Who Gets Green in Philadelphia? A Spatial Analysis of Philadelphia's Residential Tree Program

Abstract

This study evaluates the equity of the tree distribution of Philadelphia's yard tree program run by TreePhilly. The assessment focuses on the program's ability to counteract the urban heat island effect based on land surface temperatures calculated using Landsat 8 satellite imagery as well as zoning specifications from the City of Philadelphia's land use data, and socioeconomic characteristics from the American Community Survey on the census block group level. Disparities were identified using mapping, regression analysis, and spatial econometric models to determine the relationships between tree distribution and important factors such as temperature, race, income, and property characteristics. Overall, the study found that residential tree distribution was not equitable with regards to combatting the urban heat island effect and that more trees per square feet were planted in census block groups with higher white populations and lower density zoning classifications. This assessment will inform the local government on the effectiveness of its program and facilitate TreePhilly in determining where to target its outreach.

Keywords: Philadelphia, Urban heat islands, Greenspace, Spatial regression, Environmental justice, Tree distribution, Satellite imagery

1. Introduction

Cities are increasingly suffering from the Urban Heat Island (UHI) effect which causes metropolitan areas to have significantly higher temperatures than surrounding rural and suburban regions (Voogt and Oke, 2003). Considering the many benefits of greenspace, including urban heat island mitigation, the City of Philadelphia (subsequently also referred to as the City) has undertaken programs to expand urban vegetation. In partnership with the Philadelphia Horticultural Society, the City supports the LandCare program which cleans, greens, and maintains vacant lots and currently includes 12,000 lots (Philadelphia Horticultural Society, 2021). Philadelphia's Parks and Recreation has also led the TreePhilly program since 2012 (Parks and Recreation, 2021). The Street Trees program involves the deployment of trees on public streets while the Yard Trees Program offers free trees to residents to plant and maintain on their private properties.

This paper attempts to close the gap in the literature about the distribution and equity of Philadelphia's private urban vegetation programs and their impact in reducing the urban heat island effect by evaluating the Yard Trees program. While there is substantial literature focusing on the effect of Philadelphia's urban vegetation programs on crime, health, and perceptions of safety (South et al., 2018, Branas et al., 2018), there is little research surrounding the relationship of Philadelphia's programs and the urban heat island effect. Generally, the scholarship on the effectiveness of municipal greenspace programs is focused on the deployment of vegetation in public settings. Private distribution services are difficult to implement and monitor because they depend on the residents' requests and actions to achieve the program's goals (Locke and Grove, 2016). Prior research that has evaluated the Yard Tree program found it to be equitably distributed (Locke, Fichman and Blaustein, 2015), but this research was conducted within the first 2 years of its formation and the program has currently run for 9 years. Additionally, subsequent research on tree distribution programs for private property have only investigated them qualitatively (Nguyen et al., 2017).

While the planting and maintenance of trees under the Yard Trees service is conducted on private property, an assessment of the program will be valuable to the public sector given that it is organized and funded by the City of Philadelphia as a response to its Greenworks Vision which set the goal of increasing the tree canopy by 30% in all Philadelphia neighborhoods (Greenworks Philadelphia, 2009). This research will identify what neighborhoods have benefitted the most from the program and those that are taking up the service the least while comparing these areas to those that were suffering most from the urban heat island effect at the beginning of the program. It will also examine relationships between these neighborhoods and socioeconomic factors and housing characteristics to identify possible reasons for resistance to the program. The evaluation will gauge the equity of the distribution of the trees which will inform the local government on the effectiveness of its allocation of funds to the program and facilitate TreePhilly in determining where to target its outreach. By providing information on underserved neighborhoods and potential barriers to the service, this research can improve Philadelphia's future urban vegetation plans for mitigating urban heat island effects on residential properties and increasing the tree canopy across the city.

2. Literature Review

The Urban Heat Island (UHI) effect is a phenomenon that causes metropolitan areas to have significantly higher temperatures than surrounding rural and suburban regions (Voogt and

Oke, 2003). The effect tends to result from the high density of buildings and impervious pavements with low albedo retaining solar energy in metropolitan areas (Mohajerani et al., 2017). In some cities, temperature differences have been found to be up to 5.4°F (3°C) during the day and 22°F (12.2°C) at nighttime (Wong, Akbari, Bell, and Cole, 2011), while mid-latitude urban areas replacing temperate forests have been found to have temperature differences reaching 6-9°C or 10.8-16.2°F (Imhoff et al., 2010). There is conflicting research on the relationship between density and urban temperatures. For example, Schwarz and Manceur (2014) concluded that compact urban form increases urban heat island effects depending on how surface temperatures are measured. On the other hand, other studies have found that urban sprawl results in increased rates of extreme heat events (Stone, Hess and Frumkin, 2010). Nonetheless, as the world urbanizes, the urban heat island effect will increasingly become important in all cities.

Urban heat islands have profound effects on individuals and the environment. They have been linked to several negative health issues including asthma, strokes, dehydration, exhaustion, and even mortality (Kovats and Hajat, 2008). In fact, heat-related mortality is the most common weather-related cause of mortality. Urban heat islands also contribute to increased energy demand and strains on energy systems due to greater air conditioning usage (Akbari and Hashem, 2005, Wong, Eva, H. Akbari, R. Bell, and D. Cole., 2011). Unfortunately, urban residents experience these consequences disproportionately. Studies show that low-income, elderly, and racial and ethnic minority groups experience higher levels of mortality due to urban heat islands (Harlan et al., 2006, Johnson and Wilson, 2009).

Urban heat island effects can be mitigated by several mechanisms. One of the most effective methods is through urban green space. Various researchers have found that parks and vegetation reduce surface temperatures (Cao et al., 2010, Li et al., 2013, Zhou et al., 2011). Park Cool Islands, green spaces within urban islands, are able to cool through transpiration and shading. In cities where larger park cool islands are possible such as Sacramento, temperatures can drop by 5-7°C in areas with irrigated greenspace (Spronken-Smith and Oke, 1998). While Chow, Pope, Martin, & Brazel (2011) found temperatures fall between 0.7–3.6°C in Tempe, Arizona, Declet-Barreto et al. (2013) found surface temperatures fall by up to 8.4 °C in Phoenix, Arizona in park cool islands. Studies have also found correlations between higher neighborhood tree cover and lower heat-related ambulance calls during extreme heat events (Graham et al., 2016). Urban gardens are becoming increasingly popular and have been found to reduce temperatures between the spring and autumn and reduce energy consumption (Tsilini et al., 2014). Additionally, they provide non-heat-related benefits such as increasing access to healthy food, community development, and psychological wellness (Poulsen et al., 2014).

Urban heat island mitigation infrastructure is also unequally distributed in multiple cities. Apparicio et al. (2016), Flocks et al. (2011), and Landry and Chakraborty (2009) found disproportionate distribution of greenspace in Montreal, Miami, and Tampa respectively. Low-income citizens tend to live in denser areas of low albedo and higher temperatures due to less vegetation. As a result, these residents have a higher demand for air conditioning, contributing to energy poverty (Coseo, 2013), and they are less likely to benefit from the associated social benefits of greenspace (Declet-Barreto et al. 2013).

This study's city of interest, Philadelphia, has been greatly affected by the UHI effect, experiencing various "extreme weather events" over the past 3 decades (Weber, 2015). The city also suffers from a considerable amount of vacant land. As of 2015, the city had over 40,000 vacant lots, and a study found that lower-income neighborhoods had a significantly larger number of vacant lots (Pearsall, 2017). Previously, Uejio et al. (2011) found that Philadelphia neighborhoods with higher levels of heat-related mortality had greater proportions of African Americans and low value homes. While greenspace development has been on the rise in Philadelphia, urban gardens in low-income neighborhoods have faced barriers to acquiring and maintaining vacant land (Meenar and Hoover, 2012).

Philadelphia has established urban vegetation programs to combat the UHI effect. The City supports the LandCare program to green vacant lots as well as Parks and Recreation's TreePhilly program that plants trees on public streets through its Street Tree program and on private property through its Yard Trees Program. The yard trees on private property are usually requested by Philadelphia residents who contact TreePhilly through the website, calls, or during informational campaigns occasionally run by the organization in different neighborhoods. TreePhilly staff facilitate planting and provide information to residents about how to grow and maintain the tree (TreePhilly).

Research shows there has been a positive impact from some of the City of Philadelphia's greening programs. A study found that the LandCare program has contributed to urban island effect mitigation with LandCare lots being 3.21°F cooler on average than vacant lots across the city (Pearsall, 2017). In 2012, Heckert and Mennis found that properties surrounding greened vacant lots had a greater increase in value than properties surrounding non-greened vacant lots. More recent studies also found relationships between the LandCare program's projects and positive effects on mental health, blight, crime, and perceptions of safety (South et al., 2018, Branas et al., 2018). Kondo et al.'s recent study (2020) predicts that the city will prevent 403 premature deaths annually between 2014 and 2025 if it reaches its 2025 goal of 30% tree canopy coverage.

Given the rise of extreme heat events in Philadelphia, it is important that programs are locating urban vegetation interventions in areas that will maximize and distribute their benefits equitably as other cities raise environmental justice concerns. For example, research assessing the Detroit Future City Strategic Framework pointed to its green infrastructure sites' inability to address heat-related socioeconomic vulnerability (Lino and Reames, 2019). Therefore, evaluating the equity Philadelphia's green programs is essential to optimize the mitigation of the city's urban heat island.

3. Data

In order to identify what parts of the city were most susceptible to the urban heat island at the beginning of the TreePhilly program, this study uses land surface temperatures as a proxy. Land surface temperature (LST) is calculated using high spatial resolution satellite imagery and is often used as a measure in urban heat island studies (Huang, Zhou, & Cadenasso, 2011). LST points to the intensity of the urban heat island effect as a function of low albedo due to lack of vegetation, although it is not a perfect indicator of urban heat island effects (Zaeemdar and Baycan, 2017).

This study employs imagery from Landsat 8 data, specifically Band 10 and Band 11 (Thermal Infrared) to calculate the temperature in degrees Fahrenheit in each census block group. The satellite image utilized was collected on July 19, 2013 and resampled by the US Geological Survey. This image was chosen based on filtering by season, year, and cloud cover, and it was accessed by the Google Earth application programming interface. The study uses Landsat 8 data from the earliest available year (the closest year to the 2012 start of the TreePhilly program) that was collected on a typical summer day with less cloud cover to derive the land surface temperatures more accurately on a warm Philadelphia day.

The outcome of interest will be the residential trees that were planted in each census block group through the city's program. A dataset including all 17,834 yard trees, their location, and year planted from the inception of the program to September 2021 and retrieved from TreePhilly. Unfortunately, the dataset does not include information about the current status of the trees, households who requested but did not receive one, or how the households learned about the program.

To account for differences in neighborhood layout and zoning throughout the city, the study also employs Philadelphia's Land Use dataset downloaded from Open Data Philly. The shapefile includes updated planning information assigning each city parcel to 1 of 9 classifications such as residential, commercial, park or vacant land, as well 16 sub-classifications including residential low density or commercial business & professional. Specifically, this research utilizes information about 9 of the 16 classes: residential low/medium/high density, commercial consumer/business & professional/mixed residential, park/open space/cemetery, and vacant land.

Finally, demographic information on the census block group level was retrieved from the American Consumer Survey (ACS) 2014-2018 5-year estimates. These estimates were chosen because they fall in the center of the 2012-2021 period of the yard tree program. The demographic variables of interest were percent of white residents and median household income.

4. Methodology

4.1 Data Manipulation

The process and equations used to calculate LST were adapted from Twumasi et al.'s 2021 study using Landsat-8 satellite data to compare LST of 2 cities in Ghana.

LST was computed using the following equation:

$$T_s = \frac{BT}{1+\left[\left(\frac{\lambda BT}{\rho}\right)\ln \varepsilon_\lambda\right]}$$

where T_s is the LST in Celsius (˚C), BT is satellite brightness temperature (˚C), λ is the wavelength of emitted radiance and ε_λ is the emissivity.

The following variables needed to derive LST were calculated as follows:

- Land surface emissivity was approximated as $\varepsilon_\lambda = 0.004P_v + 0.986$ where P_v is the proportion of vegetation.
- The proportion of vegetation was calculated using the equation:

  $$P_v = \left(\frac{\mathrm{NDVI}-\mathrm{NDVI}_s}{\mathrm{NDVI}_v-\mathrm{NDVI}_s}\right)^2$$

  where NDVI is the normalized vegetation index and NDVI_v and NDVI_s are maximum and minimum NDVI respectively.
- The normalized vegetation index (NDVI) was calculated using the following equation:

  $$\mathrm{NDVI} = \frac{NIR(\mathrm{band5})-R(\mathrm{band4})}{nir(\mathrm{band5})+r(\mathrm{band4})}$$

  where NIR represents the near-infrared band (Band 5) and R represents the red band (Band 4).

- BT was retrieved using the brightness temperature utility function of the RIO-TOA application programming interface in Python.
- ρ = $h\frac{c}{\sigma}$ where σ is the Boltzmann constant (1.38 × 10−23 J/K), h is Planck's constant (6.626 × 10−34 J s), and c is the velocity of light (2.998 × 108 m/s).

LST was calculated for both Bands 10 and 11 and averaged then converted to Fahrenheit. The temperature assigned to each census block group was calculated using zonal statistics to average pixel values across each block group. The mean temperature across all census block groups in the dataset was 75.7 degrees Fahrenheit, ranging from 37.1 to 85.8 degrees Fahrenheit.

The datasets of the yard trees, ACS demographic information, and land use were combined to form variables for modeling. Summary statistics for the variables can be found in Table 1. From the land classification groups, 7 variables were created, including percent of the census block group zoned as Residential low density, Residential medium density, Residential high density, Commercial 1 (combination of commercial business/professional and commercial consumer), Commercial 2 (commercial mixed residential), Park/Open (combination of park/open space and cemetery) and Vacant. There were initially 1336 census block groups. After eliminating census block groups without demographic information from the ACS or any of the 7 mentioned zoning classifications there were 1202 census block groups left in the dataset.

Table 1: Summary Statistics					
	Trees Planted	**Population**	**Mean Temperature (°F)**	**White Population (%)**	**Median Income ($)**
Minimum	0.0	165	37.1	0.0	8,266
Mean	13.9	1220.4	75.7	33.5	47,795
Median	8.0	1099	79.4	20.8	42,376
Maximum	186.0	4222	85.8	100.0	185,227

4.2 Hypotheses

Because this study aims to assess the equity of the yard tree distribution program especially with regards to its efficiency in addressing heat inequities in Philadelphia, a major point of interest will be the initial temperatures of the areas where trees were planted. It is hypothesized that census block groups with higher mean temperatures will receive a higher number of trees. It is expected that areas suffering most from the urban heat island effect will be engaged with more outreach in accordance with Parks and Recreations goals. This observation would signify that the city is distributing trees fairly, at least with regards to urban heat mitigation. It is predicted that census block groups with a higher percentage of white residents and higher incomes will have received more trees. This hypothesis is based on the expectation that these populations have better access to resources and information to request yard trees as well as unequal distribution of greenspace found in other cities (Apparicio et al., 2016, Flocks et al., 2011, Lino and Reames, 2019). It is expected that census block groups with a higher percentage of their land use assigned as “residential low density” will have had a greater number of yard trees planted. This prediction is based on the expectation that individuals living in low density neighborhoods are more likely to be homeowners with more flexibility regarding changes to the property as well as more space and investment in their property’s appearance. Finally, it is hypothesized that census block groups with a higher percentage of their land zoned as vacant will have received more trees. Considering that the Philadelphia Horticultural Society has been engaged in vacant lot greening during the period of TreePhilly's program, it is expected that a spillover effect will result in greater awareness of city greening efforts in areas where these lots are greened, leading to higher number of yard tree requests in the residential properties in these areas.

4.3 Visual Analysis

The number of trees per million square feet as well as the neighborhood characteristics corresponding to the various hypotheses were represented using choropleth maps. The maps visualized how these variables change across the Philadelphia census block groups. Correlations between the variables as well as the specific regions of the city in which they exist were identified by making connections between the maps which can be found in the appendix.

4.4 Regression Analysis

Three types of regression analysis were used to determine the relationship between yard trees and temperature and socioeconomic qualities of the census block groups: logistic regression, Ordinary Least Squares regression, and spatial autocorrelation regression. The 11 dependent variables for the models were population, mean temperature, percentage of white residents, log(median household income), and the percentages of area assigned to the 7 previously mentioned zoning classifications (residential low density, residential medium density, residential high density, commercial 1, commercial 2, park/open space, and vacant).

For the logistic regression, the dependent variable is the binary outcome of having received at least one tree or not. This model provides a general understanding of what areas of the city were completely unengaged during the 9 years of the program. For the OLS model, the dependent variable is the log(number of trees planted per square feet). This model gives insight into the variation in the number of trees planted in the neighborhoods that received trees.

Considering the likelihood of the statistical relationship between the variables changing over space, spatial regression was employed to account for this phenomenon. To determine whether or not spatial patterns existed, this study utilized the Moran's I statistic which tests the null hypothesis that the spatial pattern of a variable is random (Ord and Getis, 1995). A spatial contiguity weight matrix with equal weights assigned to all contiguous census block groups was used to model dependence. The Moran's I statistic of 0.156 and corresponding Moran's I z-score of 8.89 rejected the null hypothesis and indicated spatial autocorrelation. Following LeSage's (2014) principles to guide the process of choosing a spatial econometrics model, model selection was first determined by specifying the presence of either local or global spillovers. Because an important characteristic of global spillovers is their endogenous interaction and feedback causing a change in one region to cause a sequence of adjustments in potentially all regions in the sample, specifying the context as a local spillover situation was more reasonable. In other words, characteristics of a census block group are likely to affect neighboring census block groups but not create spillovers affecting all groups in the city. Given the local specification of the problem, the study began using the Spatial Durbin Error Model (SDEM): $\mathbf{Y = X \cdot \beta + W X \cdot \theta + u}$

where $\mathbf{u = \lambda \cdot Wu + \varepsilon}$ with parameters β for exogenous explanatory variables, θ for exogenous interaction effects (of dimension equal to the number of exogenous variables), λ for the spatial correlation effect of errors known as spatial autocorrelation, and W for the spatial weight matrix (LeSage and Pace, 2009).

This model is a combination of the Spatially Lagged X (SLX) model and Spatial Error model (SEM). All 3 models include spatial lag terms *W* for the explanatory variables which permits local spillovers to neighboring observations.

The SLX model is written **as** $\mathbf{Y = X \cdot \beta + W X \cdot \theta + \varepsilon}$. It includes spatially lagged explanatory variables which is useful when the independent variables in one area affect the outcome in a neighboring area. The SEM is written as $\mathbf{Y = X \cdot \beta + u}$ where $\mathbf{u = \lambda \cdot Wu + \varepsilon}$. SEM considers the spatial autocorrelation of errors such as spatially correlated fixed effects or omitted variables with spatial patterns (LeSage and Pace, 2009).

A Likelihood ratio test and AIC values were used to decide whether to restrict the SDEM model to a SLX model or SEM. A Moran's correlation test and Breusch-Pagan test for spatial models were used to check for spatial dependence of residuals of the regression models (Breusch and Pagan, 1979).

5. Results

5.1 Visual Analysis Results

Univariate maps in Figure 1 (located in the appendix) indicate that relationships exist between the number of trees planted in each census block group and various independent variables in different regions of the city. The maps only include census block groups with a sizable enough population that demographic information was available for them in the ACS. Upper and Lower Far Northeast of Philadelphia, Upper and Lower Northwest Philadelphia, University/Southwest Philadelphia, Southwest River Wards, and South Philadelphia received the most yard trees per square feet. However, the mean temperature of the majority of the census block groups in these regions were comparable to the rest of the city. In fact, Lower Far

Northeast and University/Southwest Philadelphia already had cooler temperatures than the rest of the city at the beginning of the TreePhilly program. In the same vein, Upper and Lower Far Northeast and Upper and Lower Northwest and University/Southwest Philadelphia, where several trees were planted, were also the home to majority white residents, some of the highest incomes in the city, and most of the city's land classified as residential low density. The Center City area in the north of South Philly (a region where a sizable number of trees were planted) had a high white population and high income. However, in general, South Philly had a more diverse population, lower median income, and little land assigned as residential low density.

West, Central, Lower North, North, and Northeast Philadelphia, and Lower Southwest appeared to have received an overall lower number of trees. Some of these regions had a substantial group of census blocks groups with lower mean temperatures to begin with, but in general they had the largest minority populations, lower incomes, very little land zoned for low density residential properties, and several census block groups with higher percentages of vacant land. Census block groups on the eastern border of the city tended to receive very few yard trees despite their varying levels of their minority population and income. These census block groups also had greater amounts of land identified as vacant. Nevertheless, these census block groups also had slightly cooler mean temperatures than majority of the city at the start of the program, suggesting a slightly smaller need for yard trees. Overall, the visual analysis of the variables of interest pointed to a distribution of trees favoring non-minority, higher income, and single-family housing neighborhoods.

5.2 Logistic Regression Results

The logistic regression was performed to identify relationships between the socioeconomic and zoning factors and whether a census block group received at least 1 tree or not. The results found in Table 2 indicate that the model had a pseudo-R-squared value of 0.1529, suggesting that much of the variation in the probability of having received a tree is not explained by factors included in the model.

Nevertheless, the model had 4 significant coefficients: population, the percentage of white residents, the percent of land zoned as residential low density, and the percentage of land zoned as commercial mixed residential. As expected, population and the number of trees were positively correlated, with an additional resident corresponding to a 1.3% increase in the odds of having a tree planted in a census block group. In terms of socioeconomic factors, a 1-unit increase in the percentage of white residents of a census block group was found to increase the odds of having at least 1 yard tree planted by approximately 1.9%. Median income had no significant effect on the probability of receiving a tree. The absence of an effect could be the result of the model controlling for the white population in each census block group, given a 62.5% correlation between the percentage of white residents and median income in the city.

With regards to land use, an additional 1% in the amount of land zoned as residential low density increased the odds of receiving a yard tree by 9.62%. This effect is likely due to the fact that residential low density parcels tend to have larger single-family homes. Although the “commercial 2” (commercial mixed residential) classification had not been considered as part of the hypotheses, it had a significant reduction in the probability of receiving a tree. A 1-unit increase in the percentage of that land use decreased the odds of a yard tree being planted by 11.75%. This effect could be a result of properties sharing the same space as businesses, causing them to be in high street area of greater footfall and having smaller accommodations, making them better candidates for street trees over yard trees.

Contrary to my hypothesis, the mean temperature of the census block group at the beginning of the TreePhilly program did not have a significant effect on the probability of a yard tree being planted. This result suggests that the Yard Tree program may be failing to address the urban heat island effect in Philadelphia.

Table 2: Logistic Regression Summary

Coefficients	Estimate	Std. Error	P-value
Intercept	3.234	3.137	0.305
Population	**0.0013**	**0.000**	**0.000**
Mean Temperature	0.0101	0.012	0.406
Log (median income)	-0.3764	0.302	0.213
White	**0.0188**	**0.006**	**0.002**
Residential Low	**0.0919**	**0.0024**	**0.000**
Residential Med	0.0192	0.011	0.074
Residential High	-0.0161	0.015	0.270
Commercial 1	-0.0180	0.021	0.389
Commercial 2	**-0.1249**	**0.038**	**0.001**
Park or Open Space	-0.0048	0.012	0.698
Vacant	0.0292	0.028	0.299
Pseudo R-squared: 0.1529			
Log-Likelihood: -240.05			

5.3 Ordinary Least Squares Regression Results

The OLS regression provides more detail about the variation of number of trees planted for census block groups that received trees. Results of the regression are presented in Table 3 where the outcome variable is the log of the number of trees planted per square feet. Dependent variables with statistically significant coefficients were population, the percentage of white residents, the percentage of land zoned as residential low density, the percentage of land zoned as residential medium density, and the percentage of land classified as commercial

2 (commercial mixed residential). A 1-unit change in the percentage of white residents in a census block group approximately corresponded to a 1.45% increase the number of yard trees per square feet. As in the case of the logistic regression, median income was found to have no statistically significant effect on the number of residential trees received, which could be a result of the variable's correlation with the proportion of white residents. A 1-unit increase in the percentage of land classified as residential low density and residential medium density corresponded to an approximate increase in the number of yard trees planted of 4.34% and 3.20% respectively. These results align with the hypothesis that lower density residential neighborhoods which are likely to have more property space and be owner-occupied were likely to have a higher rate of tree requests. In the OLS regression, both the commercial 1 and commercial 2 variables were statistically significant at the 0.05 level. A 1-unit increase in the percentage of land classified as commercial business or professional corresponded to a 2.9% reduction in the number of yard trees, while a 1-unit increase in percentage of land classified as commercial mixed residential corresponded to an approximately 7.0% fall in the number of yard trees received, even after controlling for population differences. As previously mentioned, census block groups with greater amounts of land classified as commercial are more likely to have smaller residential properties which could have resulted in less interest in requesting a yard tree.

The OLS regression had an adjusted r-squared of 0.1029, indicating that a majority of the variation in the number of trees per square feet are not explained by the variables included in the model. The Moran's correlation test to check for residual spatial dependence of the model resulted in a Moran's I of 0.971, with a corresponding statistic of 5.77 and significant p-value, indicating clustering among residuals.

Table 3: OLS Regression Summary			
Coefficients	Estimate	Std. Error	P- value
Intercept	**-13.760**	**1.9963**	**8.87e-12**
Population	**0.00044**	**0.00014**	**0.00142**
Mean Temperature	0.00955	0.00884	0.28031
Log (median income)	-0.18871	0.18876	0.31763
White	**0.01440**	**0.00311**	**4.14e-6**
Residential Low	**0.04248**	**0.00772**	**3.67e-10**
Residential Med	**0.03146**	**0.00690**	**5.74e-6**
Residential High	-0.00175	0.01072	0.87025
Commercial 1	**-0.02973**	**0.01515**	**0.04994**
Commercial 2	**-0.07248**	**0.03252**	**0.02603**
Park or Open Space	-0.00992	0.00914	0.27825
Vacant	0.02276	0.01721	0.18633
Multiple R-spared: 0.1111		Adj R-squared: 0.1029	
F-statistic: 13.52		p-value: <2.2e-16	

5.4 Spatial Regression Results

The first spatial regression run was the Spatial Durbin Error model (SDEM) with a pseudo-R^2 of 0.149. As seen in the results presented in Table 4, the model had 5 significant coefficients: population, percentage of white residents, percentage of land classified as residential low density and residential medium density as well as the lag of the percentage of land classified as commercial mixed residential. It is important to note that the coefficients of the SDEM cannot be interpreted at face value and requires specialized software to produce estimates and valid t-statistics because of a global diffusion of shocks from changes to variables in one census block group (LeSage, 2014). The model's statistically significant positive lambda value signifies that the residual for a census block group increases with higher unexplained values for the number of trees planted in a neighboring census block group.

Table 4: Spatial Durbin Error Model Summary			
Coefficients	Estimate	Std. Error	P-value
Intercept	**-13.3747**	**2.9255**	**4.83e-6**
Population	**0.00050**	**0.00014**	**0.0004**
Mean Temperature	-0.00047	0.23677	0.9839
Log (median income)	-0.19042	0.20048	0.3422
White	**0.01615**	**0.00600**	**0.0071**
Residential Low	**0.03773**	**0.00865**	**1.28e-5**
Residential Med	**0.02456**	**0.00741**	**9.21e-4**
Residential High	0.00144	0.01126	0.8981
Commercial 1	-0.02519	0.01516	0.0966
Commercial 2	-0.02626	0.03519	0.4556
Park or Open Space	-0.01002	0.00929	0.2811
Vacant	0.01735	0.01866	0.3524
Lag Population	-0.00032	0.00029	0.2711
Lag Mean Temperature	0.01374	0.02779	0.6211
Lag Log (median income)	0.03892	0.25047	0.8765
Lag White	0.00046	0.00716	0.9485
Lag Residential Low	-0.00521	0.01370	0.7035
Lag Residential Med	-0.00041	0.01389	0.9765
Lag Residential High	-0.01370	0.00245	0.5770
Lag Commercial 1	-0.04260	0.00302	0.1593
Lag Commercial 2	**-0.18325**	**0.07094**	**0.0098**
Lag Park or Open Space	-0.02116	0.01785	0.2360
Lag Vacant	-0.01163	0.03254	0.7208
LAMBDA	**0.2120**		**2.98e-6**
Log likelihood: -2851.30			
AIC: 5752.6			

The SDEM model was restricted to 2 interpretable smaller spatial models: the Spatially Lagged X (SLX) model and the Spatial Error Model (SEM), and their corresponding results are shown in Table 5 and 6 respectively. The SLX model had an adjusted R-squared of 0.1098 and 5 significant coefficients. The population, the percentage of white residents and the percentage of land classified as residential low density and residential medium density were all significant as in previous models. Additionally, the spatial lag of the percentage of land classified as commercial mixed residential was also significant. A 1-unit increase in the percentage of commercial mixed residential land use in neighboring census block groups corresponded to an 18.8% decrease in the number of trees planted in a census block group.

Table 5: Spatially Lagged X Model Summary			
Coefficients	Estimate	Std. Error	P-value
Intercept	**-14.0467**	**2.65243**	**1.41e-7**
Population	**0.00050**	**0.00015**	**0.0007**
Mean Temperature	-0.00219	0.02418	0.9276
Log (median income)	-0.15899	0.20244	0.4323
White	**0.01406**	**0.00636**	**0.0272**
Residential Low	**0.03838**	**0.00907**	**2.53e-5**
Residential Med	**0.02414**	**0.00770**	**0.0017**
Residential High	0.00285	0.11702	0.8072
Commercial 1	-0.02374	0.01552	0.1270
Commercial 2	-0.02152	0.03674	0.5581
Park or Open Space	-0.00973	0.00959	0.3107
Vacant	0.01865	0.01951	0.3394
Lag Population	-0.00036	0.00027	0.1813
Lag Mean Temperature	0.01256	0.02767	0.6499
Lag Log (median income)	0.08633	0.24370	0.7232
Lag White	0.00288	0.00727	0.6913
Lag Residential Low	-0.00853	0.01323	0.5192
Lag Residential Med	-0.00104	0.01322	0.9371
Lag Residential High	-0.01854	0.02321	0.4244
Lag Commercial 1	-0.05151	0.02891	0.0751
Lag Commercial 2	**-0.20852**	**0.67656**	**0.0021**
Lag Park or Open Space	-0.02497	0.01717	0.1461
Lag Vacant	-0.01109	0.03141	0.7239
Multiple R-spared: 0.1261		Adj R-squared: 0.1098	
F-statistic: 7.734		p-value: <2.2e-16	

Table 6: Spatial Error Model Summary			
Coefficients	Estimate	Std. Error	P-value
Intercept	**-13.4057**	**2.1174**	**2.43e-10**
Population	**0.00049**	**0.00014**	**0.00040**
Mean Temperature	0.00833	0.01073	0.43726
Log (median income)	-0.22206	0.19497	0.25472
White	**0.01435**	**0.00355**	**5.45e-5**
Residential Low	**0.04229**	**0.00718**	**3.91e-9**
Residential Med	**0.03018**	**0.00708**	**2.01e-5**
Residential High	-0.00005	0.01090	0.99642
Commercial 1	-0.02563	0.01506	0.08874
Commercial 2	-0.05066	0.03353	0.13084
Park or Open Space	-0.00799	0.00920	0.38478
Vacant	0.02019	0.01782	0.25737
LAMBDA	**0.2427**		**6.64e-8**
Pseudo R-squared: 0.1421 Log likelihood: -2857.88 AIC: 5743.8			

Two likelihood ratio tests for spatial models were conducted to decide if the SDEM should be restricted to an SLX or SEM model. The test comparing the SDEM and SLX model produced a likelihood ratio of 21.824 and p-value of 2.988e10-6, rejecting the null hypothesis that the SLX model provides as good a fit for the data as the SDEM. On the other hand, the test comparing the SDEM and the SEM produced a likelihood ratio of 13.148 and p-value of 0.2838, failing to reject the null hypothesis at the 0.05 level. For that reason, the lag errors were retained, and the SEM was chosen as the final model. The selection of the SEM was also confirmed by a comparison of AIC values, with the SEM having a smaller AIC of 5743.8 as opposed to the SDEM's AIC of 5752.6. A Breusch-Pagan test for spatial models was run for both models to check for spatial heteroscedasticity. Both test results rejected the null hypothesis that spatial error variances were equal. Although the heteroscedasticity could have some affect on the standard errors of the models, all p-values for the significant coefficients of the SEM model were very small, so it is not expected to significantly affect the confidence levels of the estimates.

Table 7: Spatial Models Comparison					
	Likelihood Ratio (LR)	LR Test P-value	R^2	AIC	Spatial Heterogeneity Tests P-value
SLX	21.824	2.98e-6	0.1261	-	1.60e-7
SEM	13.148	0.284	0.1421	5743.8	7.49e-9
SDEM	-	-	0.1491	5752.6	1.38e-7

*Likelihood Ratio test is comparing SLX and SEM to SDEM
**R-squared values for SEM and SDEM are pseudo-R-squared values
***Spatial Heterogeneity was evaluated using Moran's correlation test for SLX and using the Breusch-Pagan test for spatial models for SEM and SDEM

The final model selected, SEM, had a pseudo R-squared value of 0.142 and 4 significant coefficients. As expected, the population of a census block group was significantly positively correlated with the number of trees planted. The final model found that a 1-unit increase in the percentage of white residents in a census block group corresponded to an 1.4% increase in the number of yard trees received, suggesting that areas with larger minority populations were less likely to benefit from the program. The model also found that a 1-unit increase in the percentage of land zoned as residential low density and residential medium density in a census block group corresponded to an increase in the number of trees planted of 4.3% and 3.1% respectively. These results reveal that residents living in single-family homes or condominiums and larger properties were more likely to take advantage of the program. As in previous models, mean temperature was found to have no significant effect on the number of trees planted, which implies that the program's is not being used to combat urban heating inequities in Philadelphia. Finally, the SEM had a positive significant lambda of 0.2427, indicating that higher unexplained values for the number of trees received in a neighboring census block group corresponds to a larger residual for a census block group and that the factors affecting tree distribution are spatially clustered.

6. Discussion and Conclusion

This study evaluated the equity of the tree distribution of Philadelphia's Yard Tree program run by TreePhilly, The assessment focuses on the program's ability to counteract the urban heat island effect based on land surface temperatures calculated using Landsat 8 satellite imagery as well zoning specifications from the City of Philadelphia's Land Use data, and socioeconomic characteristics from the American Community Survey on the census block group level. Disparities were identified using mapping, regression analysis, and spatial econometric models to determine the relationships between tree distribution and important factors such as temperature, race, income, and property characteristics. Overall, the study found that yard tree distribution was not equitable with regards to addressing urban heat differences because the results indicated no relationship between LST and the number of trees planted. The neighborhoods that benefited the most relative to their size were Upper and Lower Far Northeast of Philadelphia, Upper and Lower Northwest Philadelphia, University/Southwest Philadelphia, Southwest River Wards, and South Philadelphia. Meanwhile, West, Central, Lower North, North, and Northeast Philadelphia, and Lower Southwest received fewer trees per square feet.

The analysis also concluded that on average census block groups that received more trees also had larger white populations and more area zoned for residential low density and residential medium density properties. These findings align with the hypothesis that minority populations who have been historically marginalized and received less access to information and resources would be less likely to benefit from the yard tree program. Additionally, census block groups with more land classified as residential low density were expected to receive more trees because of their larger property space and the higher probability of being occupied by homeowners with greater long-term investment in their property, its comfortability, and its appearance. On the other hand, census block groups with more area zoned as commercial mixed residential were more likely to receive no trees. This outcome could be due to their smaller property sizes and locations on high streets with greater footfall, making them better candidates for street trees over yard trees. Contrary to the hypotheses, the median income of the residents did not have an effect on the number of trees received. However, this result could stem from the correlations between median income, race, and zoning specifications. The results also refuted the hypothesis that areas with more vacant land would receive more trees as a spillover effect of the Horticultural Society's greening program for vacant lots. Altogether, the study suggests that the first 9 years of the TreePhilly yard tree program has faced several social justice challenges with regards to equitable tree distribution.

The findings of this research have several implications for the City of Philadelphia as it further pursues greening efforts and completes the first decade of its residential tree program. Currently, a major component of the program is based on residents' requests for trees. However, the local government will have to make a more conscious effort to target outreach in specific areas of greater need or that are less likely to request a tree. Firstly, it would serve TreePhilly to identify Philadelphia hotspots to offer more attention to these areas, considering that there was no relationship found between land surface temperatures and trees planted per square feet. These efforts will better the program’s ability to contribute to city cooling endeavors and reduce urban heat island effects. Secondly, as most trees are being planted in lower density residential areas, it will be helpful for the City to raise awareness about the program amongst high-density and commercial mixed residential neighborhoods which may not consider themselves as ideal candidates for the program. One possible strategy could be communicating the benefits of the program to landlords seeing as their tenants will be more reluctant to request a tree for a property that he or she does not own. For properties that lack the space for yard trees, TreePhilly should be intentional about street tree planting in these neighborhoods.

To address the racial inequities of the tree distribution, Tree Philly should increase efforts to circulate information about the yard tree programs amongst minority groups, possibly through cultural groups and community centers in the city. Although the study found that median income did not have a significant relationship on the number of trees planted, the economic barriers of maintaining yard trees should not be underestimated, and TreePhilly should consider services to ease economic burdens in low-income areas that request trees. Finally, the Philadelphia Horticultural Society can facilitate in increasing tree requests by informing households in the neighborhoods of the vacant lots that it greens about TreePhilly’s program, creating a spillover effect that would boost the administration’s greening efforts.

7. Limitations and Future Improvements

This study demonstrates how spatial statistic models can be useful tools in evaluating tree distribution programs. The methodology can be expanded to assess the equity of various city programs and better gauge the social justice challenges that they face. Nevertheless, future research can make improvements to develop models that are better representations of relationships between the variables investigated. For example, considering that results of spatial models are sensitive to the spatial weight matrix, future research can determine which weight matrix specifications best fits the Philadelphia context and study how robust results are to the different weight matrix options (LeSage, 2014). Specifying a weight matrix with a more nuanced definition of the spatial neighbors of each census block group could help build models with coefficients that describe the effects of the variables of interest more accurately. Furthermore, considering the consistency of spatial heteroscedasticity, future studies can consider employing a geographically weighted model to account for non-stationarity in the statistical relationships (Brundson et al., 1996).

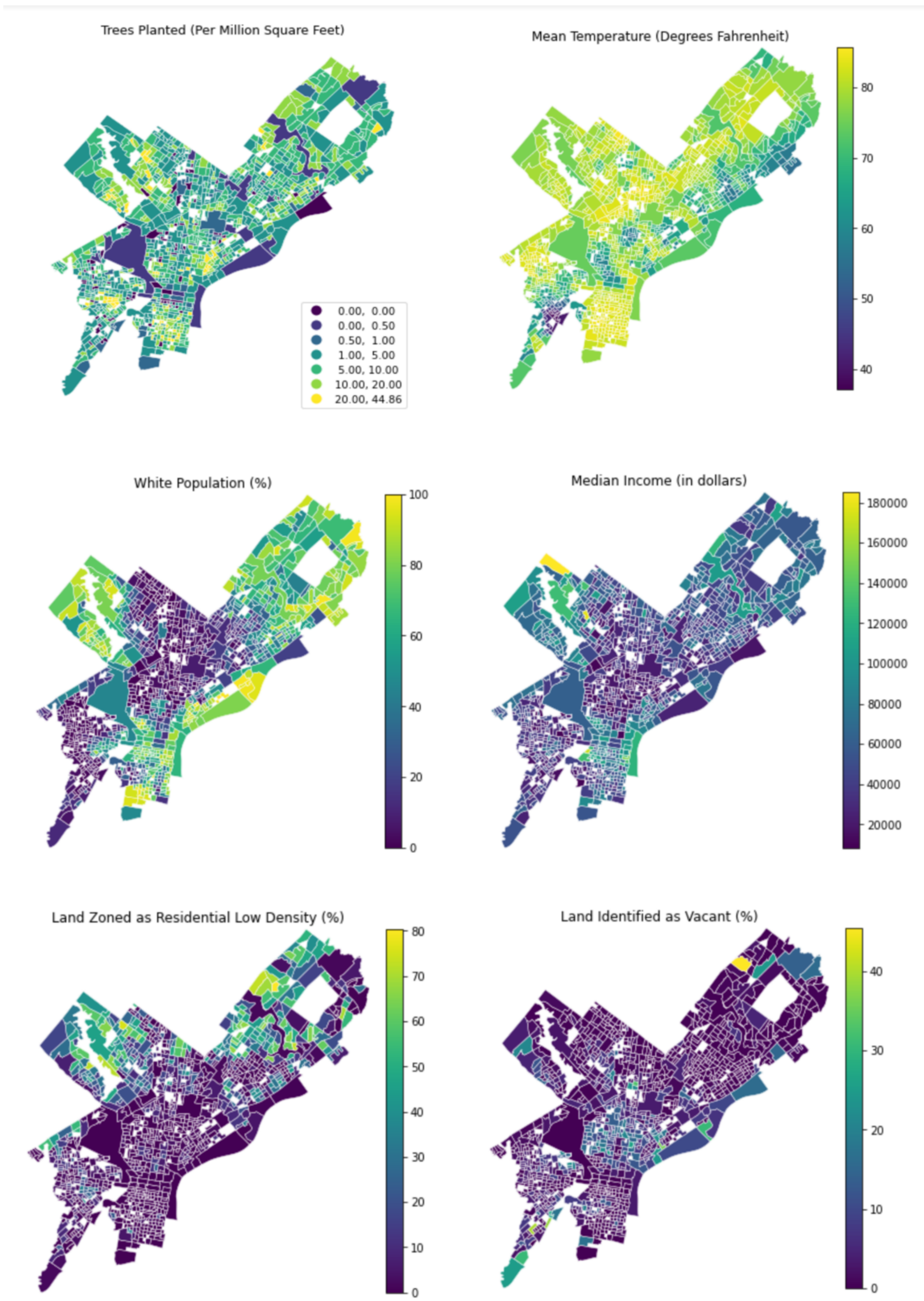
A second limitation of the research was the lack of granularity of data analysis. The study's land surface temperatures is based on one snapshot in time near the beginning of the program and the number of trees planted is aggregated from 2012 to 2021. Considering that TreePhilly includes data about when each tree was planted, it might be useful to explore the tree distribution over time to determine if the equity of the program has changed alongside the socioeconomic factors from year to year and discover spatial trends over the 9-year period of the program. Another worthwhile development would be an investigation of the relationship between temperature and tree planting by observing the changes in temperatures after a yard tree has been planted. This further study would provide more detail about how successful the yard tree program is in ameliorating the UHI effect, but it would require higher resolution imagery as well as data including the specific time each tree was planted.

Finally, this research was hindered by some limitations of the data available. Tree Planting data collected by TreePhilly does not include updates on the status of the tree, so information about the tree's maintenance is unknown. As a result, the connections made between urban cooling and the residential tree program assume that the trees planted still exist. There is also no information about households that may have requested a tree but did not receive one. Philadelphia's database also did not maintain information about what street trees were planted during the same period of the TreePhilly program, so the study was unable to investigate the relationship between street tree plantings and residential tree plantings. Additionally, the manner in which type of properties are defined could also have affected results of land classification's effect on number of trees planted. For example, The Department of Planning and Development includes hotels, motels, and correctional facilities as types of properties under "residential high density". Ideally, these parcels would be identified and dropped from the larger classification group to focus on conventional residential properties.

With the increasing amount of attention to data collection and maintenance, future research can conduct a richer, more nuanced study addressing these limitations to better understand the environmental justice situation and implications of the City of Philadelphia's greening efforts.

Appendix

Figure 1: Univariate Maps of Variables of Interest



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