24], various methods have been developed to perform quality control on data [25]. A recent study used PWS to examine the cooling efficiencies of tree cover in European cities, finding that trees have a smaller impact on air than surface temperatures, and may not have a

1
2
3 cooling effect in all cities [15]. Studies have used PWS, for example, to examine the impacts of land
4 cover on temperatures [5,15,26–28], model air temperatures [29–31], as an input to building physics
5 models [32], and to validate and bias-correct urban climate simulations [24,33].
6

7 This paper uses the dense network of PWS across the Greater London Authority (GLA) to evaluate
8 differences in air temperature according to tree canopy cover, and uses this association to estimate
9 the potential for trees to reduce heat exposure and associated mortality under historical and future
10 climate scenarios. To do this, we derive a large dataset of PWS and official station air temperature
11 data from October 2015- September 2022, inclusive. We then spatially link PWS temperatures to
12 tree canopy cover and building coverage and height data for London and temporally to
13 temperatures at Heathrow Airport. From this, a Generalized Additive Model (GAM) is developed and
14 used to predict daily average urban temperatures under different tree canopy coverage scenarios
15 with health impact calculations used to estimate how changes to tree canopy coverage may change
16 heat-related deaths.
17
18
19

20 21 2. Methods

22 23 2.1. Temperature data

24
25
26
27 Near-surface temperate data was obtained from two different sources from 01/10/2015 –
28 30/09/2022: official Met Office weather stations and Netatmo PWS stations within a wide bounding
29 domain that includes the GLA. This timeframe includes the historically hottest summer of 2018, and
30 the three exceptional heatwaves that occurred during the summer of 2022 (15th – 17th June, 17th-19th
31 July, and 9th-15th August) when temperatures reached a maximum of 39 °C at London Heathrow.
32
33

34 Hourly temperatures, station ID, and coordinates for Met Office stations were obtained from
35 September 2015- December 2022 from MIDAS Open [34]. This included the station at London
36 Heathrow, commonly used for studying the London climate and which offers a comprehensive
37 coverage of the period of interest. This was used as a reference station.
38

39 PWS station ID, and coordinates was obtained using the *Patatmo* Python module that utilizes the
40 Netatmo API (<https://dev.netatmo.com/>). This resulted in 619 stations, of which 502 were within
41 GLA administrative boundaries. Hourly air temperatures were then downloaded for PWS stations for
42 the study period. Cleaning and analysis of PWS temperatures was carried out using R. First, the
43 altitude of each station was spatially joined using a 10m resolution Digital Elevation Model of
44 London [35]. Height correction and outliers removal was performed using CrowdQC+ [25], a tool
45 developed for quality control of PWS weather data. Hourly measurements were removed if they
46 were taken by duplicate stations located at the same coordinates (Step M1); were outliers, as
47 determined by their z-score (Step M2); if more than 20% of the measurements in the month were
48 removed in the previous steps, indicating the PWS may be unreliable (Step M3); and finally if the
49 measurements were not correlated to the median temperature of other measurements (Pearson $r <$
50 0.9) and are assumed to be indoors (Step M4). We then excluded days with more than three hours
51 of data absent. This reduced the number of stations within the GLA boundaries to 490, with 520,623
52 sensor-days of valid PWS measurements.
53
54
55

56
57 The Met Office and PWS temperatures were combined into a common dataset (Figure 1), except for
58 Heathrow which was used as a reference temperature for each date. Stations located in rural areas
59 outside the GLA were used as a baseline to estimate UHI intensity. These rural areas were identified
60

via a spatial join to 2011 Office for National Statistics (ONS) rural/urban classifications [36] for different census Output Areas (OA).

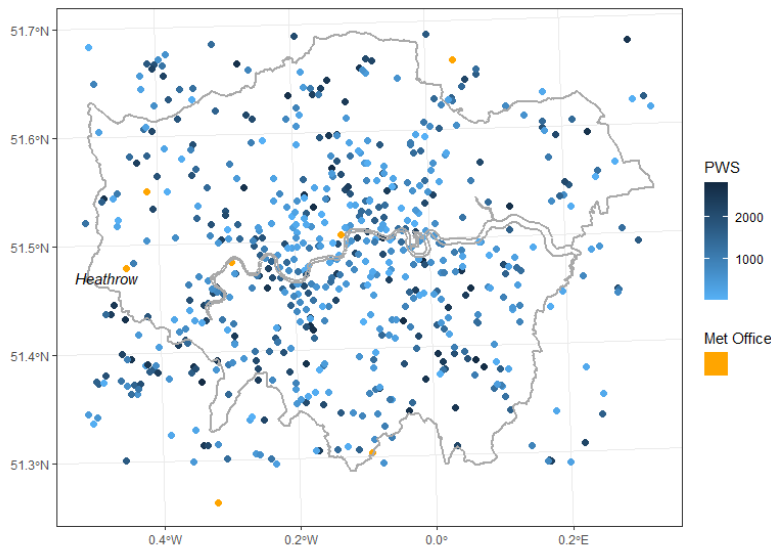


Figure 1. Netatmo stations, by days of measured data, and Met Office stations within the GLA administrative boundaries and wider domain.

2.1.1. Environmental and Population Data

Tree canopy coverage data for the GLA is from the London Data Store [37] (Figure 2a). The dataset contains 15,041 hexagons, each 350 m across, derived from high resolution (10 cm per pixel) colour infrared imagery collected in September 2016, with pixels as being either a tree canopy or not using a machine learning algorithm. Further details on how the tree canopy data was derived can be found in [38].

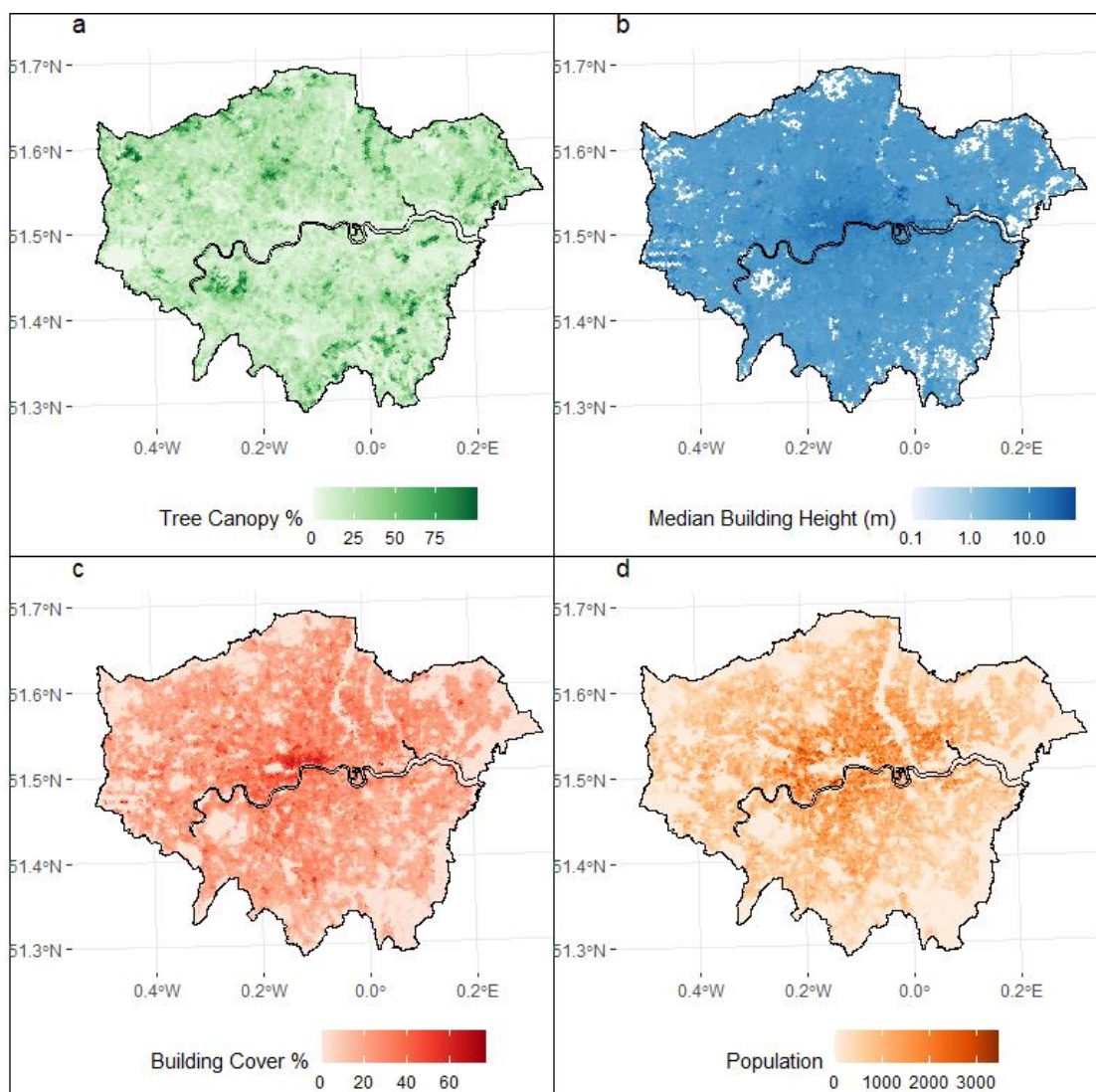
Urban temperatures also vary according to Local Climate Zones (LCZs), or local surface structure and cover. As tree canopy is assumed to be correlated with the natural component of LCZs, we derived two continuous variables to describe the height and cover of the built component. For each hexagon, a spatial join to the OS MasterMap Building Height Attribute [39] dataset was used to calculate the median height of buildings (removing buildings with low measurement confidence) (Figure 2b) and the percent area covered by all buildings (Figure 2c). OpenPopGrid [40], a 10m gridded population dataset, was used to calculate the population within each hexagon (Figure 2d). To account for broader spatial impacts, buffers around the hexagons at 200, 500, and 1000m were drawn and the area-weighted average building coverage (BC) and building height (BH) re-calculated within these buffers.

Hexagon canopy coverage was then adjusted for different scenarios:

- a) *Current Scenario*: A base case with existing tree canopy coverage.
- b) *Grey Scenario*: Tree canopy cover is reduced to near zero, representing a scenario where trees are reduced to the lowest possible amounts seen per BC. In this scenario, the tree coverage was set to 0.05th percentile for each hexagon.
- c) *London Strategy*: Tree canopy coverage each hexagon is increased 10%, as per the London Environment Strategy goals for 2050 [41].

- 1
2
3 d) *Average Strategy*: Hexagons below the population-weighted average canopy coverage are
4 increased to the average.
5
6 e) *Green Scenario*: Tree canopy cover is increased to an amount that represents a maximum
7 amount, constrained by existing BC. Quantile regression was used to identify the maximum
8 (99.5th percentile) tree coverage according to the BC within each hexagon. In cases where
9 tree coverage exceeded the 99.5th percentile, the current coverage was maintained.
10

11 Finally, to estimate the carbon benefits of these scenarios, the estimated 2.4 million tonnes of
12 carbon stored and 77,200 tonnes of carbon sequestered annually by London's trees [42] were
13 recalculated given the proportional changes in tree coverage.
14



50
51 *Figure 2. For each hexagon, a) percent tree canopy coverage b) median building height, and c) percent coverage of*
52 *buildings, and d) population density*
53

54 2.2. Analysis and Modelling

55
56
57
58 Analyses were performed to produce descriptive statistics on UHI intensity and examine how air
59 temperatures vary by the amount of tree canopy coverage.
60

Hourly temperature data was used to calculate UHI intensity for each day, defined as the maximum hourly difference between stations within the GLA boundaries (90th percentile) and the average of stations in the larger domain that are classified as rural. For the three heatwaves during the 2022 summer, the UHI intensity, hourly timeseries, and differences in 24-hour, daytime, and nighttime mean, maximum, and minimum temperatures in areas with differing amounts of tree coverage were calculated. Daily (d) 24-hour mean ($T_{mean,d}$) was calculated for all stations and joined by date to the corresponding value at the Heathrow reference station ($T_{mean,d,heathrow}$).

GAMs were then fit to the aggregated daily data using the *mgcv* package in R. GAMs were used because they allow the response variable to depend on smooth functions of the predictor variables; this can present an advantage over linear regression models which contain the assumption that response is linear in the predictor variables. Another advantage is the assumption that effects of each variable are separate, enabling extrapolation to the counterfactual scenarios. The effects of the predictor variables were assumed to be independent to enable counterfactual reasoning about the effect of changing tree cover while keeping other aspects of the built environment the same. Smoothing parameters were estimated using restricted maximum likelihood (REML), with degrees of freedom limited to 9 a priori to improve transferability for the counterfactual scenario and interpolation between data points. The response variable was $T_{mean,d}$ and the predictor variables were $T_{mean,d,heathrow}$; tree canopy cover, BC, and BH in the hexagon which the station is located; and the BC and BH within 200m, 500m, or 1000m buffers.

Models were fit for the different buffer sizes, using 5-fold cross-validation (stratified by station) to identify the buffer best able to predict temperatures at an unseen station. Model residuals were inspected, testing for spatial autocorrelation using a variogram and calculation of Morans I (for the whole dataset, summers, and each day), and examined for temporal autocorrelation using the Durban-Watson test.

2.3. Heat and Health Impact Modelling

The GAM model was then used to estimate temperature exposures from 2015-2022 under different tree coverage scenarios and the corresponding health impacts calculated. Rural temperatures from 2015-2022 were used as a baseline. For the same time period, the GAMS model was used to predict the daily mean temperature ($T_{mean,d,k}$) for each hexagon (k) under different canopy coverage scenarios. For each day, the population-weighted mean daily temperature for the GLA was calculated (Equation 1):

$$\overline{T_{mean,d}} = \frac{\sum_{i=1}^n (T_{mean,d,k}) \times P_k}{\sum_{i=1}^n P_k} \quad [1]$$

where P_k is the population within a hexagon.

Health impact calculations were then carried out to estimate daily heat-related mortality. We use the heat-mortality relationship for London from Arbutnott et al [43] (Table 1), which derived a Relative Risk (RR) of mortality for different age groups (i) using lag 0, 1 $T_{mean,d}$ (herein referred to as $T_{mean,d,lag}$) for London. When $T_{mean,d,lag}$ exceeds a temperature threshold (T_h , or 18.9 °C in London) the Relative Risk (RR) of heat related mortality increases per degree C:

$$RR_{i,d} = e^{c_a(T_{mean,d,lag} - T_h)} \quad \text{when } T_{mean,d,lag} > T_h \quad [2]$$

$$RR_{i,d} = 0 \quad \text{when } T_{mean,d,lag} \leq T_h$$

Where $c(a)$ is the natural log of the RR at 1 °C above the threshold. The Attributable Fraction (AF) of heat-related mortality is calculated as:

$$AF_{i,d} = \frac{RR_{i,d} - 1}{RR_{i,d}} \quad [3]$$

This was used alongside the number of deaths per each day of the year for different age groups ($q_{i,d}$) in London (2015 – 2022) [44,45] to calculate heat-related mortality and summed across all days and ages to estimate Attributable Mortality (AM):

$$AM = \sum_d \sum_i q_{i,d} \times AF_{i,d} \quad [4]$$

Heat attributable mortality under different scenarios was also examined using projected (1980-2010, 2041-2060, 2061-2080) climates for London for RCP8.5 from UKCP18 [46]. This data includes 12 ensemble members of average temperatures for each day of the year for these time periods. The GAM model was used to estimate $\overline{T_{mean,d}}$ for projected climates, and AM estimated using the number of deaths per day of year and age group averaged over 2015-2022.

Table 1. Heat-mortality relationship for London, from Arbuthnott et al [43].

Age Group	Threshold, T_h	RR of Mortality (95% CI), total
0-64	19.6 °C	1.022
65-74		1.024
75-		1.049

3. Results

3.1. Tree Coverage

The tree canopy coverage varied significantly, with a population-weighted average of 17.5% (range of 0 - 99.9%), and a total of 336km² of tree canopy with the GLA. The results of the quantile regression showed a correlation between the 99.5th percentile tree canopy and BC (Figure 3) (1.5% reduction in tree canopy per 1% increase in building area, p=0.00). PWS stations were relatively representative of the distribution of populated hexagons, although the maximum tree coverage was 64%. Population-weighted tree canopy coverage increased to 58% under the greening scenario (1,242 km²) and 21% (395km²) under the average scenario. Met stations were in areas with lower canopy coverage.

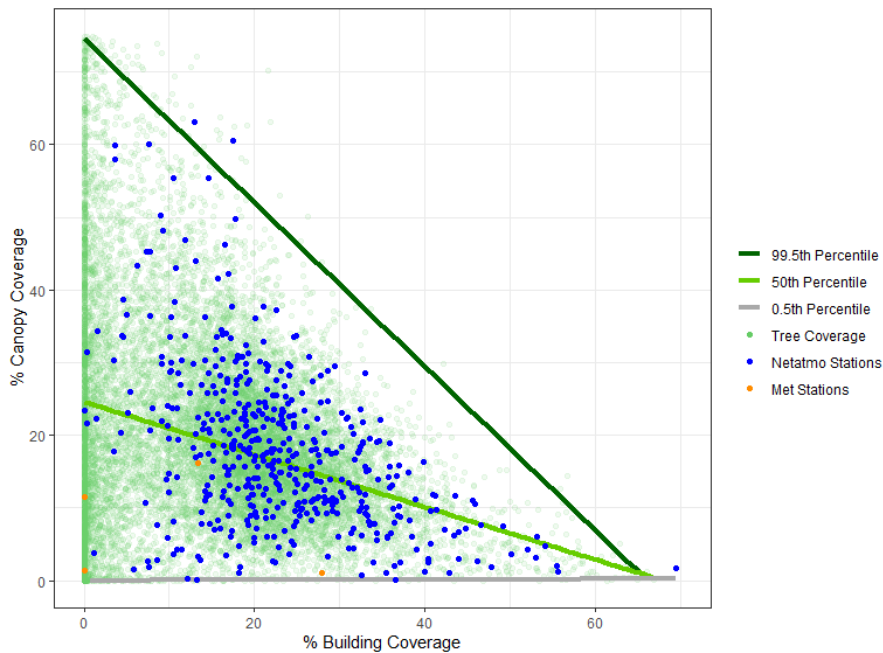


Figure 3. The variation of tree canopy coverage and building density for hexagons (green), PWS stations (blue), and Met Office stations (orange) with quantile regression for the hexagons.

3.2. Temperatures

Over the 2015-2022 period, the average UHI intensity was 3.3 °C, greatest during spring (mean of 3.8 °C, max of 7.6 °C) and lowest during winter (mean of 2.9 °C, max of 7.1 °C). An hourly timeseries of temperatures during the 2022 heatwaves (Figure 4) shows the average of all PWS within the GLA, the average of those within the top decile (40.2-99.9% tree canopy coverage), those in the bottom decile (0-5.4% canopy coverage), and in the rural areas surrounding the GLA administrative boundaries. During these heatwaves, areas in the top decile tree canopy coverage were, on average, 1.2 °C cooler than those in the lowest decile tree canopy coverage. Differences were most apparent at night, when nighttime minimum temperatures were around 2.0 °C lower in the areas with the most tree canopy, while maximum daytime temperatures were on average 0.8 °C lower. The maximum UHI intensities tended to be in the very early morning hours and averaged 4.3 °C across all heatwave days.

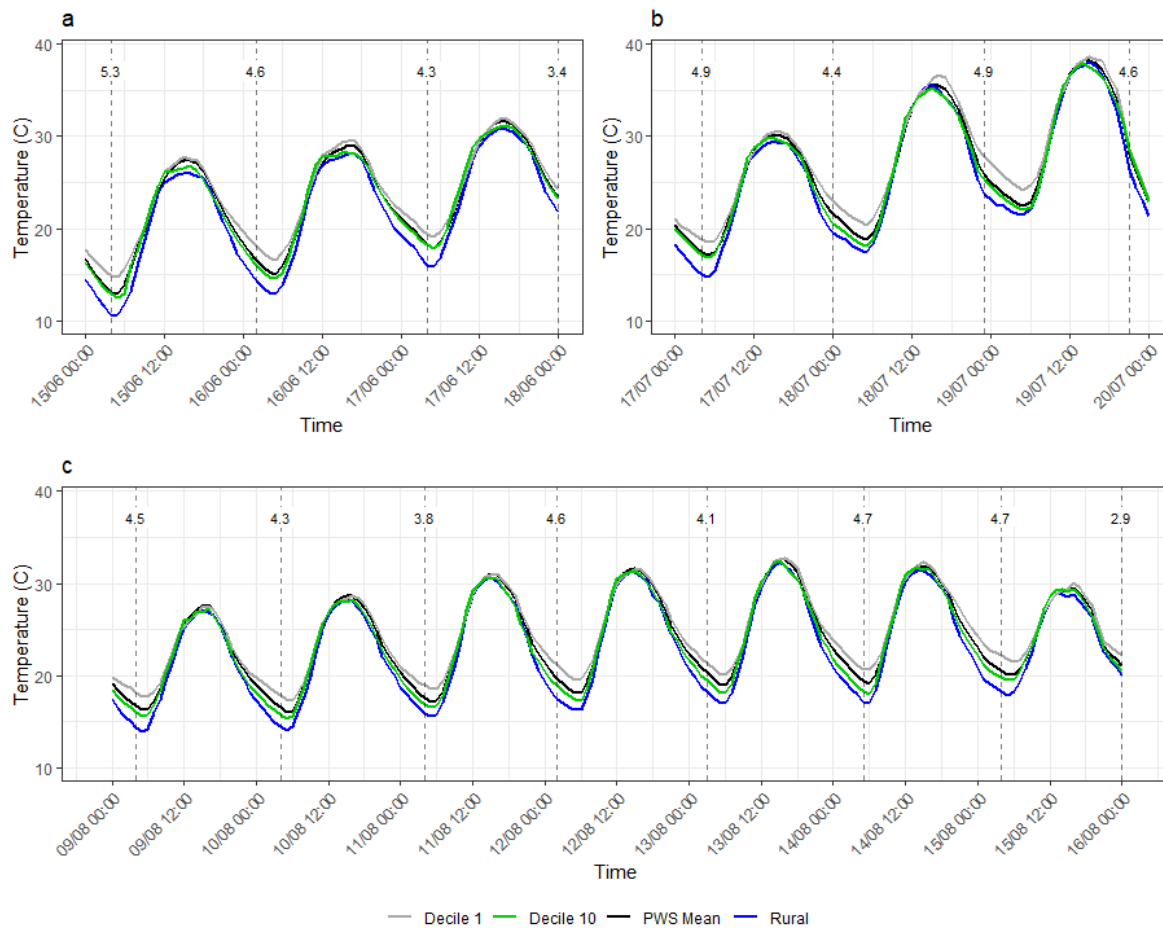


Figure 4. London PWS temperatures during the summer 2022 heatwaves (1st decile tree coverage, 10th decile tree coverage, PWS station average within the GLA, and PWS station average for surrounding rural areas). a) 15th – 17th June, b) 17th-19th July, and c) 9th-15th August. Vertical lines show the time and extent of the maximum UHI intensity on each 24 hours period (12pm-12pm).

Differences in daily mean, minimum, and maximum temperatures for stations with different levels of tree canopy coverage can be seen over the long-term data (Figure 5 and Figure 6). These figures show mean, minimum, and maximum anomalies (or differences between the stations and the average of all stations) as temperatures increase. Temperatures are, on average, 0.8 °C higher in deciles with the least tree coverage compared to the most, or around -0.019 °C (-0.0192 - 0.0187) per % increase in tree canopy. The temperature differences between the areas with the greatest and least amount of tree canopy coverage was greatest at lower temperatures (average minimum difference 1.1 °C), and the least at higher temperatures (average maximum differences 0.6 °C).

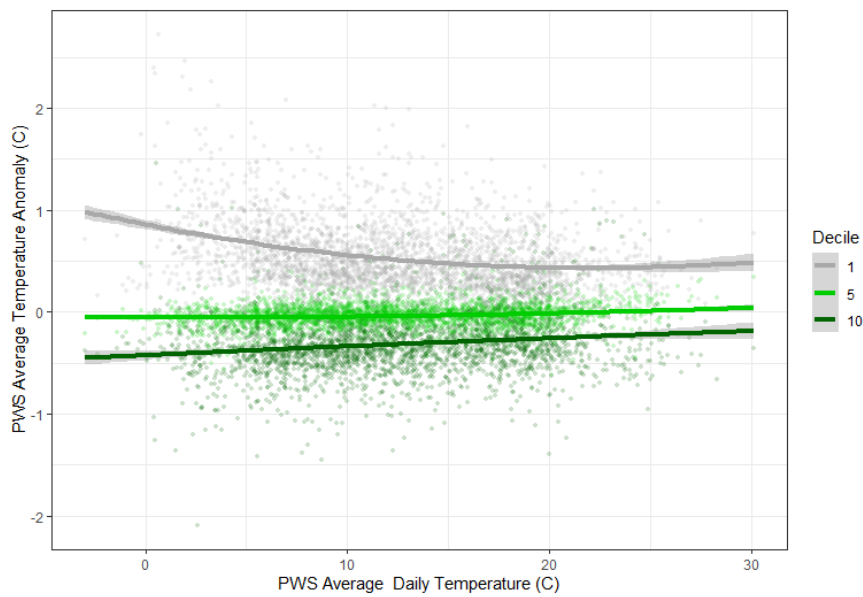


Figure 5. Daily average PWS temperature anomaly (or difference between the average PWS temperature of stations in tree coverage decile, and the average of all PWS stations) by daily average PWS temperature. The bottom (1), median (5) and top (10) decile of tree canopy coverage are shown.

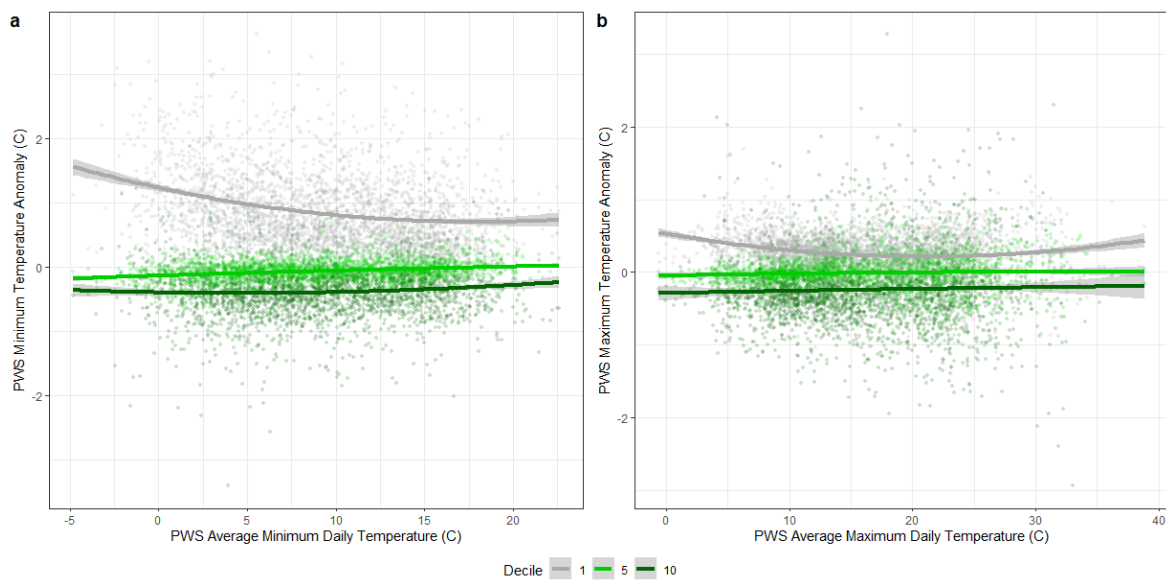


Figure 6. a) Daily minimum PWS temperature anomaly (or difference between the average minimum PWS temperature of stations in tree coverage decile, and the average minimum of all PWS stations) and average daily minimum PWS temperature, and b) Daily maximum PWS temperature anomaly (or difference between the average maximum PWS temperature of stations in tree coverage decile, and the average maximum of all PWS stations) and average daily maximum PWS temperature. The bottom (1), median (5) and top (10) decile of tree canopy coverage are shown.

3.3. Heat Exposure and Health Impact Models

As expected, data was noisy and with unexplained variance in the model. The GAM with the 1000m buffer showed the best performance as judged by chi-squared tests between models (Table S1 in the Appendix). Negligible amounts of spatial autocorrelation were present in the residuals of this model

1
2
3 (an average Morans I of 0.00041 during summers) compared to the total variation. A cyclical
4 temporal correlation was apparent with peaks during summer; closer examination alongside
5 additional Met Office data indicates that these may be due to exposure to solar radiation. As a
6 result, both spatial and temporal autocorrelation were decided to be unimportant, but we
7 acknowledge that errors may be underestimated because daily samples may not be independent.
8 The final model was able to predict daily temperatures with an R2 of 98.3% and a Root Mean Square
9 Error (RMSE) of 0.808 for stations and 0.761 for observations on held-out data. Partial dependence
10 plots can be seen in the appendix.
11
12

13 Health impact calculation results can be seen in Figure 7 and 8. Between 2015-2022, we estimate
14 that the current tree coverage avoided 153 heat attributable deaths. This represents a 16%
15 reduction of the UHI-related mortality that would have occurred under the 'grey scenario'. Relative
16 to the current tree canopy coverage, increasing tree coverage to average levels from 2017-2022
17 would have further reduced UHI mortality by 8%, the London strategy by 10%, and the green
18 scenario by 55%. During the heatwave events of 2022, we estimate that the current tree coverage
19 helped avoid around 16 heat attributable deaths (14% of UHI-associated deaths). This would
20 increase to 23 (21%), 25 (22%), and 67 (61%) under the average, London strategy, and green
21 scenarios, respectively.
22
23
24

25 Heat mortality is projected to increase around 8-fold by 2061-2080 relative to 1981-2000 as a result
26 of the rising temperatures and the more frequent exceedance of T_h under RCP8.5 (Figure 8). By
27 2061-2080, we estimate that the current tree coverage would help avoid around 42 heat-
28 attributable deaths a year. Increased coverage from the London strategy would help avoid an
29 additional 23 deaths a year relative to current levels, and the green scenario 131 deaths a year. The
30 changes also lead to substantial benefits for carbon storage and sequestration, with an additional
31 1.1 million tonnes of carbon stored and 36,500 tonnes sequestered annually under the London
32 strategy, rising to 5.6 million tonnes stored and 181,000 tonnes sequestered annually under the
33 green scenario.
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

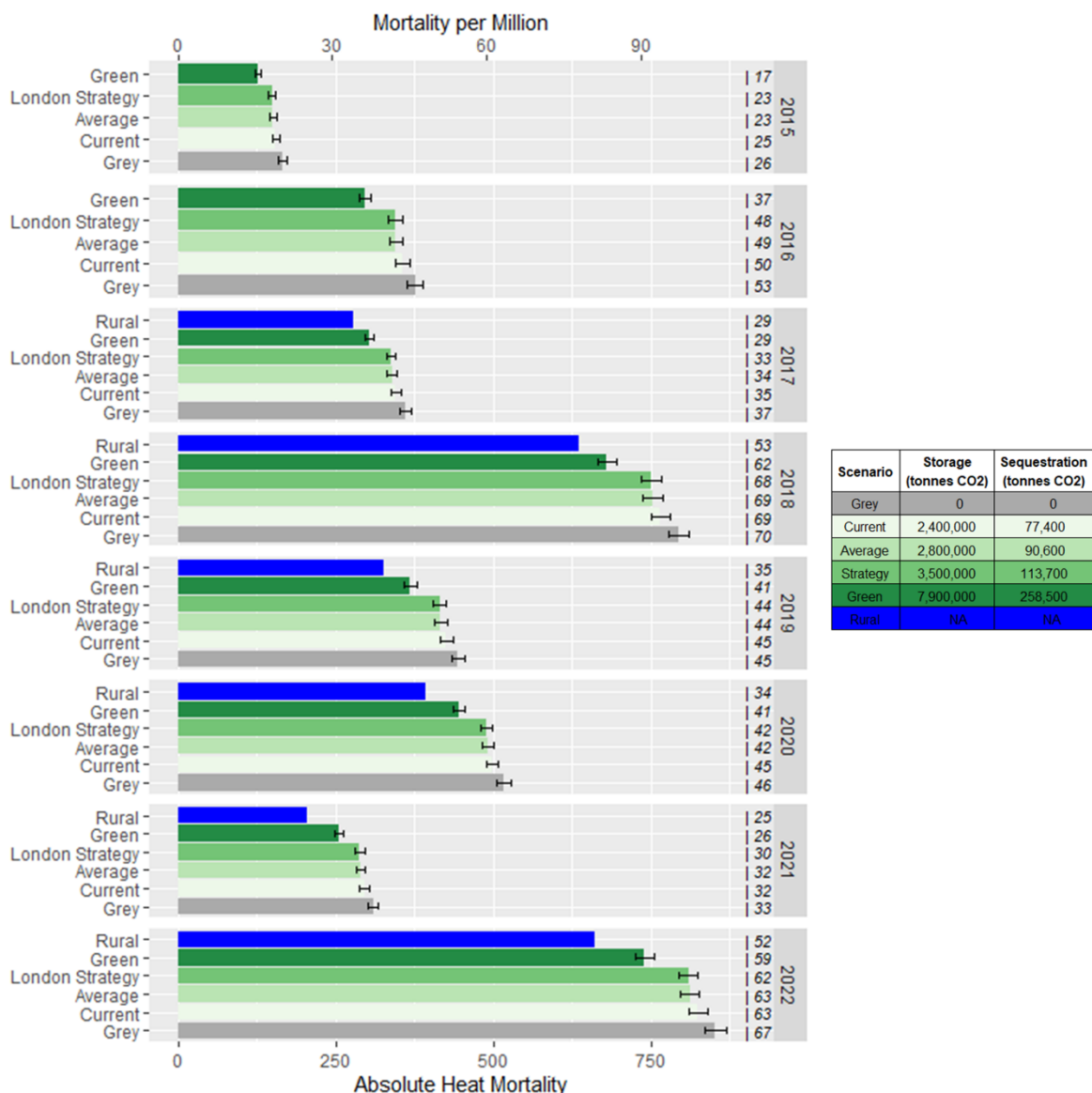


Figure 7. Estimated average yearly heat-associated mortality under the different tree canopy coverage scenarios. The number of days above T_h is shown for each year and scenario. Estimates at rural temperatures are excluded for 2015 and 2016 due to low numbers of rural weather stations. Error bars show 95% confidence interval. The estimated storage and sequestration (per annum) for the scenarios is shown in the legend. NB. Estimates after 2020 use daily mortality data that includes covid-related mortality.

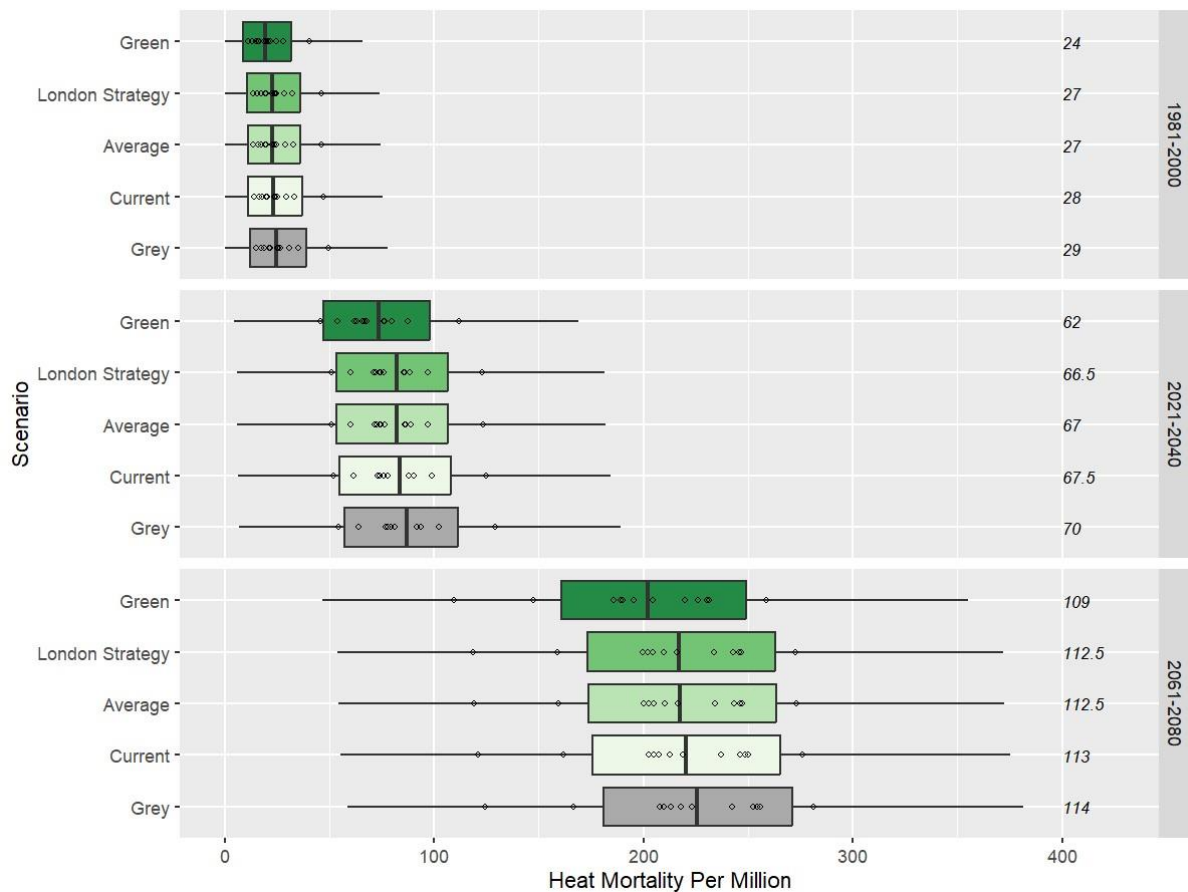


Figure 8. Estimated yearly heat-associated mortality for the different scenarios under projected climates. Distributions represent the range in annual mortality estimates across years and ensemble members. Points indicate the median estimated annual mortality for each ensemble member. The median number of days *above* T_h is shown for each epoch and scenario.

4. Discussion

This paper has used the growing number and density of PWS stations around the GLA to evaluate temperature differences by tree canopy coverage and between urban and surrounding rural areas over a period of seven years. Differences in urban temperatures were observed by tree canopy coverage. During the three heatwaves in 2022, areas with the top 10% of tree canopy coverage were 1.2 °C cooler, on average, than those in the bottom 10% tree canopy coverage. Differences were greatest at night, with temperatures around 2.0 °C lower in the areas with the most tree canopy, versus 0.8 °C lower during the day. This is likely due to the UHI effect, which is more prominent at night, and support prior studies showing the nocturnal cooling effects on greenspace in London [10]. When analysed over the entire timeseries, temperature differences are greatest during cooler weather.

From this data, a GAM model was developed to estimate the influence of tree canopy on temperatures. The model was able to achieve an RMSE of 0.761 and an R^2 of 98.3% for observations. The highly variable nature of the temperature data meant that there is a high degree of model uncertainty. We have focused here on model simplicity, but further work can help to develop the predictive power further. By including BC and BH as a covariate, we aim to account for the urban

1
2
3 heat island effect. Both are unchanged for the scenario predictions, meaning we are comparing
4 hypothetical areas with the same buildings but different tree coverage.
5

6 Applying the model to timeseries weather data from different climate scenarios enables changes in
7 heat exposure and subsequent mortality to be predicted. This novel approach enables estimation of
8 near-surface air temperature exposure under different scenarios, building upon past work that has
9 used LST or greenery as an effect modifier. The scale of future mortality under current levels of tree
10 canopy coverage are similar to estimates from other studies [47,48]. Our estimated impact of trees
11 on reducing mortality lies in between other studies. lungman et al. [16], estimated a decrease in
12 UHI-attributable mortality of 24.3% in London if tree coverage was increased from 15.5%, to 30%,
13 whereas we estimate that increasing canopy coverage from 21 to 31% (London Strategy) would
14 reduce UHI-attributable mortality by 10%, comparatively smaller. Our results are higher than those
15 of Choi et al. [49], whose analysis of heat-mortality and greenspace levels in 425 cities located in 24
16 countries, estimating that a 20% increase in greenspace could result in a 9% decrease in heat-
17 mortality annually in these cities. Results support epidemiological evidence that trees in London can
18 significantly reduce heat mortality [50].
19
20
21

22 The effectiveness of the tree canopy at reducing heat exposure and mortality is estimated to slightly
23 decrease as temperatures increase. This is due to the threshold effect of the model, where warm
24 days can be reduced below the heat mortality threshold through adaptations. As temperatures
25 increase, the numbers of days that can be reduced below this threshold decreases, and heat-related
26 mortality rises. This effect could be partially compensated for if populations adapt to heat effects in
27 future and therefore mortality thresholds rise. However, evidence on population adaptation to heat
28 effects is sparse, and time frames for adaptation are uncertain [51].
29
30
31
32

33 4.1. Limitations and uncertainties 34 35

36 A strength of this study is the large amounts of temperature data with dense coverage. A tradeoff,
37 however, is in the accuracy of the stations compared to official meteorological stations. To minimize
38 errors, we use data cleaning methods to remove outliers, stations with unreliable data, and indoor
39 stations, while all PWS stations are from the same manufacturer and are assumed to have similar
40 instrumental errors. Five official stations are used to supplement coverage, meaning a relatively
41 small number of different instruments are included in the modelling dataset, but the data from
42 these will be more with accurate than those from PWS. Our reference for UHI intensity are stations
43 outside the GLA located in rural areas, and acknowledge that the trends and amplitude of the UHI
44 we report are sensitive to these reference temperatures [52].
45
46
47

48 By using quantile regression to identify the maximum amount of local tree coverage according to
49 building density, we aimed to estimate a maximal amount of tree canopy that can be added, while
50 the London Strategy and average scenarios present more achievable targets; these scenarios are an
51 advance over prior studies that offered a percent increase in tree coverage unsupported by evidence
52 or policy. Temperatures will also depend on LCZs, but due to the correlation of the natural
53 component with tree coverage we opted to derive from a buildings dataset to reflect the built
54 component. However, tree canopy coverage and buildings are just one factor which contributes to
55 urban temperature differences and may be confounded by other parameters which we have not
56 included here. The GAM model does not include prevailing wind conditions, nor any advective
57 cooling from the river Thames or the sea. The use of hexagons with a relatively small area helps to
58
59
60

1
2
3 separate large areas of tree canopy (such as parks) from areas with residential populations. The
4 modelled temperature changes are associative and cross-sectional and do not demonstrate
5 causality, although this is equally a problem with all other studies of this type, e.g. [16].
6

7
8 The tree canopy data offers high resolution coverage derived using machine learning processed
9 aerial imagery. The report on the generation of the dataset acknowledges various limitations. These
10 include the data coming from single time point (September 2016) and a time of the year when leaf
11 structure may be breaking down. The model occasionally misclassifies trees as bushes and can miss
12 sections of canopy altogether. However, the model has an accuracy rate of 94% and produces
13 estimates that are at minimum comparable to estimates from traditional survey methods when
14 aggregated across larger areas. Estimates of the stored carbon within London's trees is based on
15 figures from a 2015 report [42], and may in fact underestimate the amount of carbon stored [53].
16

17
18 The heat-mortality estimates use a relationship between outdoor air temperature and mortality
19 derived for 1996 – 2013. This model does not include relative humidity or air pollution as
20 confounders, although previous research has not found these to be significant factors for heat
21 mortality in the UK [9,43]. This heat-mortality relationship uses daily mean temperature, however,
22 there is evidence that nighttime temperatures are particularly important for health outcomes [54].
23 Given that the greatest effect of tree coverage was seen at night, this could mean that the health
24 benefits of the tree canopy are underestimated. We have not looked at cold. For the future
25 projections, we do not model population social or technological adaptation to heat, such as
26 heatwave plans or use of air conditioning, nor do we model population demographic changes such
27 as population aging. The baseline mortality rate for 2020-2022 will include the effects of Covid-19.
28

29
30 The heat-mortality-relationship used is based on epidemiological analysis of mortality data which
31 partially pre-dates the development of many of the UK heatwave public health measures. Our
32 predicted mortality for the heat periods of the summer of 2022 is both higher than other real-time
33 models and the observed excess mortality [8], likely due to different sources of temperature data, as
34 well as different underlying methods in calculating heat-attributable mortality. During these
35 heatwaves, the UK Met Office issued Heat-Health Alert (HHA) and Red Extreme Heat (EH) weather
36 warnings to the public for the first time. It is possible that the warnings and advice from the Met
37 Office and Public Health agencies had a role in reducing the actual mortality below what was
38 expected. The estimated mortality in this study should therefore be interpreted as a theoretical
39 quantification of the role of trees rather than an absolute estimate of heat-related mortality during
40 this period.
41
42
43
44
45

46 4.2. Implications 47 48 49

50 The methods used here can be applied to other locations and with different land covers wherever
51 PWS data are available. While the results of this study can provide an indicative value for similar
52 cities, caution should be applied when generalizing as city-specific characteristics like climate, the
53 amount of potential greening, and the built environment will influence estimates and a recent PWS
54 study shows that increased tree cover in many European cities does not lead to reduced air
55 temperatures [15]. The types of trees, such as their leaf area index, and the albedo of the built
56 environment are also important considerations [55].
57

58 In addition to benefits for reducing heat exposure, trees offer a number of benefits, including
59 biodiversity, stormwater management, air pollution removal, and carbon storage and sequestration
60

1
2
3 [42]. Green spaces have been shown to have a positive influence on physical activity, stress, social
4 contacts, and restoration [56], and increased urban street tree density is associated with reduced
5 mental health issues [57]. In the UK, all-cause mortality was found to be 6% lower in the quintile
6 with the most greenspace compared to the quintile with the lowest [58].
7

8
9 Trees also have some disadvantages. Under certain circumstances, trees can risk negatively
10 impacting air quality by preventing dispersion of polluted air in narrow streets for certain wind
11 directions [59,60], while the pollen produced by certain tree species can exacerbate allergies [61].
12 Our results show areas with more trees are colder at lower temperatures, with possible increased in
13 space heating energy demand [62] if the necessary energy efficient retrofits are not carried out.
14 Types of trees are likely to be important, with deciduous trees offering beneficial shading during the
15 summer. Future research could compare the estimated costs associated with additional tree
16 coverage with the potential savings provided by reduced health care cost and examine the impacts
17 on indoor temperatures and heating or cooling demand.
18
19

20 21 5. Conclusions 22 23

24 This study examined the differences in air temperatures in London according to tree canopy
25 coverage, focusing in particular on heat. PWS data from 2015-2022 shows that areas with higher
26 tree canopy coverage were associated with reduced levels of heat compared to those with low tree
27 canopy coverage. During the heatwaves of 2022, this corresponded to a lower average difference in
28 maximum daytime temperatures (0.8 °C) and minimum temperatures (2.0 °C). Modelled impacts of
29 different climate and tree canopy coverage scenarios estimates that the existing urban tree canopy
30 coverage in London may have reduced excess heat-related mortality by around 16% during 2015-
31 2022. Increasing the tree canopy to the maximum level, given building density, is estimated to lead
32 to a reduction of 55%. The cooling benefits from trees become even greater under hotter future
33 climates. The results of this study support increasing tree canopy coverage to help mitigate high
34 urban temperatures in the future, with urban greening part of a set of broader public health actions
35 that can help reduce heat-related mortality in the future.
36
37
38

39 40 6. Acknowledgments 41 42

43 This research was funded, in part, by the Wellcome Trust through the HEROIC project
44 (216035/Z/19/Z) that finances O.B and C.S. C.H was supported by a NERC fellowship
45 (NE/R01440X/1). J.T has received funding from the European Union – NextGenerationEU instrument
46 and is funded by the Academy of Finland under grant number 353327. For the purpose of open
47 access, the author has applied a CC BY public copyright license to any Author Accepted Manuscript
48 version arising from this submission.
49
50
51

52 53 7. References 54 55

- 56
57 [1] N. Nazarian, E.S. Krayenhoff, B. Bechtel, D.M. Hondula, R. Paolini, J. Vanos, T. Cheung, W.T.L.
58 Chow, R. de Dear, O. Jay, J.K.W. Lee, A. Martilli, A. Middel, L.K. Norford, M. Sadeghi, S.
59
60

- 1
2
3 Schiavon, M. Santamouris, Integrated Assessment of Urban Overheating Impacts on Human
4 Life, *Earth's Future* 10 (2022) e2022EF002682. <https://doi.org/10.1029/2022EF002682>.
5
- 6 [2] N. Christidis, P.A. Stott, M. McCarthy, An attribution study of the UK mean temperature in year
7 2022, UK Met Office, London, 2023.
8 [https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/climat
10 e-science/attribution/uk-2022-attribution.pdf](https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/climat
9 e-science/attribution/uk-2022-attribution.pdf).
11
- 12 [3] T.R. Oke, G. Mills, A. Christen, J.A. Voogt, *Urban Climates*, Cambridge University Press,
13 Cambridge, UK., 2017.
14
- 15 [4] R. Bassett, V. Janes-Bassett, J. Phillipson, P.J. Young, G.S. Blair, Climate driven trends in
16 London's urban heat island intensity reconstructed over 70 years using a generalized
17 additive model, *Urban Climate* 40 (2021) 100990.
18 <https://doi.org/10.1016/j.uclim.2021.100990>.
19
- 20 [5] O. Brousse, C. Simpson, N. Walker, D. Fenner, F. Meier, J. Taylor, C. Heaviside, Evidence of
21 horizontal urban heat advection in London using six years of data from a citizen weather
22 station network, *Environ. Res. Lett.* 17 (2022) 044041. [https://doi.org/10.1088/1748-
24 9326/ac5c0f](https://doi.org/10.1088/1748-
23 9326/ac5c0f).
25
- 26 [6] K.L. Ebi, A. Capon, P. Berry, C. Broderick, R. de Dear, G. Havenith, Y. Honda, R.S. Kovats, W. Ma,
27 A. Malik, N.B. Morris, L. Nybo, S.I. Seneviratne, J. Vanos, O. Jay, Hot weather and heat
28 extremes: health risks, *The Lancet* 398 (2021) 698–708. [https://doi.org/10.1016/S0140-
30 6736\(21\)01208-3](https://doi.org/10.1016/S0140-
29 6736(21)01208-3).
31
- 32 [7] R. Thompson, R. Hornigold, L. Page, T. Waite, Associations between high ambient
33 temperatures and heat waves with mental health outcomes: a systematic review, *Public
34 Health* 161 (2018) 171–191. <https://doi.org/10.1016/J.PUHE.2018.06.008>.
35
- 36 [8] UK Health Security Agency, Heat mortality monitoring report: 2022, UK Health Security Agency,
37 London, 2023. [https://www.gov.uk/government/publications/heat-mortality-monitoring-
39 reports/heat-mortality-monitoring-report-2022](https://www.gov.uk/government/publications/heat-mortality-monitoring-
38 reports/heat-mortality-monitoring-report-2022) (accessed July 27, 2023).
40
- 41 [9] S. Hajat, B. Armstrong, M. Baccini, A. Biggeri, L. Bisanti, A. Russo, A. Paldy, B. Menne, T.
42 Kosatsky, Impact of High Temperatures on Mortality: Is There an Added Heat Wave Effect?,
43 *Source: Epidemiology* 17 (2006) 632–638.
44 <https://doi.org/10.1097/01.ede.0000239688.70829.63>.
45
- 46 [10] M. Vaz Monteiro, K.J. Doick, P. Handley, A. Peace, The impact of greenspace size on the extent
47 of local nocturnal air temperature cooling in London, *Urban Forestry & Urban Greening* 16
48 (2016) 160–169. <https://doi.org/10.1016/j.ufug.2016.02.008>.
49
- 50 [11] J. Schwaab, R. Meier, G. Mussetti, S. Seneviratne, C. Bürgi, E.L. Davin, The role of urban trees in
51 reducing land surface temperatures in European cities, *Nat Commun* 12 (2021) 6763.
52 <https://doi.org/10.1038/s41467-021-26768-w>.
53
- 54 [12] D.E. Bowler, L. Buyung-Ali, T.M. Knight, A.S. Pullin, Urban greening to cool towns and cities: A
55 systematic review of the empirical evidence, *Landscape and Urban Planning* 97 (2010) 147–
56 155. <https://doi.org/10.1016/j.landurbplan.2010.05.006>.
57
- 58 [13] O. Jay, A. Capon, P. Berry, C. Broderick, R. de Dear, G. Havenith, Y. Honda, R.S. Kovats, W. Ma,
59 A. Malik, N.B. Morris, L. Nybo, S.I. Seneviratne, J. Vanos, K.L. Ebi, Reducing the health effects
60

- of hot weather and heat extremes: from personal cooling strategies to green cities, *The Lancet* 398 (2021) 709–724. [https://doi.org/10.1016/S0140-6736\(21\)01209-5](https://doi.org/10.1016/S0140-6736(21)01209-5).
- [14] N. Meili, G. Manoli, P. Burlando, J. Carmeliet, W.T.L. Chow, A.M. Coutts, M. Roth, E. Velasco, E.R. Vivoni, S. Fatichi, Tree effects on urban microclimate: Diurnal, seasonal, and climatic temperature differences explained by separating radiation, evapotranspiration, and roughness effects, *Urban Forestry & Urban Greening* 58 (2021) 126970. <https://doi.org/10.1016/j.ufug.2020.126970>.
- [15] M. Du, N. Li, T. Hu, Q. Yang, T. Chakraborty, Z. Venter, R. Yao, Daytime cooling efficiencies of urban trees derived from surface temperature are much higher than those for air temperature, *Environ. Res. Lett.* (2024). <https://doi.org/10.1088/1748-9326/ad30a3>.
- [16] T. Lungman, M. Cirach, F. Marando, E.P. Barboza, S. Khomenko, P. Masselot, M. Quijal-Zamorano, N. Mueller, A. Gasparrini, J. Urquiza, M. Heris, M. Thondoo, M. Nieuwenhuijsen, Cooling cities through urban green infrastructure: a health impact assessment of European cities, *The Lancet* 401 (2023) 577–589. [https://doi.org/10.1016/S0140-6736\(22\)02585-5](https://doi.org/10.1016/S0140-6736(22)02585-5).
- [17] Z.S. Venter, T. Chakraborty, X. Lee, Crowdsourced air temperatures contrast satellite measures of the urban heat island and its mechanisms, *Science Advances* 7 (2021) eabb9569. <https://doi.org/10.1126/sciadv.abb9569>.
- [18] T. Chakraborty, Z.S. Venter, Y. Qian, X. Lee, Lower Urban Humidity Moderates Outdoor Heat Stress, *AGU Advances* 3 (2022) e2022AV000729. <https://doi.org/10.1029/2022AV000729>.
- [19] G.J. Steeneveld, S. Koopmans, B. Heusinkveld, L. vanHove, A. Holtslag, Quantifying urban heat island effects and human comfort for cities of variable size and urban morphology in the Netherlands, *Journal of Geophysical Research: Atmospheres* 116 (2011). <https://doi.org/10.1029/2011JD015988>.
- [20] D. Wolters, T. Brandsma, Estimating the Urban Heat Island in Residential Areas in the Netherlands Using Observations by Weather Amateurs, *Journal of Applied Meteorology and Climatology* 51 (2012) 711–721. <https://doi.org/10.1175/JAMC-D-11-0135.1>.
- [21] F. Meier, D. Fenner, T. Grassmann, M. Otto, D. Scherer, Crowdsourcing air temperature from citizen weather stations for urban climate research, *Urban Climate* 19 (2017) 170–191. <https://doi.org/10.1016/j.uclim.2017.01.006>.
- [22] C. I. Muller, L. Chapman, S. Johnston, C. Kidd, S. Illingworth, G. Foody, A. Overeem, R.R. Leigh, Crowdsourcing for climate and atmospheric sciences: current status and future potential, *International Journal of Climatology* 35 (2015) 3185–3203. <https://doi.org/10.1002/joc.4210>.
- [23] L.W. de Vos, A.M. Droste, M.J. Zander, A. Overeem, H. Leijnse, B.G. Heusinkveld, G.J. Steeneveld, R. Uijlenhoet, Opportunistic Sensing Networks: A Study in Amsterdam, *Bulletin of the American Meteorological Society* 101 (2020) 313–318. <https://doi.org/10.1175/BAMS-D-19-0091.A>.
- [24] O. Brousse, C. Simpson, O. Kenway, A. Martilli, E.S. Krayenhoff, A. Zonato, C. Heaviside, Spatially Explicit Correction of Simulated Urban Air Temperatures Using Crowdsourced Data, *Journal of Applied Meteorology and Climatology* 62 (2023) 1539–1572. <https://doi.org/10.1175/JAMC-D-22-0142.1>.

- 1
2
3 [25] D. Fenner, B. Bechtel, M. Demuzere, J. Kittner, F. Meier, CrowdQC+—A Quality-Control for
4 Crowdsourced Air-Temperature Observations Enabling World-Wide Urban Climate
5 Applications, *Frontiers in Environmental Science* 9 (2021).
6 <https://doi.org/10.3389/fenvs.2021.720747>.
7
8
9 [26] D. Fenner, F. Meier, B. Bechtel, M. Otto, D. Scherer, Intra and inter ‘local climate zone’
10 variability of air temperature as observed by crowdsourced citizen weather stations in
11 Berlin, Germany, *Meteorologische Zeitschrift* (2017) 525–547.
12 <https://doi.org/10.1127/metz/2017/0861>.
13
14 [27] J. Potgieter, N. Nazarian, M.J. Lipson, M.A. Hart, G. Ulpiani, W. Morrison, K. Benjamin,
15 Combining High-Resolution Land Use Data With Crowdsourced Air Temperature to
16 Investigate Intra-Urban Microclimate, *Frontiers in Environmental Science* 9 (2021).
17 <https://doi.org/10.3389/fenvs.2021.720323>.
18
19 [28] M. Varentsov, D. Fenner, F. Meier, T. Samsonov, M. Demuzere, Quantifying Local and
20 Mesoscale Drivers of the Urban Heat Island of Moscow with Reference and Crowdsourced
21 Observations, *Frontiers in Environmental Science* 9 (2021).
22 <https://doi.org/10.3389/fenvs.2021.716968>.
23
24 [29] Z.S. Venter, O. Brousse, I. Esau, F. Meier, Hyperlocal mapping of urban air temperature using
25 remote sensing and crowdsourced weather data, *Remote Sensing of Environment* 242
26 (2020) 111791. <https://doi.org/10.1016/j.rse.2020.111791>.
27
28 [30] S. Vulova, F. Meier, D. Fenner, H. Nouri, B. Kleinschmit, Summer Nights in Berlin, Germany:
29 Modeling Air Temperature Spatially With Remote Sensing, Crowdsourced Weather Data, and
30 Machine Learning, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote*
31 *Sensing* 13 (2020) 5074–5087. <https://doi.org/10.1109/JSTARS.2020.3019696>.
32
33 [31] M. Zumwald, B. Knüsel, D.N. Bresch, R. Knutti, Mapping urban temperature using crowd-
34 sensing data and machine learning, *Urban Climate* 35 (2021) 100739.
35 <https://doi.org/10.1016/j.uclim.2020.100739>.
36
37 [32] K. Benjamin, Z. Luo, X. Wang, Crowdsourcing Urban Air Temperature Data for Estimating Urban
38 Heat Island and Building Heating/Cooling Load in London, *Energies* 14 (2021) 5208.
39 <https://doi.org/10.3390/en14165208>.
40
41 [33] K. Hammerberg, O. Brousse, A. Martilli, A. Mahdavi, Implications of employing detailed urban
42 canopy parameters for mesoscale climate modelling: a comparison between WUDAPT and
43 GIS databases over Vienna, Austria, *International Journal of Climatology* 38 (2018) e1241–
44 e1257. <https://doi.org/10.1002/joc.5447>.
45
46 [34] Met Office, Met Office MIDAS Open: UK Land Surface Stations Data (1853-current), Centre for
47 Environmental Data Analysis (2019).
48 <http://catalogue.ceda.ac.uk/uuid/dbd451271eb04662beade68da43546e1>.
49
50 [35] Environment Agency, LIDAR Composite DTM 2019 - 10m, (2020).
51 [https://www.data.gov.uk/dataset/8311f42d-bddd-4cd4-98a3-e543de5be4cb/lidar-](https://www.data.gov.uk/dataset/8311f42d-bddd-4cd4-98a3-e543de5be4cb/lidar-composite-dtm-2019-10m)
52 [composite-dtm-2019-10m](https://www.data.gov.uk/dataset/8311f42d-bddd-4cd4-98a3-e543de5be4cb/lidar-composite-dtm-2019-10m) (accessed April 25, 2023).
53
54 [36] Office for National Statistics, 2011 rural/urban classification for small-area geographies,
55 London (2011). [http://www.ons.gov.uk/ons/guide-method/geography/products/area-](http://www.ons.gov.uk/ons/guide-method/geography/products/area-classifications/2011-rural-urban/index.html)
56 [classifications/2011-rural-urban/index.html](http://www.ons.gov.uk/ons/guide-method/geography/products/area-classifications/2011-rural-urban/index.html).
57
58
59
60

- 1
2
3 [37] GLA, Curio Canopy - London Tree Canopy Cover, London Datastore (2020).
4 <https://data.london.gov.uk/dataset/curio-canopy> (accessed April 25, 2023).
5
6 [38] Breadboard Labs, Measurement & spatial analysis of London's tree canopy cover: 2018
7 methodology report, Breadboard Labs, London, UK, 2018.
8 <https://data.london.gov.uk/dataset/curio-canopy> (accessed April 25, 2023).
9
10 [39] Ordnance Survey, OS MasterMap Topography Layer, (2021).
11 [https://digimap.edina.ac.uk/help/files/resource-hub/downloads/osmanuals/os-mastermap-](https://digimap.edina.ac.uk/help/files/resource-hub/downloads/osmanuals/os-mastermap-topography-layer-user-guide_v1_9.pdf)
12 [topography-layer-user-guide_v1_9.pdf](https://digimap.edina.ac.uk/help/files/resource-hub/downloads/osmanuals/os-mastermap-topography-layer-user-guide_v1_9.pdf).
13
14 [40] A.P. Murdock, A.J.P. Harfoot, D. Martin, S. Cockings, C. Hill, OpenPopGrid: an open gridded
15 population dataset for England and Wales, GeoData, University of Southampton (2015).
16 <http://openpopgrid.geodata.soton.ac.uk/>.
17
18 [41] GLA, London Environment Strategy, Greater London Authority, London, UK., 2018.
19 [https://www.london.gov.uk/programmes-and-strategies/environment-and-climate-](https://www.london.gov.uk/programmes-and-strategies/environment-and-climate-change/london-environment-strategy)
20 [change/london-environment-strategy](https://www.london.gov.uk/programmes-and-strategies/environment-and-climate-change/london-environment-strategy) (accessed June 23, 2020).
21
22 [42] K. Rogers, K. Sacre, J. Goodenough, K. Doick, Valuing London's urban forest: results of the
23 London i-Tree Eco Project: Treeconomics London, Greater London Authority, London, UK.,
24 2015. [https://www.london.gov.uk/sites/default/files/valuing_londons_urban_forest_i-](https://www.london.gov.uk/sites/default/files/valuing_londons_urban_forest_i-tree_report_final.pdf)
25 [tree_report_final.pdf](https://www.london.gov.uk/sites/default/files/valuing_londons_urban_forest_i-tree_report_final.pdf) (accessed September 21, 2023).
26
27 [43] K. Arbuthnott, S. Hajat, C. Heaviside, S. Vardoulakis, Years of life lost and mortality due to heat
28 and cold in the three largest English cities, *Environment International* 144 (2020) 105966.
29 <https://doi.org/10.1016/j.envint.2020.105966>.
30
31 [44] Office for National Statistics (ONS), Daily death occurrences, England and Wales: 2021 and
32 2022 - Office for National Statistics, (2023).
33 [https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/death-](https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/adhocs/1724dailydeathoccurrencesenglandandwales2021and2022)
34 [s/adhocs/1724dailydeathoccurrencesenglandandwales2021and2022](https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/adhocs/1724dailydeathoccurrencesenglandandwales2021and2022) (accessed March 5,
35 2024).
36
37 [45] Office for National Statistics (ONS), Daily deaths occurrences, England and Wales, 1981 and
38 2020, (2022).
39 [https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/death-](https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/adhocs/14173dailydeathsoccurrencesenglandandwales1981and2020)
40 [s/adhocs/14173dailydeathsoccurrencesenglandandwales1981and2020](https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/adhocs/14173dailydeathsoccurrencesenglandandwales1981and2020) (accessed March 5,
41 2024).
42
43 [46] J.A. Lowe, D. Bernie, P.E. Bett, L.M. Bricheno, S.C. Brown, D. Calvert, R. Clark, Karen, Eagle, T.L.
44 Edwards, G. Fossier, P. Maisey, R.N. McInnes, C. Mcsweeney, K. Yamazaki, S. Belcher, UKCP
45 18 Science Overview Report, Met Office, Reading, UK, 2019.
46
47 [47] S. Vardoulakis, K. Dear, S. Hajat, C. Heaviside, B. Eggen, A.J. McMichael, Comparative
48 assessment of the effects of climate change on heat- and cold-related mortality in the
49 United Kingdom and Australia, *Environmental Health Perspectives* 122 (2015) 1285–1292.
50 <https://doi.org/10.1289/ehp.1307524>.
51
52 [48] S. Hajat, S. Vardoulakis, C. Heaviside, B. Eggen, Climate change effects on human health:
53 projections of temperature-related mortality for the UK during the 2020s, 2050s and 2080s,
54 *Journal of Epidemiology and Community Health* 68 (2014) 641–8.
55 <https://doi.org/10.1136/jech-2013-202449>.
56
57
58
59
60

- 1
2
3 [49] H.M. Choi, W. Lee, D. Roye, S. Heo, A. Urban, A. Entezari, A.M. Vicedo-Cabrera, A. Zanobetti, A.
4 Gasparrini, A. Analitis, A. Tobias, B. Armstrong, B. Forsberg, C. Íñiguez, C. Åström, E.
5 Indermitte, E. Lavigne, F. Mayvaneh, F. Acquaotta, F. Sera, H. Orru, H. Kim, J. Kyselý, J.
6 Madueira, J. Schwartz, J.J.K. Jaakkola, K. Katsouyanni, M.H. Diaz, M.S. Raettli, M. Pascal, N.
7 Rytí, N. Scovronick, S. Osorio, S. Tong, X. Seposo, Y.L. Guo, Y. Guo, M.L. Bell, Effect
8 modification of greenness on the association between heat and mortality: A multi-city multi-
9 country study, *eBioMedicine* 84 (2022). <https://doi.org/10.1016/j.ebiom.2022.104251>.
- 10
11
12 [50] P. Murage, S. Kovats, C. Sarran, J. Taylor, R. McInnes, S. Hajat, What individual and
13 neighbourhood-level factors increase the risk of heat-related mortality? A case-crossover
14 study of over 185,000 deaths in London using high-resolution climate datasets, *Environment*
15 *International* 134 (2020) 105292. <https://doi.org/10.1016/J.ENVINT.2019.105292>.
- 16
17
18 [51] K. Arbutnott, S. Hajat, C. Heaviside, S. Vardoulakis, Changes in population susceptibility to
19 heat and cold over time: assessing adaptation to climate change, *Environmental Health* 15
20 (2016) S33. <https://doi.org/10.1186/s12940-016-0102-7>.
- 21
22 [52] H. Liu, B. He, S. Gao, Q. Zhan, C. Yang, Influence of non-urban reference delineation on trend
23 estimate of surface urban heat island intensity: A comparison of seven methods, *Remote*
24 *Sensing of Environment* 296 (2023) 113735. <https://doi.org/10.1016/j.rse.2023.113735>.
- 25
26 [53] K. Calders, H. Verbeeck, A. Burt, N. Origo, J. Nightingale, Y. Malhi, P. Wilkes, P. Raunonen,
27 R.G.H. Bunce, M. Disney, Laser scanning reveals potential underestimation of biomass
28 carbon in temperate forest, *Ecological Solutions and Evidence* 3 (2022) e12197.
29 <https://doi.org/10.1002/2688-8319.12197>.
- 30
31 [54] P. Murage, S. Hajat, R.S. Kovats, Effect of night-time temperatures on cause and age-specific
32 mortality in London, *Environmental Epidemiology* (2017) 1.
33 <https://doi.org/10.1097/EE9.000000000000005>.
- 34
35 [55] J. Zhao, X. Zhao, D. Wu, N. Meili, S. Fatichi, Satellite-based evidence highlights a considerable
36 increase of urban tree cooling benefits from 2000 to 2015, *Global Change Biology* 29 (2023)
37 3085–3097. <https://doi.org/10.1111/gcb.16667>.
- 38
39 [56] M.J. Nieuwenhuijsen, H. Khreis, M. Triguero-Mas, M. Gascon, P. Davdand, Fifty Shades of
40 Green: Pathway to Healthy Urban Living, *Epidemiology* 28 (2017) 63.
41 <https://doi.org/10.1097/EDE.0000000000000549>.
- 42
43 [57] M.S. Taylor, B.W. Wheeler, M.P. White, T. Economou, N.J. Osborne, Research note: Urban
44 street tree density and antidepressant prescription rates—A cross-sectional study in London,
45 UK, *Landscape and Urban Planning* 136 (2015) 174–179.
46 <https://doi.org/10.1016/j.landurbplan.2014.12.005>.
- 47
48 [58] R. Mitchell, F. Popham, Effect of exposure to natural environment on health inequalities: an
49 observational population study, *The Lancet* 372 (2008) 1655–1660.
50 [https://doi.org/10.1016/S0140-6736\(08\)61689-X](https://doi.org/10.1016/S0140-6736(08)61689-X).
- 51
52 [59] A.P.R. Jeanjean, R. Buccolieri, J. Eddy, P.S. Monks, R.J. Leigh, Air quality affected by trees in real
53 street canyons: The case of Marylebone neighbourhood in central London, *Urban Forestry &*
54 *Urban Greening* 22 (2017) 41–53. <https://doi.org/10.1016/j.ufug.2017.01.009>.
- 55
56
57
58
59
60

- 1
2
3 [60] R. Buccolieri, A.P.R. Jeanjean, E. Gatto, R.J. Leigh, The impact of trees on street ventilation, NOx
4 and PM2.5 concentrations across heights in Marylebone Rd street canyon, central London,
5 Sustainable Cities and Society 41 (2018) 227–241. <https://doi.org/10.1016/j.scs.2018.05.030>.
6
7 [61] P. Cariñanos, M. Casares-Porcel, Urban green zones and related pollen allergy: A review. Some
8 guidelines for designing spaces with low allergy impact, Landscape and Urban Planning 101
9 (2011) 205–214. <https://doi.org/10.1016/j.landurbplan.2011.03.006>.
10
11 [62] R. Pandit, D.N. Laband, Energy savings from tree shade, Ecological Economics 69 (2010) 1324–
12 1329. <https://doi.org/10.1016/j.ecolecon.2010.01.009>.
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60