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Street tree diversity and urban heat

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ABSTRACT

Higher diversity within a city's street trees may offer greater cooling benefits than less diverse urban forests. California's urban forests are among the most diverse in the world and offer an opportunity to test the relationship between diversity and cooling at a large scale. For 136 urban ZIP codes, we connect the most comprehensive data to date on California's urban forests to both local station and satellite weather data for the period 2010–2018. We test whether biodiversity, measured by the Shannon-Wiener index and the new Top Diversity 50 index, is correlated with extreme heat in summer. After controlling for local averages in weather and tree canopy cover, we find that urban forest biodiversity is associated with lower maximum and higher minimum temperatures for June to September. Our specification makes it unlikely that reverse causality drives our result. Instead, we suggest that greater tree species diversity may boost daytime cooling through several pathways, including mutualism and greater aboveground biomass, a mechanical relationship where greater biodiversity implies a greater likelihood of having species with excellent shade, and cooling benefits from structural diversity in urban settings.

1. Introduction

Tree cover in cities is decreasing just as cities face more frequent hot daily temperatures from climate change. Among 20 US cities, 17 saw tree cover decline over a 6 year period (Nowak and Greenfield, 2020), and this pattern held true among the 20 most populous cities in the Los Angeles Basin (Lee et al., 2017). Urban trees provide many ecosystem services to residents including carbon sequestration, reduction in pollution and stormwater runoff, and the focus of this study, regulation of microclimates (Livesley et al., 2016). Loss in green cover shifts the surface energy balance through changes in the absorption and reflection of solar radiation (Bowler et al., 2010), causing the core of an urban area to be much warmer than surrounding areas and results in an 'urban heat island' (Oke, 1982). Concerns over tree cover loss are growing given that the average temperature in Los Angeles is expected to increase by 2–7℉ over the next forty years (Burillo et al., 2019).

Trees reduce surface and air temperatures through shade and evapotranspiration (Dimoudi and Nikolopoulou, 2003). Recent research has explored what elements of tree planting offer the greatest benefits, such as cooling buildings and associated energy savings. In some research an increase in the leaf area density of trees has shown to cool temperatures by 2.2 °C, mitigating the urban heat island effect (Tamaskani Esfehankalateh et al., 2021). Diverse urban forests might have greater variation in structural features among tree species, such as large crowns, short trunks, dense canopies, and greater leaf density, that may aid cooling (Kong et al., 2017; Tsoka et al., 2021; Tamaskani Esfehankalateh et al., 2021). Recently, Wang et al. (2021) explored this hypothesis in Changzhou, China using Landsat land surface temperatures and found that greater biodiversity could strengthen urban forests' cooling effect. While this conclusion is encouraging, differences in population density, built environment, greenspace structure and abundance, and climate makes it difficult to generalize these results to other settings (Mirzaei and Haghighat, 2010).

Exposure to extreme heat negatively affects human physiology. Several studies utilized natural experiments to document the human response to heat exposure, finding a strong, negative effect on cognition (Garg et al., 2020; Park, 2022), as well as mental health and decision-making (Baylis, 2020; Heyes and Saberian, 2019; Mullins and White, 2020). In a study in California, White (2017) found that exposure to extreme heat increases hospital and emergency department visits, on a day under 40°F there is a 6.1% decrease in emergency department visits. Exposure to extreme heat also increases the incidence of workplace injury (Adam-Poupart et al., 2014; Kjellstrom and Crowe, 2011).

Most concerning, the frequency and severity of heatwaves are predicted to increase over time, which will prolong urban resident's exposure to elevated temperatures (Perkins et al., 2012). Heatwaves,

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characterized by stagnant, warm air that raises minimum temperatures over several days, are associated with increases in cases of heat stroke, heat exhaustion, and heat-related mortality (Kovats and Hajat, 2008; Luber and McGeehin, 2008). A major concern raised by the increased frequency of heat waves is the impact from high nighttime temperatures, especially among the elderly. Laaidi et al. (2012) found that repeated exposure to high nighttime temperatures in urban areas increased the risk of death among elderly populations. There is a greater risk of mortality when warm night temperatures follow a hot day than when a hot day follows a cool night (Murage et al., 2017). Public investing in street trees may provide communities unable to afford to increase spending on air conditioning in response to extreme heat an equitable option for urban cooling (Doremus et al., 2022).

This paper focuses on street tree diversity as a potential tool for reducing human exposure to extreme heat in urban areas.[1] We focus on the urban heat island effect in the summer rather than the winter, in which hot areas become hotter, potentially exposing residents to extreme heat. Using richly detailed data on street tree diversity for 136 urban ZIP codes, this paper assesses whether ZIP codes with greater biodiversity are associated with lower daily temperature in the summer between 2010 and 2018. To isolate the effect of tree diversity on cooling from that of canopy cover, we control for local tree cover. In our preferred model specification, we include a fixed effect for areas encompassed by ZIP codes that share the same first three digits. This controls for local averages in weather, allowing us to focus on how temperature varies with biodiversity within a small geographic area.

Our study builds on the results from Wang et al. (2021), testing whether the negative relationship between tree species diversity and cooling holds at a much greater scale, and doing so within a drier climate with exceptional species richness. Together, results at the macro and micro level from two distinct settings would make a compelling case that street tree diversity is a potential strategy for mitigating urban heat and an urban planning strategy to maximize cooling capacity of urban forests without increasing their area.

2. Empirical analysis

2.1. Data

Our analysis uses urban forest species composition data and local weather data gathered from two sources. The dataset represents 136 California ZIP codes mostly concentrated in highly urbanized areas along the coast of California (Fig. 1). The 136 ZIP codes are categorized into forty three-digit ZIP codes. The weather data from (National Centers for Environmental Information, 2021) and (PRISM Climate Group, Oregon State University, 2004) report daily temperatures in degrees Fahrenheit from 2010 to 2018. We restricted observations to June through September because this time corresponds to the hottest months in different regions of California. Table 1 presents summary statistics of the variables included in our analysis.

2.1.1. Urban forests characteristics

To estimate urban forest biodiversity among 136 ZIP codes in California, we used species composition data from the California Urban Forest Inventory which is the largest and most comprehensive database of urban trees in California (Love et al., 2022).[2] This inventory consists of individual urban tree records obtained from private arborist companies and multiple municipal inventories. Arborists collected data for

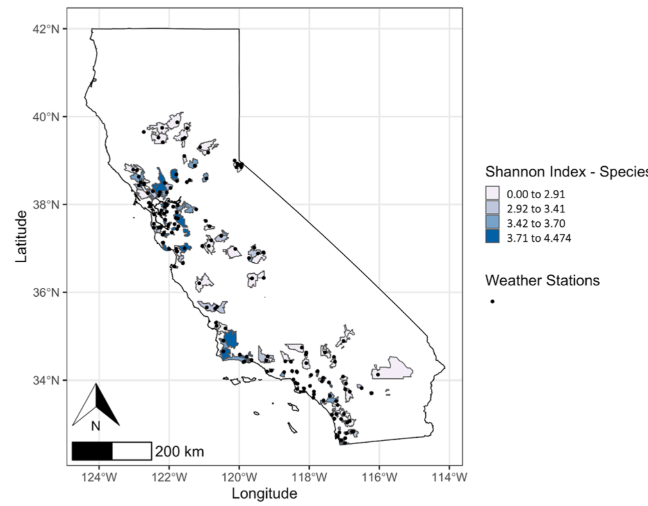

Fig. 1. Shannon-Wiener indices of California Zip Codes. Note: Heat map of Shannon-Wiener indices for 136 California ZIP codes gathered from Love et al. (2022). Shannon-Wiener index is calculated at the ZIP code level and time invariant. Data used was gathered over the course of 2014 to 2019.

Table 1
Summary Statistics.

	Mean	SD	Min	Max	N
Panel A: Weather Station Data					
Maximum Temperature	84.67	10.91	40.33	130.00	145,453
Minimum Temperature	59.55	7.39	-1.00	97.00	145,377
Over 90 Fahrenheit	0.35	0.48	0.00	1.00	145,453
Panel B: PRISM Data					
Maximum Temperature	83.46	10.42	38.58	118.20	149,328
Minimum Temperature	58.44	6.69	23.18	88.27	149,328
Over 90 Fahrenheit	0.30	0.46	0.00	1.00	149,328
Panel C: Tree Data					
Shannon-Wiener index	3.21	0.72	0.00	4.37	136
Tree Records	7586.44	9168.72	2.00	83,408	136
Tree Canopy Cover	8.41	11.72	0.00	58.31	136

Note: Table 1 provides summary statistics on temperature and urban forest characteristics. Urban forests variables are gathered from Love et al. (2021). Panel A includes summary statistics for temperature outcome variables derived from National Centers for Environmental Information (n.d.). Panel B displays summary statistics for daily temperature data gathered from PRISM Climate Group (2004). All temperature data obtained is for 136 California ZIP codes from 2010 to 2018. Maximum and minimum temperatures are reported in degrees Fahrenheit. The indicator variable for over 90 degrees Fahrenheit takes the value of one if the day is over 90 degrees Fahrenheit, and zero otherwise. Panel C displays summary statistics for tree data derived from the CUF Inventory for each of the 136 ZIP codes (Love et al., 2022). N indicates the number of observations at the weather station level (A), the number of observations at the PRISM level data (B), and the zip code level of observance for tree diversity (C)

public street trees and some public parks as contracted. The full dataset consists of over 7 million publicly managed trees across the state of California (Love et al., 2022). From these data, we calculated two measures of urban tree diversity at the ZIP code level: the Shannon-Wiener index and, following Love et al. (2022), the Top Diversity 50 index (TD-50). The Shannon-Wiener index is a widely-used metric of diversity in many fields including urban forestry, and thus in this study, it is the variable of main interest (Wang et al., 2020). Eq. 1 below shows the calculation of the Shannon-Wiener index at the species and ZIP code level. The share of trees in species i is represented by $p_i = \frac{n_i}{N}$, where n_i is the number of trees in species i and N is the total count of trees in the ZIP code. In Eq. 1 the number of species is represented by K. The heat map in Fig. 1 demonstrates the geographic scope of the data and distribution of Shannon-Wiener indices.

[1] We use the term street tree throughout this paper to refer to trees that line streets in urban areas. However, we would like to note that there is a small share of the trees in our inventory that are located in green-blue spaces, such as parks.

[2] https://datastudio.google.com/u/0/reporting/880d448d-de26–48d3-b563–0c6317e456e4/page/jWHKB

$$Shannon - Wiener \quad index = -\sum_{i=1}^{K} p_i \ln(p_i) \quad (1)$$

The TD-50 index is a new measure of urban forest biodiversity that is easier to interpret than the Shannon-Wiener index. The TD-50 measures the cumulative number of species accounting for the top 50% abundance of trees in a given ZIP code. The TD-50 index was calculated by first determining the relative abundance of each species in a given ZIP, then sorting by species abundance from highest to lowest, and finally, determining the number of species accounting for the top 50% of trees in that ZIP code. The more species comprising the top 50% of trees, the higher the diversity of the urban forest is in that ZIP code. The TD-50 index allows for an intuitive comparison of species diversity between areas. For example, Love et al. (2022) compared urban tree diversity among cities in California and found that only 3 tree species comprised 50% of trees in Cerritos (TD-50 of 3) while 16 species comprise 50% of trees in San Mateo (TD-50 of 16), indicating higher urban forest diversity in San Mateo than Cerritos. The TD-50 measure is highly correlated with the Shannon-Wiener index and is used as a robustness check to determine whether patterns are concordant across multiple measures of biodiversity (Love et al., 2022).

In addition to tree biodiversity, we used the CUF Inventory to summarize the structural characteristics of the urban forests within the 136 ZIP codes. We calculated the variance in diameter at breast height (DBH) and height across each ZIP code for trees with data available. We did not include crown width in these measurements, as only 4% of our data had that attribute. 97% of the tree data is associated with DBH data (1,041,864 trees), and 71% is associated with height data (760,870 trees). We also examined trends in foliage-type of the trees, with each species categorized as evergreen, deciduous, partly deciduous, coniferous, or palm. These attributes come from SelecTree, a database of California's urban trees meant to help guide species selection (SelecTree, 2022).

Tree canopy cover contributes to urban heat island mitigation (Dimoudi and Nikolopoulou, 2003), thus in some specifications we controlled for tree canopy cover (Methods Section 2.2; Table 2;). Gridded tree canopy cover data was obtained from the National Land Cover Database (NLCD; Coulston et al., 2012). Specifically, we downloaded canopy cover data where each 30 m resolution cell denoted percent canopy cover in that area during 2011, which falls within the period of study (2010–2018). We used these data to calculate percent canopy cover per ZIP code. To do this, we included the cells that had a majority overlap with the ZIP code. For this set of cells, we then took the average of the percent canopy cover per cell for the cells within that ZIP code.

Table 2
Maximum Over 90℉ Indicator.

	No fixed effects	3-digit ZIP code fixed effects	3-digit ZIP code and month fixed effects	3-digit ZIP code and month fixed effects	3-digit ZIP by month, year-month FE
Panel A: Weather Station Data					
Shannon index	-0.15 * **	-0.07 * **	-0.07 * **	-0.07 * **	-0.07 * **
	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Tree Canopy Cover				0.00	
				(0.00)	
R^2	0.05	0.34	0.35	0.35	0.38
Observations	145,453	145,453	145,453	145,453	145,453
Panel B: PRISM Data					
Shannon index	-0.15 * **	-0.07 * **	-0.07 * **	-0.07 * **	-0.07 * **
	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Tree Canopy Cover				-0.002	
				(0.002)	
R^2	0.05	0.31	0.32	0.32	0.35
Observations	149,328	149,328	149,328	149,328	149,328

Note: Table 2 provides regression results for the over 90 degrees Fahrenheit indicator. The indicator variable takes the value of one if the day has a maximum temperature over 90 degrees Fahrenheit, and zero otherwise. Shannon-Wiener index is used as the measure of urban forest diversity in all regressions. Results reflect the use of weather station data from National Centers for Environmental Information (n.d.) in Panel A and PRISM Climate Group (2004) in Panel B. The use of fixed effects is shown in each column header. Column 5 controls for percent tree canopy cover gathered from National Land Cover Database (2012). Tree canopy cover is the percent cover for each ZIP code. Each regression includes a constant that is not reported. Standard errors are clustered by 3-digit ZIP code and reported in parentheses. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

2.1.2. *Temperature data: weather stations*

Our primary source of air temperature data was downloaded from the National Centers for Environmental Information (no date). Specifically, we downloaded daily maximum and minimum air temperature values corresponding to weather stations in each of the 136 ZIP codes. The daily observations are recorded in degrees Fahrenheit for June through September from 2010 to 2018. Of the 136 ZIP codes, 105 contain one weather station, twenty-two contain the average of two stations, eight contain the average of three stations and one contains the average of six stations. Some weather stations are associated with multiple ZIP codes.

The three outcome variables for this analysis are the daily maximum, daily minimum, and an indicator for the daily maximum exceeding 90℉. The indicator variable for whether a day exceeds 90℉ creates a threshold for extreme heat as it relates to human health and comfort. While most ZIP codes have complete temperature data, others have sporadic missing daily observations. There are 3875 missing daily maximum temperature observations and 3951 missing daily minimum temperature observations. In total, our dataset consists of 145,377 daily temperature observations at the zip-month-year level.

The largest limitation of the weather station data is that air temperature data is measured at a single location that may not reflect micro differences in temperature experienced throughout a ZIP code. Areas near trees might be cooler than open spaces that lack shade. These observations do not account for those microclimatic differences. Another limitation is that the placement and elevation of each weather station is not randomly assigned and may bias temperature measurement in unpredictable ways.

2.1.3. *Temperature data: PRISM*

Though the weather station data are highly reliable (Behnke et al., 2016), to ensure our results are robust we also obtained daily temperature data from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) climate group (PRISM Climate Group, 2004). These gridded data help test whether missing temperature data or non-random weather station placement affect the magnitude and direction of associations between temperature and biodiversity. PRISM offers gridded daily temperature data at a 4 km resolution. We downloaded daily maximum and minimum temperatures between 2010–2018 using the *prism* package designed for the statistical software R (Hart and Bell, 2015; Core Team, 2022). We used these data to calculate the same three outcome variables listed in the above section: an indicator for the daily maximum exceeding 90°F as well as maximum and minimum daily temperatures within each of the 136 ZIP codes.

The major limitation of using PRISM data to assess temperatures in urbanized areas is the relatively large resolution (4 km). A single 4 km grid cell may include both urban and non-urban areas (e.g., surrounding agricultural fields), whereas weather stations are located directly in urbanized areas. This may limit our ability to assess the temperature specifically in urban areas which are often warmer than surrounding areas due to the urban heat island effect (Imhoff et al., 2010). While both sources of temperature data (weather stations and gridded PRISM data) have limitations, together they provide a robust assessment of daily urban temperatures during the study period.

2.2. *Model specification*

Our goal is to investigate the relationship between temperature and urban tree diversity *within a local area.* We do this using a fixed effects ordinary least squares model where our suite of fixed effects controls for shared patterns in weather. In our most complete specification, they control for the average temperature within a local geographic area, as well as the average temperature in California for that month-year. For example, to estimate the effect of biodiversity on maximum temperature in ZIP code 90604 during July 2017, we compare the maximum temperature in that ZIP code to how it differs from the average within that three-digit zip code area, 906 as well as the average across California in July 2017. The expression below includes each term estimated in the most complete specification

$$y_{ijt} = \alpha_j + \beta \quad Biodiversity_i + \gamma_t + \varepsilon_{ijt} \tag{2}$$

In this expression, the indices are i for a particular ZIP code, j for a three-digit ZIP code, and t is the month-year within the panel. The term y_{ijt} is our outcome variable, which is either maximum or minimum temperature or an indicator variable for the temperature exceeding 90°F. The first term α_j is a vector of intercepts that control for local geographical patterns in weather. Our spatial unit for local averages is the three-digit ZIP code area, the same used by Giacinto et al. (2021). These fixed effects control for common weather within an area, for example ZIP codes in the Central Valley of California will have higher average temperatures in the summer than ZIP codes in San Diego. By including this measure, we were able to estimate the relationship between temperature and biodiversity within a local area.

The term $Biodiversity_i$ is a measure of a ZIP code's urban tree diversity as measured by either the Shannon-Wiener or TD-50 index, and the coefficient β is the parameter of interest. We also include the percent of the ZIP code covered by tree canopy. This is necessary because if biodiversity scales with the amount of tree cover, then β may also reflect omitted variable bias from tree cover instead of the effect of tree species diversity on temperature. By including tree canopy cover in our model, we control for this potential source of bias. As noted earlier, our inventory data include a small share of trees from parks and other green-blue spaces. If tree diversity is correlated with being located in a blue-green space, our specification will suffer from confounding. Canopy cover, which is also likely correlated with blue-green spaces, helps address this confounding. However, confounding from blue-green spaces remains a limitation of our approach.

The coefficients γ_t are a set of temporal fixed effects to control for shared large-scale patterns in weather that occur across the state. We begin by using month fixed effects, which will soak up average differences in temperature between June and August, across all ZIP codes. In our specification with the most controls, we allow this difference to vary across years by including year-month fixed effects. In this case, these fixed effects would control for extreme heat in response to the 2018 North American Heat Wave in July relative to other years in July. ε_{ijt} is an error term that captures factors that affect heat that are not included in the regression specification. We assume that unobservables are likely correlated within a geographic area, so we cluster the standard errors at the three-digit ZIP code level. This is standard practice within the economics of weather literature (Dell et al., 2014). Because we have more than thirty clusters, the standard clustering method performs well (Cameron et al., 2008). We run a series of regressions, building in more controls across specifications, to assess the risk of omitted variable bias.

To assess the role of structural diversity in mitigating heat, we also estimated a model that included variation in tree diameter, share of trees in each ZIP code that are deciduous, and tree height. This model, reported in the appendix, is a fixed effects ordinary least squares model where the outcome is the maximum temperature within a 3-digit ZIP code. The model includes fixed effects for each month, canopy cover, the variance of DBH within a ZIP code, the share of trees deciduous within a ZIP code, and the variance of height within a ZIP code as covariates. We ran this model with and without Shannon diversity as a predictor.

3. Results

We found that ZIP codes with greater tree diversity (as measured by the Shannon-Wiener index) were associated with fewer total days over 90°F within the year, and this result was similar when using weather station and PRISM data (Fig. 2). This pattern was consistent with results from our linear regression models. Across all model specifications presented in Table 2, the probability that a given day would exceed 90°F was lower in ZIP codes with greater tree diversity as measured by the Shannon-Wiener index (Table 2). In our simplest specification without any fixed effects, we found that the probability of a day exceeding 90°F was lowered by 15% for every increase of 1 unit on the Shannon-Wiener diversity index scale (Table 2). This pattern was robust when we included fixed effects to control for average temperature within a three-digit ZIP code (Table 2, columns 2–5). The results from this specification indicate that within a three-digit ZIP code area, ZIP codes with greater tree diversity were less likely to have days that exceeded 90°F. When including these fixed effects, the probability of a day exceeding 90°F was 7% lower for every increase of 1 unit on the Shannon-Wiener diversity index scale (Table 2). These results were robust when we controlled for canopy cover, indicating that the effect of tree diversity on the probability that a day exceeds 90°F was independent of the effect of canopy cover on this variable. Moreover, these results were consistent between

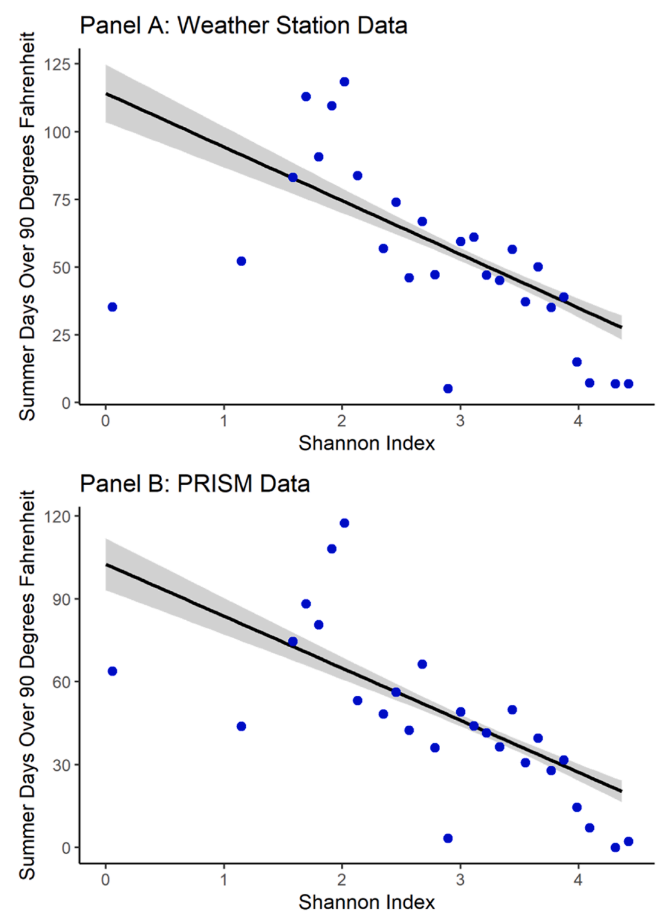

Fig. 2. Street tree biodiversity and heat across two data sources. Note: Fig. 2 reflects the relationship between the Shannon-Wiener index and the number of days the maximum temperature exceeds 90 degrees Fahrenheit for a given ZIP code. Shannon-Wiener indices for 136 California ZIP codes are gathered from Love et al. (2022). Temperature outcomes are derived from National Centers for Environmental Information in Panel A and PRISM Climate Group (2004) in Panel B. Fig. 2 was created using the program "binscatter" (Stepner, 2013). Binscatter creates bins within the dataset (like a histogram) and plots the average within that bin.

both weather data sources (Table 2, panel A vs. B).

The results for our linear regression models for the realized daily maximum temperature follow a similar pattern to the previously mentioned results. We found that ZIP codes with greater tree diversity were also associated with lower daily maximum temperature, and this result was consistent across all model specifications and when using weather station and PRISM data (Table 3; Fig. 3). The estimated decrease in maximum temperature for every unit increase in the Shannon-Wiener index is 2.40°F, as shown in columns 2, 3 and 6. The estimate drops to a decrease of 2.24°F when tree canopy cover is accounted for. The result using no fixed effects is also negative, but with an estimate of 3.47°F. Panel A of Fig. 3 illustrates the relationship between Shannon-Wiener index and daily maximum temperature during California's four summer months.

We also explored how the Shannon-Wiener Index coefficient changes when including measures of structural diversity among the covariates. When predicting the maximum temperature, we found that the absolute value of the coefficient for the Shannon-Wiener index grew, e.g. the effect remained and was stronger than that found in models without tree height and width variance. The estimated decrease in maximum temperature for every unit increase in the Shannon-Wiener index is 2.93°F, a slightly larger decrease than the coefficient estimated in a model without tree structural characteristics (Table D). In the model including the Shannon-Wiener index, the coefficient on tree canopy was not significant while the coefficients on DBH and height were significant. However, without the Shannon-Wiener index, height was not significant (Table D). The estimated decrease in maximum temperature for every one-inch increase in DBH variance was 0.03°F (Table D). This coefficient was the same with and without the Shannon-Wiener index included in the model. We also ran a model that included the percentage of trees in a given in a ZIP code that were deciduous to try to account for structure. The estimated decrease in maximum temperature for every unit increase in the Shannon-Wiener index is 3.55°F, a slightly larger decrease than

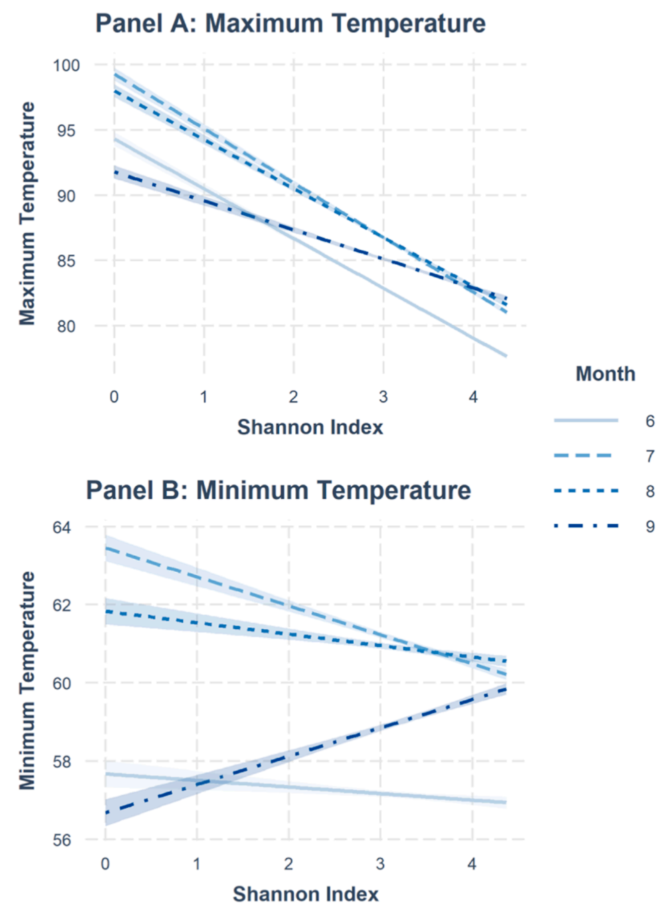

Fig. 3. Street tree biodiversity and heat across California's four summer months. Note: Fig. 3 reflects the relationship between temperature outcome and Shannon-Wiener index by month. Shannon-Wiener index data gathered from Love et al. (2022). Temperature outcomes sourced from National Centers for Environmental Information. Temperature is recorded in degrees Fahrenheit. Each line plots the predicted values from a regression that regresses temperature on the Shannon-Wiener index for a subset of the data. For example, Panel A month 6 plots the predicted values that come from a regression of maximum temperature on the Shannon-Wiener index for the month of June. The slope of the line corresponds to the coefficient on the Shannon-Wiener index in the regression and the intercept is the regression intercept.

the coefficient estimated in a model without tree structural characteristics, and slightly larger decrease than a model without including the percentage of trees deciduous. The coefficients for height and DBH variance are the same in this model. The estimated decrease in maximum temperature for every 1% increase in share deciduous is 0.1°F. In the model that didn't include Shannon-Wiener diversity as a predictor, the percentage of trees deciduous was not a significant factor. Together, the negative coefficient on the variance in DBH and the persistent, and large, negative coefficient on the Shannon-Wiener index suggest both that structural diversity may be a pathway by which diversity mitigates heat and that the Shannon-Wiener index captures aspects of diversity beyond those measured in variance in diameter or height.

The results for our linear regression models for the realized daily minimum temperature outcome contrasts those of the previously discussed outcomes. In our model without fixed effects, we find that ZIP codes with greater biodiversity were associated with lower daily minimum temperature, but this result is not significant (Table 4). In contrast, the models that include fixed effects found that ZIP codes with greater tree species diversity were associated with higher daily minimum temperature. In other words, nights are warmer in areas with relatively

Table 3
Maximum Temperature.

	No fixed effects	3-digit ZIP code fixed effects	3-digit ZIP code and month fixed effects	3-digit ZIP code and month fixed effects (controls for tree canopy)	3-digit ZIP by month, year-month FE
Panel A: Weather Station Data					
Shannon index	-3.47 * * (1.26)	-2.40 * ** (0.67)	-2.40 * ** (0.67)	-2.24 * ** (0.65)	-2.40 * ** (0.67)
Tree Canopy Cover				0.00 (0.00)	
R^2	0.05	0.46	0.48	0.48	0.52
Observations	145,453	145,453	145,453	145,453	145,453
Panel B: PRISM Data					
Shannon index	-3.60 * ** (1.05)	-2.63 * ** (0.92)	-2.63 * ** (0.92)	-2.99 * ** (0.96)	-2.63 * ** (0.92)
Tree Canopy Cover				0.00 (0.00)	
R^2	0.06	0.45	0.48	0.48	0.52
Observations	149,328	149,328	149,328	149,328	149,328

Note: Table 3 provides regression results for the daily maximum temperature. The maximum temperature is reported in degrees Fahrenheit. Shannon-Wiener index is used as the measure of urban forest diversity in all regressions. Results reflect the use of weather station data from National Centers for Environmental Information (n.d.) in Panel A and PRISM Climate Group (2004) in Panel B. Column 5 controls for percent tree canopy cover gathered from National Land Cover Database (2012). Tree canopy cover is the percent cover for each ZIP code. Column 5 controls for tree canopy cover gathered from National Land Cover Database (2012). Each regression includes a constant that is not reported. Standard errors are clustered by 3-digit ZIP code and reported in parentheses. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$

Table 4
Daily Temperature Minimum.

	No fixed effects	3-digit ZIP code fixed effects	3-digit ZIP code and month fixed effects	3-digit ZIP code and month fixed effects (controls for tree canopy)	3-digit ZIP by month, year-month FE
Panel A: Weather Station Data					
Shannon index	-0.13 (0.85)	1.10 * ** (0.40)	1.10 * ** (0.40)	0.70 * (0.40)	1.10 * ** (0.40)
Tree Canopy Cover				0.00 (0.00)	
R^2	0.00	0.42	0.47	0.48	0.53
Observations	145,377	145,377	145,377	145,377	145,377
Panel B: PRISM Data					
Shannon index	-0.16 (0.78)	0.61 * * (0.25)	0.61 * * (0.25)	0.50 * * (0.23)	0.61 * * (0.25)
Tree Canopy Cover				0.00 (0.00)	
R^2	0.00	0.46	0.53	0.53	0.60
Observations	149,328	149,328	149,328	149,328	149,328

Note: Table 4 provides regression results for the daily minimum temperature. The minimum temperature is reported in degrees Fahrenheit. Shannon-Wiener index is used as the measure of urban forest diversity in all regressions. Results reflect the use of weather station data from National Centers for Environmental Information (n.d.) in Panel A and PRISM Climate Group (2004) in Panel B. The use of fixed effects is shown in each column header. Column 5 controls for percent tree canopy cover gathered from National Land Cover Database (2012). Tree canopy cover is the percent cover for each ZIP code. Each regression includes a constant that is not reported. Standard errors are clustered by 3-digit ZIP code and reported in parentheses. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

greater biodiversity. There is an estimated increase of 1.10℉ for every unit increase in Shannon-Wiener index and 0.70℉ when tree canopy cover is included. These results were consistent across all model specifications, and when using weather station and PRISM data. Panel B of Fig. 3 illustrates the relationship between Shannon-Wiener index and daily minimum temperature during California's four summer months. The minimum temperature, however, shows different results than the linear models. We found that higher minimum temperature with greater tree diversity is driven by the month of September.

The ZIP codes within our study area represented a wide range of tree sizes and foliage types, making our results more robust. Most trees are deciduous or evergreen (Fig. 4). The mean tree DBH was 11 in. with a standard deviation of eight inches (Fig. 5, A). The tree height mean was 24 feet with a standard deviation of 13 feet (Fig. 5, B).

3.1. Robustness of results

Table 5 compares the results of the two diversity indices. Panel A uses the Shannon-Wiener index and includes a summary of the results using our primary measure from Tables 2, 3 and 4. Panel B uses the TD-50 index. Each panel compares two sets of fixed effects and the inclusion of canopy cover for each outcome. Across the two metrics, the direction of the estimated effect for each outcome remains the same when tree canopy cover is included.

4. Discussion

In this study, we found that ZIP codes with higher tree species diversity were associated with lower daily maximum temperatures and a lower probability that a given day will exceed 90℉, an important temperature threshold beyond which human health is negatively affected. In contrast, we found that urban forest diversity is positively associated with minimum temperatures, suggesting that diverse forests more effectively insulate urban areas at night relative to less diverse forests. By implementing a series of controls and fixed effects designed to isolate the effect of tree species diversity on daily temperatures, our results suggest that, independent of canopy cover, diverse urban forests can contribute to mitigating high daytime temperatures while insulating urban areas at night. These results were robust across two different measures of biodiversity and two sources of daily temperature data. Below we discuss potential mechanisms to explain the patterns detected in this study. Finally, we discuss how our findings may help guide policies designed to address the urban heat island effect by increasing the cooling capacity of urban forests.

4.1. Why might biodiversity help cool urban areas?

Several mechanisms may explain why ZIP codes with more diverse urban forests are associated with lower summer maximum temperatures. We discuss five primary candidates. First, increasing tree diversity may increase the likelihood that species with greater cooling capacities

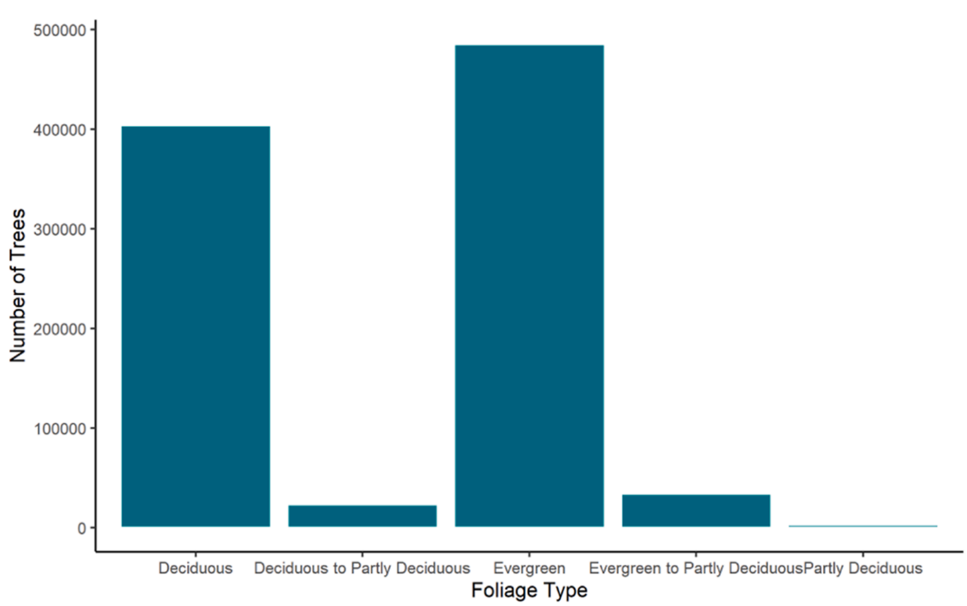

Fig. 4. Foliage Type of California's Urban Trees. Note: Fig. 4 reflects the foliage-type of the trees within the 136 ZIP Codes from the CUF Inventory (Love et al., 2022).

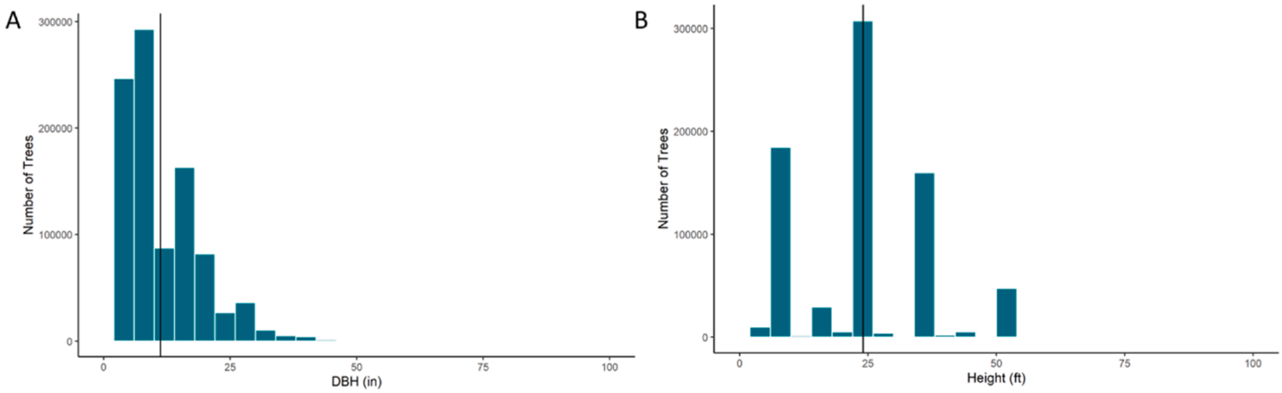

Fig. 5. Structural Characteristics of California's Urban Trees. Note: Fig. 5 reflects the structural characteristics of the trees within the 136 ZIP Codes from the CUF Inventory (Love et al., 2022). A) The DBH of the trees. The line reflects the mean at 11 in.. (n = 1041,864) B) The height of the trees. The line reflects the mean at 24 feet. (n = 760,870).

Table 5
Robustness.

	Over 90℉ Indicator		Maximum Temperature		Minimum Temperature	
	3-digit ZIP code and month fixed effects (controls for tree canopy)	3-digit ZIP by month, year-month FE	3-digit ZIP code and month fixed effects (controls for tree canopy)	3-digit ZIP by month, year-month FE	3-digit ZIP code and month fixed effects (controls for tree canopy)	3-digit ZIP by month, year-month FE
Panel A: Shannon-Wiener index						
Shannon index	-0.07 * **	-0.07 * **	-2.24 * **	-2.40 * **	0.70 *	1.10 * **
	(0.02)	(0.02)	(0.65)	(0.67)	(0.40)	(0.40)
Tree Canopy	0.00		0.00		0.00	
Cover	(0.00)		(0.00)		(0.00)	
R^2	0.35	0.38	0.48	0.52	0.48	0.53
Panel B: TD-50 index						
TD-50	-0.02 * **	-0.02 * **	-0.48 * **	-0.53 * **	0.21 *	0.22 * *
	(0.005)	(0.005)	(0.15)	(0.15)	(0.11)	(0.11)
Tree Canopy	-0.0001		-0.000		-0.02	
Cover	(0.0005)		(0.000)		(0.02)	
R^2	0.35	0.38	0.48	0.52	0.47	0.53
Observations	145,453	145,453	145,453	145,453	145,377	145,377

Note: Table 5 provides regression results for the three outcome variables: over 90℉ indicator, maximum temperature, minimum temperature. Each outcome variable includes two regressions with the same use of fixed effects which are shown in the column header. Maximum and minimum temperatures are reported in degrees Fahrenheit. All regressions reflect use of weather station data from National Centers for Environmental Information (n.d.). Results in Panel A summarize regressions using Shannon-Wiener index as the measure of urban forest diversity and TD-50 is used in Panel B. The use of fixed effects is shown in each column header. Columns one, three, and five include a control for percent tree canopy cover gathered from National Land Cover Database (2012). Each regression includes a constant that is not reported. Standard errors are clustered by 3-digit ZIP code and reported in parentheses. * ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$.

are present in the urban forest, i.e., the sampling effect hypothesis (Cardinale et al., 2006). Tree species vary markedly in their transpirational cooling capacity, canopy sizes, and capacities to cool under various environmental conditions (Rahman et al., 2019; Rana and Ferrara, 2019). In ZIP codes with high levels of tree diversity, there may be a greater portion of trees with greater cooling capacities, which would increase cooling provided by trees independent of canopy cover.

A second pathway may be that species diversity may also reflect patterns in structural diversity, which could influence the cooling capacities of urban forests. This depends on the particular species present in the forest, and if their shapes and characteristics are similar across species. California's urban forests are diverse both in species and in structure and characteristics, with species that are evergreen, deciduous, coniferous and palms as well as a wide range of DBH and heights represented in the urban forests (Love et al., 2022). Previous work has demonstrated that structurally diverse, multi-layered urban forests are more effective at reducing urban heat island effects than structurally homogeneous forests (Zhang et al., 2013). Structurally diverse forests can intercept or reflect solar radiation at multiple vegetation layers rather than just the top-most canopy layer, which can help limit the amount of radiation that is absorbed by hard surfaces. If diverse forests are also structurally diverse forests, this may help explain why we observed lower summer maximum temperatures in ZIP codes with higher urban forest biodiversity. In this work, we confirmed that variance in structural characteristics may not be the only reason that increased biodiversity results in lower maximum temperatures. DBH contributed significantly to the model with and without inclusion of the Shannon-Wiener index, while height did not. The robustness of the Shannon-Wiener coefficient to inclusion of variance in height and diameter, and the negative coefficient on variance in diameter, suggest that structural differences may contribute to lower temperatures. Future work on this topic could further explore the mechanisms driving the patterns observed in this study relating higher urban tree biodiversity to lower maximum temperatures.

A third possible explanation is that more diverse urban forests are more resilient to stress. For a tree to provide ecosystem services, it must be alive and healthy (Livesly et al., 2016). To create resilient urban forests, urban foresters often focus on increasing the diversity of their urban forest by planting many different tree species (Ordóñez and Duinker, 2014; Brandt et al. 2016; Ordóñez and Duinker, 2015; Abeyta et al., 2013). Having a diverse urban forest minimizes overall tree loss to stressors such as climate related changes in temperature or storms, as well as pests (Huff et al., 2020; Nitschke et al., 2017; Paquette et al., 2021; Raupp et al., 2006; Wood and Dupras, 2021). The primary mechanism by which trees provide cooling is through interception of solar radiation (shading) and transpirational cooling, and trees with larger canopies and a higher leaf density are more effective at cooling (Tamaskani Esfehankalateh et al., 2021; Tsoka et al., 2021). Having more living and healthy trees results in a cooler urban forest. Having more diverse urban forests could result in having a higher proportion of trees that survive stressors and continue to cool cities.

Fourth, this pattern could be a case of reverse causality where the underlying temperature drives diversity rather than diversity increasing cooling services in urban environments. In other words, the patterns detected here may reflect species-climate relationships, where more tree species are capable of growing in ZIPs with less extreme summer temperatures. While this may be true, it is unlikely the driver of the patterns detected in this study. When evaluating the relationship between our temperature outcome variables and biodiversity, some specifications included a three-digit ZIP code fixed effect, which controlled for geographic variation in underlying climatic conditions at the three-digit ZIP code level. When fixed effects are included in model specifications, we still detected a cooling effect in those ZIPs with higher urban forest biodiversity. With these fixed effects, the patterns detected in this study suggest that there were fewer days over 90°F and cooler maximum temperatures in areas with more diverse urban forests independent of baseline temperatures among ZIPs.

Finally, the pattern might be due to omitted variable bias. One variable our study did not account for is if there is a relationship between urban forest diversity and blue-green spaces in urban areas. The relationship between temperature mitigation and quantity and location of blue-green spaces is complicated. Many studies have shown that both blue and green spaces can contribute to urban cooling (Yang et al., 2020; Yu et al., 2020; Asgarian et al., 2015; Taleghani, 2018; Sun and Chen, 2012; Akbari and Kolokotsa, 2016). Our study controls for green space by including overall canopy cover as a predictor in our models. However, we do not account for blue spaces. It is possible that blue spaces may be sites of higher diversity, although that trend is less clear for planted urban trees (Hassall and Anderson, 2015; Hill et al., 2017). Our data includes public tree inventories that vary in proximity to blue space, some without any proximal blue spaces. The effect of how blue spaces cool urban areas is complex; studies have found that the size and location of the water body predicts how far out from the water body the cooling effect can be felt (Yu et al., 2020; Murakawa et al., 1991; Sun and Chen, 2012; Hathway and Sharples, 2012, Gunawardena et al., 2017). Future studies should more deeply explore the relationship between planted urban tree diversity and blue space to test if some of the effect of tree diversity on temperature mitigation could be due to a relationship with blue space as well as green space.

Unexpectedly, we found that increased tree diversity was associated with warmer nighttime (i.e., minimum) summer temperatures (Table 4), which opposes the pattern we detected between tree diversity and maximum summer temperatures. These results together suggest that diverse forests act as buffers against drastic changes in daily temperature. Why might this be the case? Trees do not provide cooling services at night either through shading or transpirational cooling, which limits their ability to actively cool temperatures at night regardless of diversity. There has been work that shows that tall trees trap heat (Wujeska-Klause and Pfautsch, 2020), but whether or not diversity in species drives warmer temperatures is unknown and should be explored in future work.These results support previous work that has demonstrated that the greatest urban forest cooling occurs during the hottest parts of both the day and the year (Hamada and Ohta, 2010; Wang et al., 2021; Zhang et al., 2013), suggesting that cooling effects are strongest when temperatures are highest at multiple temporal scales (i.e., on daily and seasonal bases).

4.2. Alternative measures of diversity

The relationship between temperature and tree diversity are consistent across two diversity measures: the Shannon-Wiener and TD-50 diversity indices. These two metrics reflect diversity of urban forests through differing approaches. The coefficient of the Shannon-Wiener index reflects the estimated change from a one unit increase in the Shannon-Wiener index (Table 5, panel A). The coefficient of the TD-50 reflects the estimated change from one more species in that ZIP code's top 50% of trees (Table 5, panel B). The direction of the effect for both measures can be interpreted similarly. In other words, a ZIP code with a higher TD-50 or Shannon-Wiener index is considered more diverse. Our results show the same pattern for the three outcomes using both indices.

While the use of both metrics lead to similar results, the TD-50 index is a more intuitive metric because each unit increase corresponds to one more species of tree accounting for the top 50% of all trees in a given area in contrast to the relatively arbitrary units of Shannon-Wiener index. This makes the TD-50 index a useful metric of urban forest diversity because it may help to facilitate communication between scientists and policy makers seeking to implement policy designed to set diversity targets. In addition, the TD-50 measure is highly correlated with the Shannon-Wiener index (Love et al., 2022), making it a robust metric of diversity.

5. Conclusion

Global rising temperatures and the subsequent threat to human health, environment, and sustainability urges research into how to mitigate these effects. While the current literature on mitigating urban heat islands has reached a consensus on the effectiveness of tree canopy cover in reducing temperatures, the role of tree diversity is poorly understood. This paper uses the most comprehensive and detailed data on the composition of California's street trees to date to test whether urban forest diversity is correlated with lower temperatures in warm months. After controlling for average local weather patterns and total tree canopy cover, we find that greater tree diversity is associated with fewer days above 90°F, a temperature threshold known to decrease human wellbeing. Biodiversity is associated with lower maximum temperatures but, surprisingly, higher minimum temperatures. This pattern is consistent with a mechanism where higher biodiversity is linked to greater variation in tree structure, leaf density, and leaf composition, which may buffer areas from extreme high temperatures but also possibly limit airflow at night, insulating urban areas.

The results from this paper suggest that, in addition to canopy cover, tree diversity can be a useful tool in reducing the strain of high temperatures in cities in California. Both the current study and previous literature indicate that tree diversity may amplify the cooling effect of urban trees and, together, these studies can help urban foresters implement effective policies. For example, policies that aim to decrease the urban heat island effect could do so by setting higher urban forest diversity targets. Dead or dying trees could be replaced by a more diverse set of new species. This type of policy may be especially important in highly urbanized areas with limited area to expand the urban forest and where tree planting strategies can help optimize ecosystem services.

Rising temperatures are predicted to increase the frequency and severity of heat waves which lead to increases in heat-related illness or death, as well as increase demand for air-conditioning. The results from the analysis indicate that biodiversity can serve as a tool in combating the effects of rising temperatures in urban areas. Public investments in street trees may have an equity component: publicly supported cooling services may help low-income households, which may be unable to increase energy spending on air conditioning in response to extreme heat.

While the results from this paper are promising, they are only correlational and are limited by the use of cross-sectional tree data and macro-level weather station data. Although the analysis includes controls for local climate, relying on variation in biodiversity within a three-digit ZIP code, like many correlational strategies the results could be explained by reverse causality. Another limitation is that, due to the nature of our tree data, these patterns could reflect bias in sampling effort of urban trees. Finally, there is a risk of confounding if our results are actually driven by cooling effects from blue-green spaces that may be correlated with tree diversity. Future research should use a causal inference framework, more micro-scale temperature data, additional data on weather conditions which may affect the 'feel' of air temperature, as well as more detailed urban forest biodiversity and greenspace data. An experiment, simulation, or field study should also be considered in future research. An experimental design would allow for a causal inference between biodiversity and urban heat island mitigation. In addition to improving the scope of tree and temperature data, a future study should include income and socioeconomic characteristics and address concerns about non-random tree-planting patterns. Applying these recommendations in future research would help improve the understanding of how to move forward with policy in addressing the built environment, public health, and urban planning.

Author statement

All ***authors*** have seen and approved the final version of the manuscript being submitted. They warrant that the article is the ***authors***' original work, has not received prior publication and is not under consideration for publication elsewhere.

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.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2023.128180.

References

Abeyta, D., Lanham, E., Hansen, R., Mize, R., & Our City Forest. (2013). The City of San Jose Tree Policy Manual and Recommended Best Management Practices. 〈https://www.sanjoseca.gov/home/showpublisheddocument/2520/636633198872030000〉.

Adam-Poupart, A., Smargiassi, A., Busque, M.-A., Duguay, P., Fournier, M., Zayed, J., Labrèche, F., 2014. Summer outdoor temperature and occupational heat-related illnesses in Quebec (Canada). Environ. Res. 134, 339–344. https://doi.org/10.1016/j.envres.2014.07.018.

Akbari, H., Kolokotsa, D., 2016. Three decades of urban heat islands and mitigation technologies research. Energy Build. 133, 834–842. https://doi.org/10.1016/j.enbuild.2016.09.067.

Asgarian, A., Amiri, B.J., Sakieh, Y., 2015. Assessing the effect of green cover spatial patterns on urban land surface temperature using landscape metrics approach. Urban Ecosyst. 18 (1), 209–222. https://doi.org/10.1007/s11252-014-0387-7.

Baylis, P., 2020. Temperature and temperament: evidence from Twitter. J. Public Econ. 184, 104161 https://doi.org/10.1016/j.jpubeco.2020.104161.

Behnke, R., Vavrus, S., Allstadt, A., Albright, T., Thogmartin, W.E., Radeloff, V.C., 2016. Evaluation of downscaled, gridded climate data for the conterminous United States. Ecol. Appl. 26 (5), 1338–1351. https://doi.org/10.1002/15-1061.

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. Landsc. Urban Plan. 97 (3), 147–155. https://doi.org/10.1016/j.landurbplan.2010.05.006.

Brandt, L., Derby Lewis, A., Fahey, R., Scott, L., Darling, L., Swanston, C., 2016. A framework for adapting urban forests to climate change. Environ. Sci. Policy 66, 393–402. https://doi.org/10.1016/j.envsci.2016.06.005.

Burillo, D., Chester, M.V., Pincetl, S., Fournier, E.D., Reyna, J., 2019. Forecasting peak electricity demand for Los Angeles considering higher air temperatures due to climate change. Appl. Energy 236, 1–9. https://doi.org/10.1016/j.apenergy.2018.11.039.

Cameron, A.C., Gelbach, J.B., Miller, D.L., 2008. Bootstrap-based improvements for inference with clustered errors. Rev. Econ. Stat. 90 (3), 414–427. https://doi.org/10.1162/rest.90.3.414.

Cardinale, B.J., Srivastava, D.S., Emmett Duffy, J., Wright, J.P., Downing, A.L., Sankaran, M., Jouseau, C., 2006. Effects of biodiversity on the functioning of trophic groups and ecosystems. Nature 443 (7114), 989–992. https://doi.org/10.1038/nature05202.

Coulston, J.W., Moisen, G.G., Wilson, B.T., Finco, M.V., Cohen, W.B., Brewer, C.K., 2012. Modeling percent tree canopy cover: a pilot study. Photogramm. Eng. Remote Sens. 78 (7), 715–727. https://doi.org/10.14358/PERS.78.7.715.

Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52 (3), 740–798. https://doi.org/10.1257/jel.52.3.740.

Dimoudi, A., Nikolopoulou, M., 2003. Vegetation in the urban environment: microclimatic analysis and benefits. Energy Build. 35 (1), 69–76. https://doi.org/10.1016/S0378-7788(02)00081-6.

Doremus, J.M., Jacqz, I., Johnston, S., 2022. Sweating the energy bill: extreme weather, poor households, and the energy spending gap. J. Environ. Econ. Manag. 112, 102609 https://doi.org/10.1016/j.jeem.2022.102609.

Garg, T., Jagnani, M., Taraz, V., 2020. Temperature and Human Capital in India. J. Assoc. Environ. Resour. Econ. 7 (6), 1113–1150. https://doi.org/10.1086/710066.

Giacinto, J.J., Fricker, G.A., Ritter, M., Yost, J., Doremus, J., 2021. Urban forest biodiversity and cardiovascular disease: potential health benefits from California's street trees. PLOS ONE 16 (11), e0254973. https://doi.org/10.1371/journal.pone.0254973.

Gunawardena, K.R., Wells, M.J., Kershaw, T., 2017. Utilising green and bluespace to mitigate urban heat island intensity, 1040–1055 Sci. Total Environ. *584–585*. https://doi.org/10.1016/j.scitotenv.2017.01.158.

Hamada, S., Ohta, T., 2010. Seasonal variations in the cooling effect of urban green areas on surrounding urban areas. Urban For. Urban Green. 9 (1), 15–24. https://doi.org/10.1016/j.ufug.2009.10.002.

Hart, E., & Bell, K. (2015). prism: Access data from the Oregon State Prism climate project [Computer software]. Zenodo. https://doi.org/10.5281/ZENODO.33663.

Hassall, C., Anderson, S., 2015. Stormwater ponds can contain comparable biodiversity to unmanaged wetlands in urban areas. Hydrobiologia 745 (1), 137–149. https://doi.org/10.1007/s10750-014-2100-5.

Hathway, E.A., Sharples, S., 2012. The interaction of rivers and urban form in mitigating the Urban Heat Island effect: a UK case study. Build. Environ. 58, 14–22. https://doi.org/10.1016/j.buildenv.2012.06.013.

Heyes, A., Saberian, S., 2019. Temperature and decisions: evidence from 207,000 Court Cases. Am. Econ. J.: Appl. Econ. 11 (2), 238–265. https://doi.org/10.1257/app.20170223.

Hill, M.J., Biggs, J., Thornhill, I., Briers, R.A., Gledhill, D.G., White, J.C., Wood, P.J., Hassall, C., 2017. Urban ponds as an aquatic biodiversity resource in modified landscapes. Glob. Change Biol. 23 (3), 986–999. https://doi.org/10.1111/gcb.13401.

Huff, E., Johnson, M., Roman, L., Sonti, N., Pregitzer, C., Campbell, L., McMillen, H., 2020. A literature review of resilience in urban forestry. Arboric. Urban For. 46 (3), 185–196. https://doi.org/10.48044/jauf.2020.014.

Imhoff, M.L., Zhang, P., Wolfe, R.E., Bounoua, L., 2010. Remote sensing of the urban heat island effect across biomes in the continental USA. Remote Sens. Environ. 114 (3), 504–513. https://doi.org/10.1016/j.rse.2009.10.008.

Kjellstrom, T., Crowe, J., 2011. Climate change, workplace heat exposure, and occupational health and productivity in central America. Int. J. Occup. Environ. Health 17 (3), 270–281. https://doi.org/10.1179/oeh.2011.17.3.270.

Kong, L., Lau, K.K.-L., Yuan, C., Chen, Y., Xu, Y., Ren, C., Ng, E., 2017. Regulation of outdoor thermal comfort by trees in Hong Kong. Sustain. Cities Soc. 31, 12–25. https://doi.org/10.1016/j.scs.2017.01.018.

Kovats, R.S., Hajat, S., 2008. Heat stress and public health: a critical review. Annu. Rev. Public Health 29 (1), 41–55. https://doi.org/10.1146/annurev.publhealth.29.020907.090843.

Laaidi, K., Zeghnoun, A., Dousset, B., Bretin, P., Vandentorren, S., Giraudet, E., Beaudeau, P., 2012. The Impact of Heat Islands on Mortality in Paris during the August 2003 Heat Wave. Environ. Health Perspect. 120 (2), 254–259. https://doi.org/10.1289/ehp.1103532.

Lee, S.J., Longcore, T., Rich, C., Wilson, J.P., 2017. Increased home size and hardscape decreases urban forest cover in Los Angeles County's single-family residential neighborhoods. Urban For. Urban Green. 24, 222–235. https://doi.org/10.1016/j.ufug.2017.03.004.

Livesley, S.J., McPherson, E.G., Calfapietra, C., 2016. The Urban Forest and Ecosystem Services: Impacts on Urban Water, Heat, and Pollution Cycles at the Tree, Street, and City Scale. J. Environ. Qual. 45 (1), 119–124. https://doi.org/10.2134/jeq2015.11.0567.

Love, N.L.R., Nguyen, V., Pawlak, C., Pineda, A., Reimer, J.L., Yost, J.M., Fricker, G.A., Ventura, J.D., Doremus, J.M., Crow, T., Ritter, M.K., 2022. Diversity and structure in California's urban forest: What over six million data points tell us about one of the world's largest urban forests. Urban For. Urban Green. 74, 127679 https://doi.org/10.1016/j.ufug.2022.127679.

Luber, G., McGeehin, M., 2008. Climate Change and Extreme Heat Events. Am. J. Prev. Med. 35 (5), 429–435. https://doi.org/10.1016/j.amepre.2008.08.021.

Mirzaei, P.A., Haghighat, F., 2010. Approaches to study urban heat island – abilities and limitations. Build. Environ. 45 (10), 2192–2201. https://doi.org/10.1016/j.buildenv.2010.04.001.

Mullins, J.T., White, C., 2020. Can access to health care mitigate the effects of temperature on mortality? J. Public Econ. 191, 104259 https://doi.org/10.1016/j.jpubeco.2020.104259.

Murage, P., Hajat, S., Kovats, R.S., 2017. Effect of night-time temperatures on cause and age-specific mortality in London. Environ. Epidemiol. 1 (2), e005 https://doi.org/10.1097/EE9.0000000000000005.

Murakawa, S., Sekine, T., Narita, K., Nishina, D., 1991. Study of the effects of a river on the thermal environment in an urban area. Energy Build. 16 (3–4), 993–1001. https://doi.org/10.1016/0378-7788(91)90094-J.

National Centers for Environmental Information (NCEI). (n.d.). Climate Data Online [dataset]. Retrieved March 18, 2021, from 〈https://www.ncdc.noaa.gov/cdo-web/〉.

Nitschke, C.R., Nichols, S., Allen, K., Dobbs, C., Livesley, S.J., Baker, P.J., Lynch, Y., 2017. The influence of climate and drought on urban tree growth in southeast Australia and the implications for future growth under climate change. Landsc. Urban Plan. 167, 275–287. https://doi.org/10.1016/j.landurbplan.2017.06.012.

Nowak, D.J., Greenfield, E.J., 2020. The increase of impervious cover and decrease of tree cover within urban areas globally (2012–2017). Urban For. Urban Green. 49, 126638 https://doi.org/10.1016/j.ufug.2020.126638.

Oke, T.R., 1982. The energetic basis of the urban heat island. Q. J. R. Meteorol. Soc. 108 (455), 1–24. https://doi.org/10.1002/qj.49710845502.

Ordóñez, C., Duinker, P.N., 2014. Assessing the vulnerability of urban forests to climate change. Environ. Rev. 22 (3), 311–321. https://doi.org/10.1139/er-2013-0078.

Ordóñez, C., Duinker, P.N., 2015. Climate change vulnerability assessment of the urban forest in three Canadian cities. Clim. Change 131 (4), 531–543. https://doi.org/10.1007/s10584-015-1394-2.

Paquette, A., Sousa-Silva, R., Maure, F., Cameron, E., Belluau, M., Messier, C., 2021. Praise for diversity: a functional approach to reduce risks in urban forests. Urban For. Urban Green. 62, 127157 https://doi.org/10.1016/j.ufug.2021.127157.

Park, R.J., 2022. Hot Temperature and High-Stakes Performance. J. Hum. Resour. 57 (2), 400–434. https://doi.org/10.3368/jhr.57.2.0618-9535R3.

Perkins, S.E., Alexander, L.V., Nairn, J.R., 2012. Increasing frequency, intensity and duration of observed global heatwaves and warm spells. Geophys. Res. Lett. 39 (20), 2012GL053361 https://doi.org/10.1029/2012GL053361.

PRISM Climate Group, Oregon State University. (2004). *PRISM Climate Data* [dataset]. 〈http://prism.oregonstate.edu〉.

R. Core Team. (2022). *R: A language and environment for statistical computing* [Computer software]. R Foundation for Statistical Computing. 〈https://www.R-project.org/〉.

Rahman, M.A., Moser, A., Rötzer, T., Pauleit, S., 2019. Comparing the transpirational and shading effects of two contrasting urban tree species. Urban Ecosyst. 22 (4), 683–697. https://doi.org/10.1007/s11252-019-00853-x.

Rana, G., Ferrara, R.M., 2019. Air cooling by tree transpiration: a case study of Olea europaea, Citrus sinensis and Pinus pinea in Mediterranean town. Urban Clim. 29, 100507 https://doi.org/10.1016/j.uclim.2019.100507.

Raupp, M., Cumming, A., Raupp, E., 2006. Street Tree Diversity in Eastern North America and Its Potential for Tree Loss to Exotic Borers. Arboric. Urban For. 32 (6), 297–304. https://doi.org/10.48044/jauf.2006.038.

SelecTree. (2022). *SelecTree: A Tree Selection Guide* [Web Application]. 〈https://selectree.calpoly.edu/〉.

Stepner, M. (2013). *BINSCATTER: Stata module to generate binned scatterplots* [Computer software]. 〈https://EconPapers.repec.org/RePEc:boc:bocode:s457709〉.

Sun, R., Chen, L., 2012. How can urban water bodies be designed for climate adaptation? Landsc. Urban Plan. 105 (1–2), 27–33. https://doi.org/10.1016/j.landurbplan.2011.11.018.

Taleghani, M., 2018. Outdoor thermal comfort by different heat mitigation strategies- a review. Renew. Sustain. Energy Rev. 81, 2011–2018. https://doi.org/10.1016/j.rser.2017.06.010.

Tamaskani Esfehankalateh, A., Ngarambe, J., Yun, G.Y., 2021. Influence of tree canopy coverage and leaf area density on urban heat island mitigation. Sustainability 13 (13), 7496. https://doi.org/10.3390/su13137496.

Tsoka, S., Leduc, T., Rodler, A., 2021. Assessing the effects of urban street trees on building cooling energy needs: The role of foliage density and planting pattern. Sustain. Cities Soc. 65, 102633 https://doi.org/10.1016/j.scs.2020.102633.

Wang, X., Dallimer, M., Scott, C.E., Shi, W., Gao, J., 2021. Tree species richness and diversity predicts the magnitude of urban heat island mitigation effects of greenspaces. Sci. Total Environ. 770, 145211 https://doi.org/10.1016/j.scitotenv.2021.145211.

White, C., 2017. The Dynamic Relationship between Temperature and Morbidity. J. Assoc. Environ. Resour. Econ. 4 (4), 1155–1198. https://doi.org/10.1086/692098.

Wood, S.L.R., Dupras, J., 2021. Increasing functional diversity of the urban canopy for climate resilience: Potential tradeoffs with ecosystem services? Urban For. Urban Green. 58, 126972 https://doi.org/10.1016/j.ufug.2020.126972.

Wujeska-Klause, A., Pfautsch, S., 2020. The best urban trees for daytime cooling leave nights slightly warmer. Forests 11 (9), 945. https://doi.org/10.3390/f11090945.

Yang, G., Yu, Z., Jørgensen, G., Vejre, H., 2020. How can urban blue-green space be planned for climate adaptation in high-latitude cities? A seasonal perspective. Sustain. Cities Soc. 53, 101932 https://doi.org/10.1016/j.scs.2019.101932.

Yu, Z., Yang, G., Zuo, S., Jørgensen, G., Koga, M., Vejre, H., 2020. Critical review on the cooling effect of urban blue-green space: a threshold-size perspective. Urban For. Urban Green. 49, 126630 https://doi.org/10.1016/j.ufug.2020.126630.

Zhang, Z., Lv, Y., Pan, H., 2013. Cooling and humidifying effect of plant communities in subtropical urban parks. Urban For. Urban Green. 12 (3), 323–329. https://doi.org/10.1016/j.ufug.2013.03.010.