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Geospatial Modeling of Urban Tree Cover Inequalities in Connecticut Cities

Hiruni Witharana

Edwin O Smith High School, 1235 Storrs Rd, Storrs, CT, 06268, USA; hiruwitharana08@gmail.com
Mentor: Mayra I. Rodriguez Gonzalez

ABSTRACT: The goal of this study is to model the driving factors behind urban tree canopy cover disparities in West Hartford (WH), East Hartford (EH), and Hartford (HT), Connecticut. The first objective involved a statistical analysis using socioeconomic variables and the current percent tree canopy cover (PTCC) from 197 census blocks in WH, EH, and HT. The second objective entailed performing a geospatial analysis using 70-year time series aerial imagery (1952-2021) for two case-study census blocks in EH and WH. The results from the census block-level analysis of WH, EH, and HT revealed a negative correlation between the PTCC and ethnicity ($R = -0.461$), PTCC and income level ($R = -0.435$), PTCC and land surface temperature ($R = -0.859$), and PTCC and health burden ($R = -0.371$). Additionally, the aerial image analysis results between the two case-study sites revealed a significant difference in PTCC ($p < 0.05$) for all years considered. These findings support our hypothesis that past discriminatory practices, such as redlining, may have a legacy effect on present-day tree canopy cover.
KEYWORDS: Earth and Environmental Sciences, Geosciences, Tree Canopy Demographics, Geospatial Analysis.

Introduction

Urban populations are rising, posing new challenges in a changing climate. Already, over 55% of the global population resides in cities.[1] In the United States, cities harbor nearly 81% of the population.[2] Increased urbanization can lead to diverse employment opportunities, but has also contributed to significant environmental degradation. Urbanization has led to heightened air and water pollution, habitat loss, land degradation, and greenhouse gas emissions.[3] Studies have shown that these conditions significantly affect the health and well-being of urban communities.[4] A key solution to restoring these damages is to increase the concentration of urban tree cover (UTC) in cities.[5]

Urban trees, widely recognized as green infrastructure, offer a myriad of benefits to city residents, including biophysical, economic, individual health, and social cohesion.[6] Trees can improve air quality by absorbing and intercepting airborne pollutant particles, such as carbon dioxide, carbon monoxide, and sulfur dioxide.[7] Studies suggest that lower concentrations of pollutant particles exist in areas with a higher tree density.[8,9] Beyond their role in improving air quality, trees contribute to increased biodiversity and mitigate stormwater runoff by retaining water in their root systems, where excess nutrients, such as nitrogen and phosphorus, along with other pollutants, can be filtered and removed.[10,11] Increasing urban tree cover density has also reduced quantities of surface runoff left over from storms. However, the capacity of trees to manage stormwater is species-dependent, with variations in root architecture and leaf surface area significantly influencing rates of water interception, infiltration, and uptake.[12]

Simultaneously, urban trees can enhance communities' overall mental and physical health by promoting time spent outdoors and fostering social interaction with community members.[13] Various research groups have documented a positive association between resident mental health and urban tree cover (UTC).[14] Such findings suggest that trees may reduce residents' anxiety levels.[15] Moreover, increasing the density of UTC in residential neighborhoods can significantly improve the overall emotional well-being of a community. In addition to its benefits towards mental health, urban trees play an equally significant role in one's physical health. Urban greenery encourages outdoor exercise, which benefits one's physical health. Additionally, participating in outdoor activities in a shared green space can enhance social connectivity among community members.[16]

Trees are known to reduce energy costs by providing shade to homes and increasing property value, making it important to consider where they are planted.[17,18] When trees are planted strategically, they help lower surface temperatures, often counteracting the formation of heat islands. Heat Islands are urban areas with higher surface temperatures than nearby communities. Trees can help reduce heat islands by preventing solar radiation from being absorbed by sidewalks, buildings, and other concrete infrastructures.[19] Studies suggested that increasing average percentage of urban tree cover could decrease daily surface temperatures and electricity bills.[20,21] For instance, researchers in South Korea found that increasing urban tree canopy cover in a neighborhood by 60% lowered the daily average temperature by 5.23 °C. Thus, the presence of trees in cities is crucial to fostering a safer and cleaner living environment. Alongside reducing energy costs, trees can also increase property values. Researchers have observed a positive association between tree cover density and property values.[22,23] Such a relationship showcases the economic value of urban trees' ecosystem services in urban communities.

Despite its benefits to the natural and human environment, urban tree cover remains disproportionately distributed in most American cities.[24] Urban tree cover disparities within U.S. cities are often associated with race, income, and population density.[7] As a result, urban communities across the U.S. that lacked access to urban tree cover were often identified as either low-income or non-white.[25,26] These findings indicate that communities of color or low-income overall are less likely to access the financial, health, and environmental benefits of urban tree cover.

Urban tree cover (UTC) disparities are primarily linked to sociopolitical history, especially redlining.[10] Redlining was a discriminatory practice exercised in the 1930s that prevented people of color or low-income individuals from taking out loans on property outside their residential neighborhood.[27] Studies suggest that the historical practice of redlining did have a legacy effect on present-day tree cover in U.S. cities.[7,28] The Home Owners' Loan Corporation (HOLC) assigned grades to neighborhoods to inform investors of their perceived value, providing the foundation for many redlining policies. With communities graded D (the HOLC grade for hazardous; heavily redlined) having comparatively lower percent UTC than A-graded communities (the HOLC grade for best; least redlined), redlining may have promoted intergenerational disparities in access to UTC benefits.

Finding answers to the complex question of 'what drives urban tree cover inequalities in cities?' requires long-term observations of tree cover change across space and time because some drivers are legacy effects of past activities. Among the questions that arise when studying UTC disparity is: what was the tree canopy cover a decade(s) ago? Where in the city disparities exist(ed), and how have these changed over time? In this context, remote sensing observations, especially modern and historical aerial images dating back to the early 1930s, can capture long-term trends in urban tree cover within and among cities, offering unique opportunities to link tree cover change with cities' sociopolitical history. Researchers have successfully utilized remote sensing-based approaches to study UTC disparities in cities across the globe.[29–31] For instance, Merry *et al*.[32] quantified the change in urban tree cover in Atlanta, Georgia, by identifying the total area of tree canopy crowns in a selected area of each aerial image from 1951 to 2010. Jung *et al*.[33] conducted a study in Philadelphia, Pennsylvania, and Portland, Oregon, using multitemporal satellite imagery to analyze changes in UTC growth. Similarly, Canetti *et al*.[34] used high-resolution satellite images (5m) to observe changes in UTC from 2005 to 2012 in Araucaria Parana, Brazil.

Connecticut is among the many states in the U.S. that offer a free and publicly accessible aerial imagery archive, with images dating from 1934 to the present. This extensive time frame, coupled with time series aerial images, provides a unique opportunity to study long-term trends in UTC changes and offers valuable resources for research. The goal of this project was to determine whether time-series aerial imagery (both modern and historical) could be used to track urban tree cover changes over decades. We pursued two vertically integrated objectives, each with specific hypotheses. The first objective is to understand the drivers of present-day tree cover inequality and its subsequent consequences. Three research questions guided this objective: 1) What is the relationship between tree canopy cover distribution and socioeconomic variables? We hypothesize that disparities in urban tree cover are linked to socioeconomically marginalized neighborhoods. 2) How can the relationship between urban tree canopy cover distribution and land surface temperature be modeled? We hypothesize that variations in land surface temperature correlate with tree canopy cover. 3) What is the relationship between urban tree canopy cover distribution and human health? We hypothesize that higher-level health burdens are associated with areas with less tree canopy coverage.

The second objective explored how historical and modern aerial imagery could be utilized to analyze changes in urban tree canopy cover from the early 1950s to 2021. Two research questions also guided this objective: 1) How can multitemporal aerial imagery quantify tree canopy cover change over time? We hypothesized that these images can effectively map and study changes in tree canopy cover over time. 2) How have past discriminatory practices like redlining left legacy effects on present-day tree canopy cover? We hypothesized that redlining has been a significant factor in driving current disparities in tree canopy distribution.

Methods

Study Area:

The study area selected three towns in Connecticut: 1) Hartford, 2) East Hartford, and 3) West Hartford based on socioeconomic and demographic criteria, including income, ethnicity, built-up density, and sociopolitical history (Figure 1). Our analysis was conducted at the census block level within this region (Figure 3). Table 1 provides an overview of the general characteristics of the census blocks in the study area.

In the 1930s, redlining became widespread in many U.S. cities, including Hartford. This discriminatory urban planning practice led to stark disparities between neighborhoods. Nonwhite neighborhoods were systematically deprived of essential resources and were often in far poorer conditions compared to white neighborhoods. Redlining policies denied people of color the opportunity to move into white neighborhoods. The Homeowners Loan Corporation (HOLC) assigned grades to neighborhoods to guide investors on their value. These grades ranged from **A**, representing the "Best" (typically white neighborhoods), to **D**, deemed "*Hazardous*" (often nonwhite neighborhoods). As a result, neighborhoods graded **D** may have received significantly less financial support from the federal government compared to higher-graded areas.

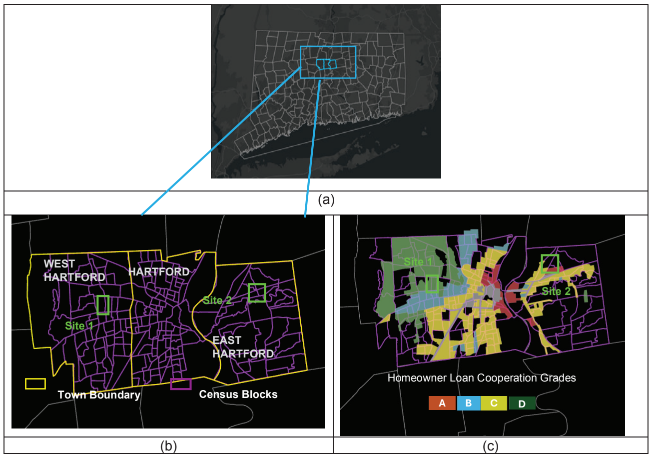

Figure 1: Study area map. (a) Town map of the State of Connecticut. (b) Census blocks of Hartford, East Hartford, and West Hartford (middle). (c) Redlining zones overlay on census blocks (bottom). Green hollow boxes show the two candidates' census blocks (Site-1 and Site-2) selected for multitemporal image analysis.

Table 1: General characteristics of census blocks from three candidate towns.

Town	Number of Census Blocks	Population	Median Income
East Hartford	41	50971	$65,925
Hartford	93	121562	$37,037
West Hartford	62	64034	$132,163

Approach and Data Analysis:

Figure 2 exhibits the overall experimental design. To address Objective 1, we downloaded demographic data on population, median income, and ethnicity from the US Census Bureau. We also obtained data on surface temperature differences, health burdens, and current tree canopy distribution from American Forests. Additionally, we used data portals such as Living Atlas and CT GEODATA to identify census-block study sites in West Hartford and East Hartford and to access data on HOLC grade overlays within the study area.

We then identified a set of explanatory variables to develop individual regression models, with tree canopy coverage as the response variable (Table 2). The explanatory variables included the percentage of people of color, people in poverty, normalized surface temperature differences, and normalized health burden.

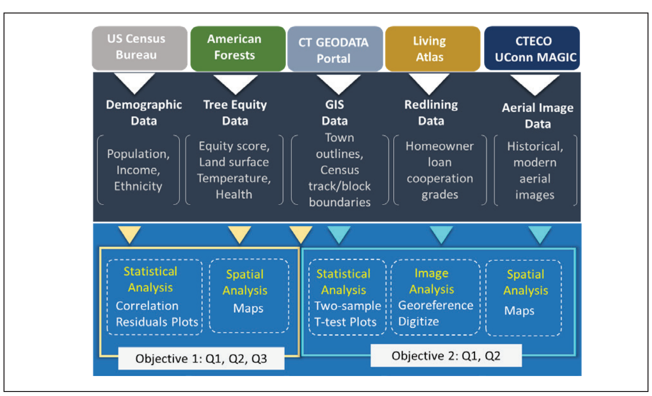

Figure 2: Simplified process diagram of the experimental design and analysis methods. Q1, Q2, Q3 depict the research questions.

Table 2: Variables selected for linear regression models.

Response Variable	Explanatory Variable
% Tree Canopy Coverage	% People of Color
	% People in Poverty
	Normalized temperature difference
	Normalized health burden

To address Objective 2, we selected two case-study census blocks from West Hartford (Site 1 (WH)) and East Hartford (Site 2 (EH)) for detailed investigation (Figure 3). We chose these sites to reflect differences in ethnicity, income level, and the impact of past discriminatory practices, such as redlining. Site 1 represents a predominantly white, high-income neighborhood, while Site 2 is a predominantly low-income neighborhood with a significant population of people of color (Table 4). According to the Homeowner Loan Corporation (HOLC) Grades (Table 5), Site 2 falls within a redlined zone. Until the 1968 Fair Housing Act, this discriminatory practice withheld financial services from neighborhoods with significant racial and ethnic minority populations.

We downloaded aerial images from 1934 to 2021 from the UConn MAGIC and CTECO databases for both study sites (Table 3). Accurate calculation of Percent Tree Canopy Cover (PTCC) requires precise delineation of tree crowns, so we focused on images taken during the leaf-on season (summer) for analysis (highlighted in Table 3). Our dataset included time-series images from 1952, 2006, 2014, and 2021.

While the 2006, 2014, and 2021 images were already georeferenced, the 1952 images were not. To address this, we used GIS software (ESRI ArcGISPro, Redlands, CA) to georeference these images, assigning geographical coordinates relative to a reference image or map containing a spatial reference system.[35] We identified landmarks such as road intersections and buildings in reference and candidate images to assign these coordinates.

Once all images were georeferenced, we randomly generated 30 points for each site, ensuring a minimum separation of 30 meters between points. Each point was buffered by 25 meters. Using GIS software, we manually digitized urban tree canopy cover within each of these circular plots as polygons (see yellow circles in Figure 4 and Figure 5). This digitization was performed for each selected year and both study sites. The PTCC for each circular plot was calculated by dividing the total average area of tree cover in each site by the total area of land, then multiplying by 100 (as shown in Equation 1). Finally, we used a two-sample t-test to compare PTCC between Site 1 (WH) and Site 2 (EH) for each year, identifying whether the difference in PTCC was statistically significant (Figure 10).

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Figure 3: Thirty random sampling locations from each study site: (a) West Hartford and (b) East Hartford. Randomly selected points are shown in red dots with 25m buffer zone depicted as yellow circles.

Table 3: Characteristics of multitemporal aerial images. Rows highlighted in orange indicate the images used to address Objective 2.

Acquisition Year	Leaf Status	Spectral Bands	Spatial Resolution	Georeference Status	Source
1934	Leaf Off	Grayscale	~1m	No	UConn MAGIC
1952	Leaf On	Grayscale	~1m	No	UConn MAGIC
1970	Leaf Off	Grayscale	~1m	No	UConn MAGIC
1986	Leaf Off	Grayscale	~1m	No	UConn MAGIC
1990	Leaf Off	Grayscale	~1m	Yes	CTECO
2004	Leaf Off	Grayscale	~1m	Yes	NAIP/CTECO
2006	Leaf On	Color	~1m	Yes	NAIP/CTECO
2008	Leaf On	Color	~1m	Yes	NAIP/CTECO
2010	Leaf On	Color	~1m	Yes	NAIP/CTECO
2012	Leaf On	Color	~1m	Yes	NAIP/CTECO
2014	Leaf On	Color	~1m	Yes	NAIP/CTECO
2016	Leaf On	Color	~1m	Yes	NAIP/CTECO
2018	Leaf On	Color	~1m	Yes	NAIP/CTECO
2021	Leaf On	Color	~1m	Yes	NAIP/CTECO

Table 4: Two candidate census blocks used in Objective 2.

Candidate census block	Median income ($)	% People of color
Site 1	190,952	15
Site 2	41,640	91

Table 5: Homeowner Loan Corporation Grades.

Zone Grade	Grade Descriptions
A	"Best"
B	"Still Desirable"
C	"In Decline"
D	"Hazardous"

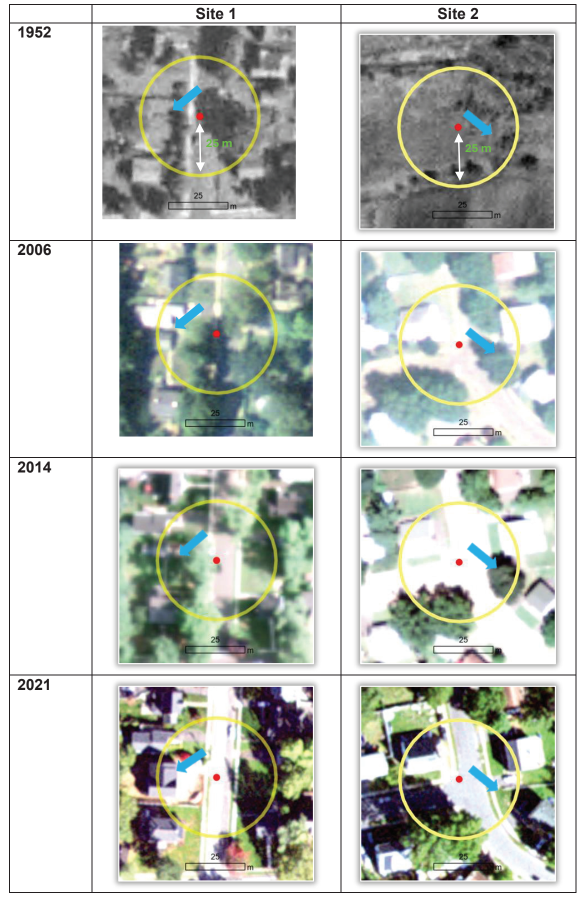

Figure 4: A rendition of time series aerial imagery. Zoomed-in views of two random locations (red dots) with a 25m buffer zone (yellow circle) selected from Site-1 (right row) and Site-2 (left row). Tree canopy cover observed in the East Hartford site did not increase significantly from 1950 to 2021. Conversely, tree canopy cover increased at a greater rate in the West Hartford site throughout the same period.

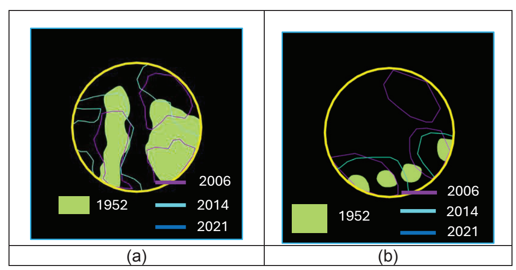

Figure 5: Overlay of manually digitized tree cover extent from multi-year images of a randomly selected point from (a) Site 1 West Hartford, (b) Site 2 East Hartford. The tree canopy cover in the West Hartford site maintained consistently high canopy cover during the 1950-2021 period. The East Hartford site consistently reported low canopy cover throughout this same period.

$$\text{Tree Canopy Cover \%} = \left(\frac{\text{AREA}_{(\text{Trees})}}{\text{AREA}_{(\text{Land})}} \right) * 100$$

Equation 1: The formula used to calculate the PTCC over time in each circular plot of the two study sites (Site 1 and Site 2). To calculate PTCC, the total average area of tree cover in each circular plot must be divided by the total area of land, and then it should be multiplied by 100.

Result and Discussion

Objective 1 Results:

We found a negative correlation between the percentage of people of color (POC) and the percentage of tree canopy cover (PTC). As the percentage of POC in a neighborhood increases, the PTC decreases accordingly (Figure 6). The strength of this association is relatively moderate, with an R-value of -0.461 and an R^2 value of 0.212. According to our linear model, the percentage of people of color explains at least 21.2% of the variability in tree canopy coverage.

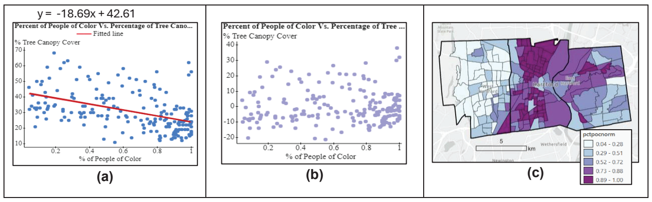

Figure 6: **(a)** A scatterplot of % people of color vs. %tree canopy cover **(b)** A residual plot between %people of color and %tree canopy cover **(c)** A census block level map of %people of color. There is a negative correlation between the percentage of people of color and the percentage of tree canopy cover. As the percentage of people of color in a community increases the percentage of tree canopy cover correspondingly decreases.

We also discovered a negative correlation between the percentage of people living in poverty and the percentage of tree canopy cover (Figure 7a). The strength of this association is relatively moderate, with an R-value of -0.435 and an R^2 value of 0.189. According to our linear model, at least 18.9% of the variability in the percentage of tree canopy cover can be explained by the percentage of people in poverty.

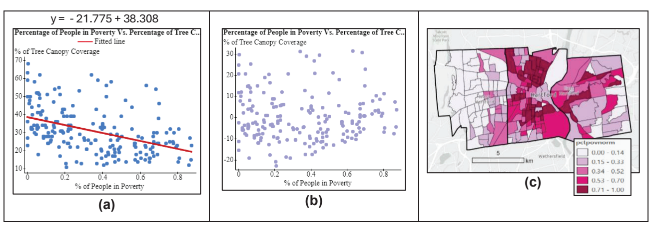

Figure 7: **(a)** A scatterplot of %people in poverty vs. %tree canopy cover **(b)** A residual plot between %people in poverty and %tree canopy cover **(c)** A census block map of %people in poverty. There is a negative correlation between the percentage of people in poverty and the percentage of tree canopy cover. As the percentage of people in poverty in a community increases the percentage of tree canopy cover correspondingly decreases.

Surface temperature difference within a neighborhood similarly showcases a negative correlation with the percentage of tree canopy cover (Figure 8a). The strength of this association is strong, with an R-value of -0.859 and an R^2 value of 0.738. According to our linear model, at least 73.8% of the variability in the percentage of tree canopy coverage can be explained by temperature difference.

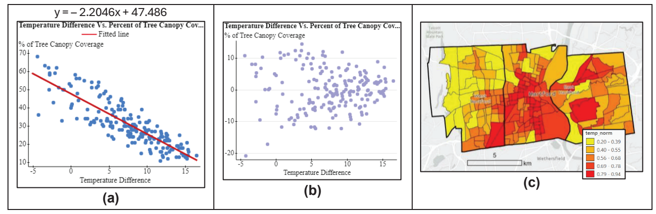

Figure 8: **(a)** A scatter plot of %surface temp difference vs. %tree canopy cover **(b)** A residual plot between %surface temp difference and %tree canopy cover **(c)** A census block level map of %temp difference. There is a negative correlation between the percentage of surface temperature difference and the percentage of tree canopy cover. As the percentage of surface temperature difference increases, the percentage of tree canopy cover correspondingly decreases.

A negative linear association exists between the percentage of health burden and the percentage of tree cover (Figure 9a). The strength of this association is relatively moderate, with an R-value of 0.371 and an R^2 value of 0.138. According to our linear model, the percentage of health burden explains at least 13.8% of the variability in tree canopy coverage.

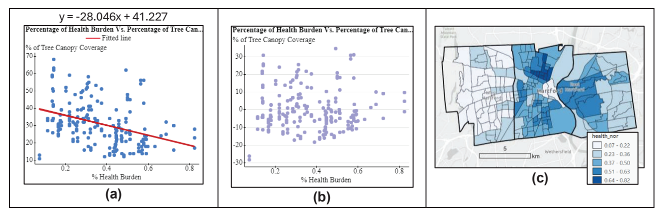

Figure 9: **(a)** A scatter plot of %health burden vs. %tree canopy **(b)** A residual plot between %health burden and %tree canopy cover **(c)** A census block level map of %health burden. There is a negative correlation between the percentage of health burden and the percentage of tree canopy cover. As the percentage of health burden increases the percentage of tree canopy cover correspondingly decreases.

Objective 2 Results:

A pairwise comparison of the percent canopy cover in each year interval was created to display significant differences between the two study sites (Figure 10).

In Site 1 (West Hartford), 1952, the mean tree canopy cover was 47.38%. Over the past 54 years, the value has decreased by 3.28%. By 2006, the tree canopy cover was 44.1%. In 2014, the average percentage of tree cover slightly increased to 46.35%. However, in 2021, the mean percentage of tree cover slightly decreased to 34.63% (Figure 10).

In 1952, the mean tree canopy cover in Site 2 (East Hartford) was 5.91%. Over 54 years, the mean value increased to 12.82%. By 2014, the canopy cover declined by 5.77%, with a resulting mean percentage of 7.05%. In 2021, the average tree cover percentage slightly decreased to 5.97%. (Figure 10)

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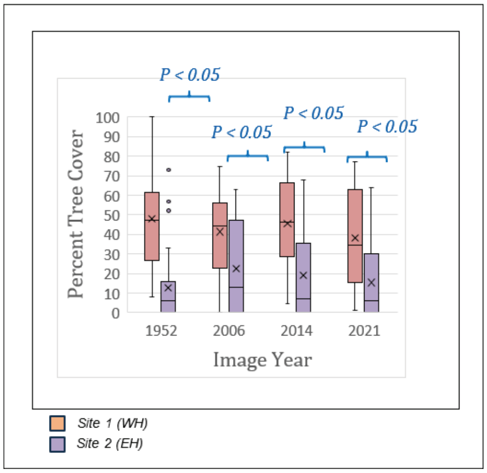

Figure 10: A comparison of PTCC was calculated based on 30 random plots from Site 1 and Site 2 from 1952 to 2021. P-values indicate the significance of pairwise comparisons based on t-tests.

Discussion:

Results suggest that neighborhoods with a higher percentage of people of color and a higher percentage of people living in poverty have lower percentages of tree canopy cover. This disparity may stem from the high costs of tree planting and maintenance, which are often beyond the financial means of marginalized communities. On the other hand, the greater proportion of rental residences in such neighborhoods may prevent residents from planting more trees, as the responsibility for communal afforestation is often unknown. Ultimately, the legacy effects of policies like redlining could have long-term impacts on these communities.[27]

The aerial imagery analysis of Site-2 (EH) revealed that throughout the 70-year observation period (1952-2021), the average percentage of tree canopy cover was 7.94%. Conversely, in Site-1 (WH), the mean tree canopy cover was 43.12%. The tree canopy cover of Site-1 stays relatively consistent throughout the 70 years. Figure 10 showcases Site-1's consistently high average percent value and low variability, indicating prevalent urban tree planting amid increasing urban development over this timespan. In contrast, Site-2 (Figure 10) shows a consistently low canopy cover, high variability, and an overall negative trend across the 70 years. The results could potentially highlight the low level of attention paid to tree planting. The three key variables that differed between the two sites were ethnic composition, income, and the discriminatory practice (redlining zone). Site-1 was labeled Zone-D for redlining and had a high %POC. Site-2 was labeled Zone-A for redlining and had a high percentage of Caucasian people (low %POC). Previously, we hypothesized that the mean percentage of tree canopy cover between the two census blocks for each selected year would be statistically significant. If these values were statistically significant, this would suggest that redlining could be one variable that has a lasting effect on present-day tree canopy cover. T-tests were performed yearly for each pair of mean percent values (1952, 2006, 2014, 2021). For the two mean values to be significantly different, the p-value must be lower than 0.05. For each t-test, the p-value was less than 0.05. These findings suggest that redlining may have a lasting impact on urban tree cover in communities.

Throughout this project, several aspects could have contributed to the error. One source of error is related to the gray-scale aerial images (1952 - 2021; Table 1), which had poor image quality and spatial resolution of historical images, making it difficult to visually identify and digitize tree crowns. This often resulted in spatial uncertainties in the area estimation of tree canopy cover. One source of error comes from the gray-scale aerial images (1952–2021; Table 1), which had poor image quality and low spatial resolution, making it difficult to visually identify and digitize tree crowns. These limitations caused spatial uncertainties in estimating tree canopy cover. Therefore, image quality can impact the detection accuracy of urban tree cover. The process of georeferencing was also a potential source of error. We found it difficult to locate long-term (time-invariant) ground control points, such as roads or buildings, in many of the 1952 time series images. A further step to enhance map accuracy could have involved field validation. Image-based area measurements can be compared directly with in situ field observations.

The sample size of buffered points across both study sites may have also been another source of error. For each study site, 30 points were randomly distributed and buffered to estimate tree canopy cover. An average of these 30 points then determined the percentage of urban tree cover in each study area. The accuracy of this calculation could have been higher with a larger sample size at each site. Additional study sites in East Hartford and West Hartford with similar demographic and population criteria would also have strengthened the analysis. By expanding in this way, the results would provide more evidence of the legacy effect of redlining on present-day urban tree cover.

Aerial imagery serves as a powerful 'citizen science' data source to educate the public. The visual presentation of urban tree cover growth over time, combined with the impact of demographic and sociopolitical (redlining) variables on access to tree cover, effectively conveys that urban tree cover disproportionately affects communities of color. Additionally, aerial imagery of urban tree cover can pinpoint areas in neighborhoods where further tree planting is needed. This approach can be helpful for communities that lack access to tree cover and have decided to integrate greenery to a greater extent.

■ Conclusion

This study demonstrated that urban tree canopy cover is negatively correlated with the following variables: ethnicity, income, surface temperature, and health burden. Neighborhoods with high percentages of people of color experience noticeably higher summer temperatures compared to predominantly white neighborhoods. Similarly, health burden inversely associates with tree cover, disproportionately affecting low-income and minority communities. Results from Objective 2 showed that researchers can quantify urban tree cover using multitemporal imagery. Over the past 70 years, the study sites in East Hartford have consistently exhibited low canopy cover, whereas the West

Hartford site has maintained consistently high canopy cover. The tree canopy between the two sites differed statistically in all years, suggesting that past discriminatory practices, such as redlining, may have lasting effects on present-day disparities in tree canopy cover. Visualizing changes in urban tree canopy cover alongside socioeconomic variables raises awareness of the disparities faced by marginalized and formerly redlined communities. Additionally, using aerial imagery to identify areas for future tree planting can be highly beneficial. A potential future direction for this project involves expanding similar imagery analysis to other urban communities in Connecticut. Developing an app to educate the public about tree cover disparities and assist with tree planting programs would further enhance community engagement and action.

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■ Author

Hiruni Witharana is a Junior at Edwin O Smith High School in Mansfield, Connecticut. She is interested in pursuing a career in environmental science and engineering.