Investigating Tree Canopy Cover and Racial, Economic, and Educational Factors in Madison, Wisconsin

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Abstract: Our research analyzed the relationship between tree canopy and racial, economic, and educational factors in Madison, Wisconsin. Tree canopy is associated with mental and physical health benefits, such as urban heat and pollution reduction, and the reduction of stress-related diseases. Yet, it is often unequally distributed across demographics, precluding the equitable distribution of the subsequent health benefits. Our research uses GIS and statistical methods to analyze patterns between selected demographics and tree canopy cover. The results indicate that White, well-educated, and wealthy communities enjoy positive relationships with tree canopy, while Minority, Hispanic, poor, and less educated populations are negatively associated with tree canopy. Our findings show racial and ethnic demographics display relationships of varying strength, while economic, educational, and temporal factors are the strongest predictors of tree canopy cover.

Keywords: tree canopy, urban forestry, environmental justice, equity, environmental racism

Introduction

Tree canopy cover is an important characteristic of the urban environment and has significant implications for a community's quality of life. Access to tree canopy has consistently been shown to have positive health impacts. Tree canopy cover improves physical health by reducing surface temperature through increased shading, increased evaporation, and lowered heat absorption (Elmes et al., 2017, p. 339). One Montreal-based study found that urban parks were up to 4.5 degrees Fahrenheit cooler than other nearby urban spaces (Kelbaugh, 2019, p. 153). Reducing urban heat reduces potential health hazards such as hyperthermia, respiratory difficulties, heat exhaustion, and heatstroke (Kolosna & Spurlock, 2019, p. 215). Urban trees also improve health by reducing pollution levels within urban areas. In 2010, trees in the United States removed 17.4 million tons of air pollution. Although the most pollution is removed by rural trees, pollution removed by urban trees is more impactful on human health due to higher concentrations of pollution in urban areas. (Nowak et al., 2014, p. 124). Trees absorb fine particulate matter smaller than 2.5 microns (PM2.5), improving overall air quality. In Atlanta, trees remove 64.5 tons of PM2.5 annually, improving air quality in the city by 0.24% and preventing $1,600 in damage to human health per hectare of tree cover (Nowak et al., 2013). Furthermore, urban residents with more exposure to greenery have reduced rates of stress-related diseases (Mills et al., 2016, p. 188). Green spaces promote exercise which improves health, and urban neighborhoods with more canopy cover have lower levels of obesity, high blood pressure, and asthma (Beyer et al., 2014, p. 3454; Ulmer et al., 2016, p. 60). Not only can trees help with long-term health, but they can also make areas safer by decreasing crime and violent episodes (Frey, 2017; Kuo & Sullivan, 2001, p. 347; Schwarz et al., 2015, p. 13). Trees also have mental health benefits. Neighborhood green spaces help reduce stress, depression, and anxiety. They may also reduce mental fatigue, improve work performance, and improve community cohesion which benefits mental health (Schwarz et al., 2015, p. 2). Additionally, tree canopy coverage may improve neighborhood satisfaction (Kolosna & Spurlock, 2019, p. 215). Importantly, the mental health benefits of urban vegetation may not be uniform across a variety of demographics, and health improvements from greenspaces are more pronounced in poor and elderly communities (Beyer et al., 2014, p. 3454).

The health impacts of tree canopy cover, along with environmental justice concerns from historic and contemporary racial segregation, warrant further investigation of demographic relationships with tree canopy. The consequences of redlining, the racist practice of designating minority communities as “declining” and thus depriving them of investment, have persisted long after the practice ended. Urban heat islands more readily occur in areas that were formerly designated as “declining” (class D), experiencing higher mean land surface temperatures (Wilson, 2020, p. 450). Additionally, a national examination of heat risk-related land cover (HRRLC) found that HRRLC increased alongside levels of racial segregation (Jesdale et al., 2013, pp. 811, 814–815). Understanding that tree canopy cover has large mitigating impacts on urban heat, these findings indicate that disparities in tree canopy probably negatively impact minority communities because of racist historical practices (Elmes et al., 2017, p. 350). Numerous studies throughout the US have implicated race as a predictor of tree canopy, alongside education, and income (Cendrowski, 2019, p. 4; Schwarz et al., 2015, p. 12; Zhou & Kim, 2013, p. 94). However, the correlated variables which influence tree canopy cover vary from city to city, and it is not feasible to use results from one city to affect change in another.

Madison, Wisconsin is a small Midwestern city situated on an Isthmus, between Lake Mendota to the north and Lake Monona to the south, with a population of approximately 250,000 residents. Although contemporary Madison is perceived to be forward-thinking and progressive, like much of the US, it has a history of pushing Black communities and other ethnic groups into their own enclaves. The practices of redlining and annexing parts of the city to control non-White populations were unfortunately prevalent and continue to impact contemporary population distributions (Robinson, 2018, pp. 48–49). The reality of Madison's racial inequality, the health impacts of tree canopy, the implications of race, income, and education as predictors of tree canopy, and the uniqueness of each city's interactions between these variables create a unique opportunity for study. We may predict that tree canopy in Madison is unequally distributed, but we cannot understand precisely how and where those distributions are unequal.

In this paper, we investigate **how levels of tree canopy change with racial/ethnic, economic, and educational factors in the Madison metro area.** Specifically, we analyze the proportions of race/ethnicity, educational attainment, median and bracketed income levels, and the possible confounding variables of building age, housing tenure, median rent, property value, and resident age. We calculated these values for both 2015 and 2020, to understand how these relationships have changed over the five-year period. We use geographic information systems (GIS) to derive tree canopy percentage values, and statistically analyze these with demographic data to quantify these relationships. Our aim is to facilitate remediation of disparities within Madison through identification and quantification. Our study is, therefore, specific to Madison. However, our methodology is generalizable to other studies of tree canopy cover, and we believe it produces the most accurate results able to be derived from publicly available information.

The research area includes the City of Madison, Village of Shorewood Hills, Village of Maple Bluff, and the City of Monona. The Villages of Shorewood Hills and Maple Bluff, and the City of Monona, create a contiguous region and belong to the de facto Madison geography (see Figure 1). Additionally, the two villages have stark demographic differences from the surrounding area and provide the opportunity to compare Madison with municipalities that share the same physical geography. There were no known areas in our region of study that posed an issue to our data collection. We use Census block groups as the area unit for our GIS analysis and Jenks/Natural Breaks for our map symbology.

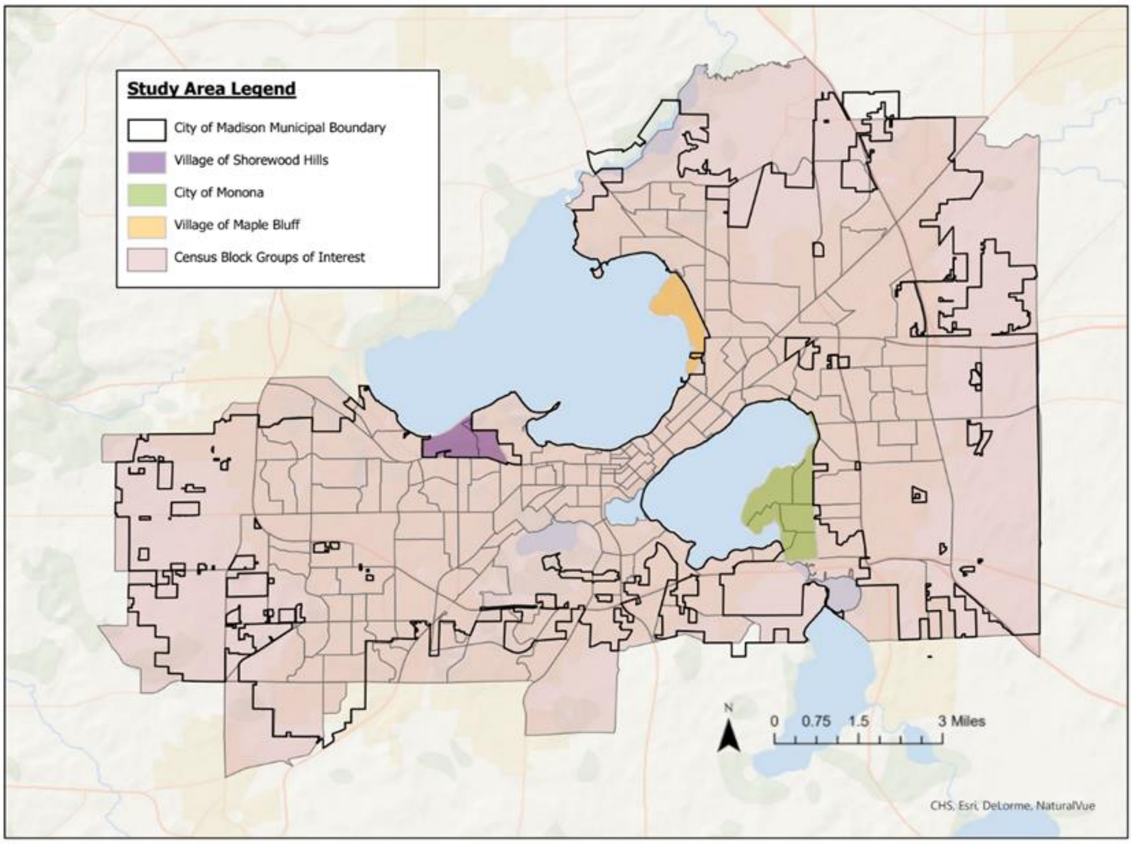

Figure 1: Map of the Study Area - Composed of the Cities of Madison (pink) and Monona (green), and the Villages of Maple Bluff (orange) and Shorewood Hills (purple).

Materials and Methods

We used Tiger/Line block group shapefiles, trimmed to the research area, as our base layer of geographic analysis. We use American Community Survey data from 2015 and 2020 for our demographic data (US Census Bureau, 2015, 2020). As we analysed both 2015 and 2020 data, two different Tiger/Line boundary data files were used – one for each year. We use a combination of state, county, and municipal open data portals to obtain data layers of building footprints, lakes, rivers, parks, and golf courses (City of Madison, 2022a, 2022b; Dane County, 2022a, 2022b, 2022c, 2022d; Wisconsin Department of Natural Resources, 2022a, 2022b). Parks and golf courses not included in these data layers were added to the layer by tracing the OpenStreetMap base map and cross-checking with Google Maps. We obtained 2020 high-resolution LiDAR-derived tree canopy data from Land INFO LLC in two vector data sets (Land INFO LLC, 2020). Using ArcGIS, we projected each data layer to Universal Transverse Mercator (UTM) Zone 16N coordinates to ensure measurement accuracy.

We controlled for buildings, water, parks, and golf courses by removing the area from our calculations. Using ArcGIS Pro, we intersected the different control data layers to eliminate double counting. We removed water area from the parks and golf courses data layers, and we removed building footprints on parks and golf courses from the building footprints data layer. After intersecting, we rasterized each layer to .25 m^2 cells. We used the extract by mask tool with the Tiger/Line block group shape file as the base layer and the water, parks/golf courses, trees, and buildings data files as the mask layers. This allowed us to maintain the unique geographic identifier (GEOID) of each block group in the extracted data of each feature; this is crucial to the subsequent analysis. This step was conducted for both 2015 and 2020 boundaries. To control for trees in parks and golf courses, we identified trees within those boundaries and subtracted their area from our total tree canopy area calculations. Madison has the highest number of parks per capita in the U.S. (*Annual City Parks Data Released by The Trust for Public Land*, 2011), and 95 percent of residents live within a ten minute walk from a park (*ParkScore - Madison, WI*, 2022). Controlling for trees within parks and golf courses will provide a more accurate analysis of tree canopy distribution in residential areas. Using the area of the extracted data layers (each raster cell is .25 m^2), we calculated the percent of tree canopy in each census block group. A mathematical summary of our tree canopy calculations may be found below in Figure 2.

$C_n = Area\ of\ Census\ Block\ Group$

$W_n = Area\ of\ Lakes\ and\ Rivers$

$B_n = Area\ of\ Building\ Footprints$

$P_n = Area\ of\ Public\ Parks$

$G_n = Area\ of\ Golf\ Courses$

$n\ =\ Denotes\ an\ Individual\ Census\ Block$

$$A_n = C_n - W_n - B_n - P_n - G_n$$

Where $\boldsymbol{A_n}$ is the area of the census block without water features, building footprints, public parks, or golf courses areas.

$T_n = Area\ of\ Tree\ Canopy$

$T_{Pn} = Area\ of\ Trees\ in\ Public\ Parks$

$T_{Gn} = Area\ of\ Trees\ in\ Golf\ Courses$

$$R_{Tn} = \frac{(T_n - T_{Pn} - T_{Gn})}{A_n}$$

Where $\boldsymbol{R_{Tn}}$ is the proportion of tree canopy cover per census block, **excluding** area covered by water features, buildings, public parks, and golf courses.

Figure 2: Mathematical representation of percent tree canopy calculations.

After calculating the percentage of tree canopy in each census block, we combined these values in a vector shape file along with our prepared demographic data tables. We exported the completed shape file for use in Stata to conduct our statistical analyses. The results of this process were two shape files, one for 2015 boundaries and demographics and one for 2020. We incorporated the shape files into Stata and conducted univariate analyses on our variables. We used 67 variables which were part of both the ACS 2015 and 2020 data sets; a full list of these variables is available in the appendix. These variables were divided into five categories: basic demographics (i.e., population, gender, age), race and ethnicity, income, education, and housing. Most of these variables posed no issues to statistical analyses, having adequate sample sizes. However, many of the individual grade level attainment variables (e.g., kindergarten) had very small sample sizes, presenting a barrier to their statistical usefulness. This was also true of the American Indian / Alaskan Native and Native Hawaiian / Pacific Islander racial demographics, and these facts are ultimately represented by very large P-values in our bivariate analyses.

Our bivariate analyses consisted of three different methods, ordinary least squares (OLS) regression, spatial autoregression (SAR), and multiple regression analysis, using tree canopy percentage as the dependent variable and demographic variables as the independent variable. First, we performed OLS regressions using individual demographic variables in each census block group. We then performed spatial autoregression, using generalized spatial two stage least squares estimation, between tree canopy percentages and individual demographic variables. We also performed multiple OLS regression analysis to supplement our individual regression analyses; however, as most of our variables are proportions of a total, this method proved to be less useful and merely helped to confirm our findings rather than provide new insight. We ranked each variable on three factors – standardized regression coefficient (Beta coefficient), P-value, and R^2 value - using OLS regression results (our OLS regression and SAR results were nearly identical) and summed the rankings to create an index for variable comparison (see Table 6 in the appendix).

Results and Analysis

Results: GIS

The GIS processes outlined in the methods section were run twice to produce maps that visualize percent canopy cover for the 2015 and 2020 census block group boundaries. As we were unable to obtain canopy cover data for 2015, we used the 2020 canopy cover data for each map with their respective boundary data. Seeing how the canopy cover is spatially distributed enables our study to identify and analyze patterns and outliers. Between 2015 and 2020, the City of Madison and surrounding area experienced significant population growth and change. In 2015, the approximate population of the study area was 287,000. In 2020, the estimated population was 305,000, an increase of six percent from five years earlier. Figures 3 and 4 show the changes in boundary the distribution of canopy cover across census block groups. The 2020 results revealed that most census blocks groups with higher percent canopy cover were in the near west neighborhoods of Madison, the Maple Bluff area, and the Monona area. The Census block groups with lower percent canopy cover were mainly found in the downtown area of Madison and scattered about the far east and west portions of Madison (see Figure 3).

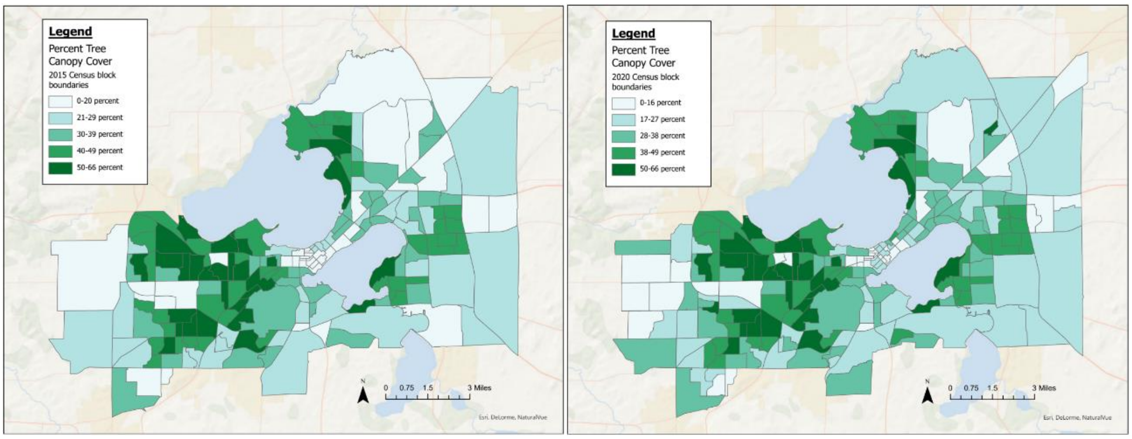

Figure 3: Percent canopy cover using 2015 Census block group boundaries (left) and 2020 Census block group boundaries (right).

Results: Housing Demographic Factors

We are highlighting a few important results of the many housing demographics. A complete list of statistical results can be found in Table 1 of the appendix. The housing demographics we investigated revealed that housing tenure was the greatest predictor of tree canopy cover across both 2015 and 2020. Between the two years, the results for owner occupied housing were extremely consistent, and both had p-values of 0.000, large R^2 values (> 0.278), and large beta coefficients (> 0.527). In Madison, renter occupied housing predominantly exists where there are low percentages of percent canopy cover (see Fig. 4). One example of this is in the downtown Madison area, where there are large concentrations of renters and nearly the lowest percentages of canopy cover. Residents in Madison that own homes in older neighbourhoods are significantly advantaged regarding tree canopy cover compared to those that do not own homes and live in apartments/developing areas. This is likely due to the rapid development in the Madison area consisting of the construction of many new multi-use apartment buildings, cutting down older trees to make way for new apartment blocks and infrastructure. This development is also probably linked to the observed changes in the structure age variable. Structure age became more significant in 2020

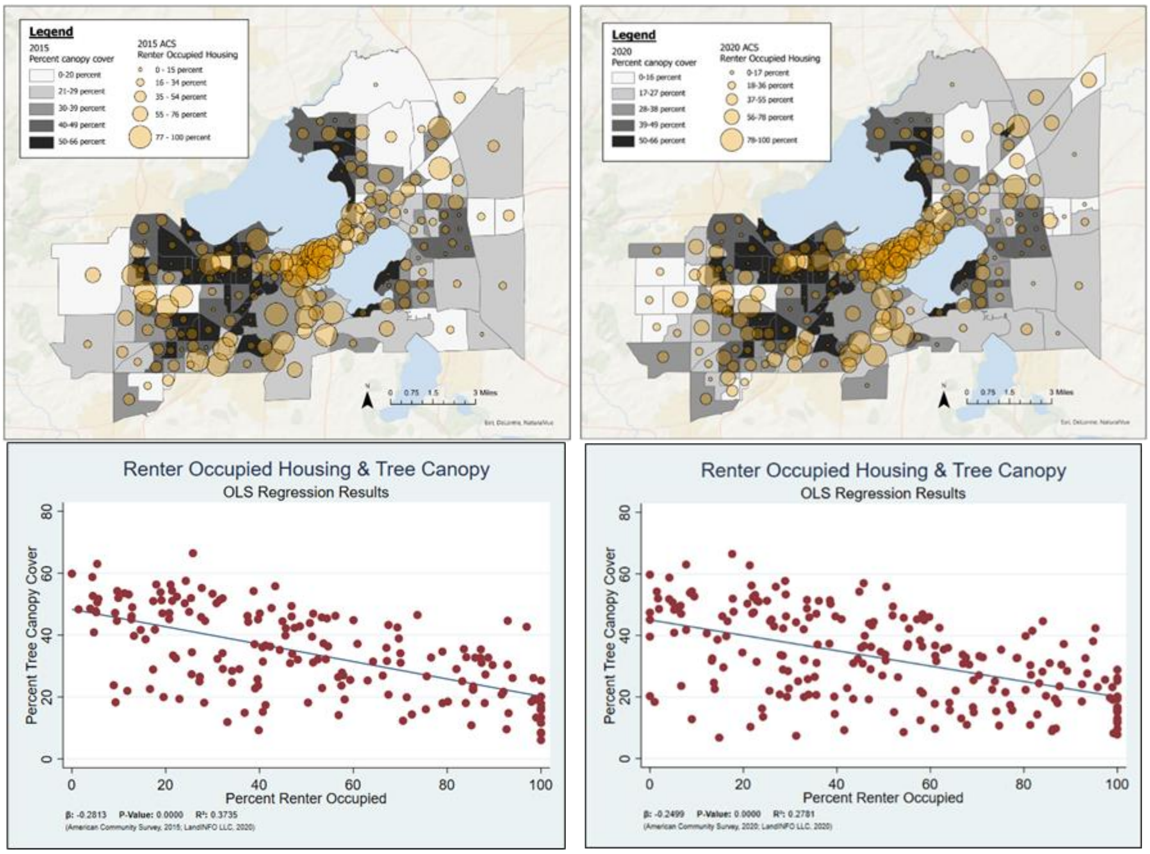

Figure 4: Renter-occupied housing and tree canopy cover map and regression results using 2015 ACS data and 2020 tree canopy data (left). Renter-occupied housing and tree canopy cover map and regression results using 2020 ACS data and 2020 tree canopy data (right).

compared to 2015 and the results showed a strong negative relationship between median structure age and canopy cover, indicating that older structures have more tree canopy. The 2015 results analyzing the median year structures were built had a beta coefficient of -0.3951, an R^2 of 0.156, and a p-value of 0.000 compared to the 2020 statistical results which had a beta coefficient of -0.4801, R^2 of 0.231, and p-value of 0.000. Another strong predictor of canopy cover was property value. In 2015 and 2020, property value was the fifth strongest predictor on our compiled list of 67 ranked variables. The 2015 property value statistical results produced a very large beta coefficient of 0.46697, R^2 of 0.218, and p-value of 0.000 compared to the 2020 property values results with a beta coefficient of 0.3858, R^2 of 0.149, and p-value of 0.000. These results confirm consistently strong, significant, and positive relationships in both years.

Results: Income Demographic Factors

Individual income demographic results can be found in Table 2 of the appendix; the following results section will highlight some important variables. Median household income had a strong positive relationship with canopy cover in both 2015 and 2020 but decreased in significance on our list of ranked variables, falling from second place to fourth (see Figure 5).

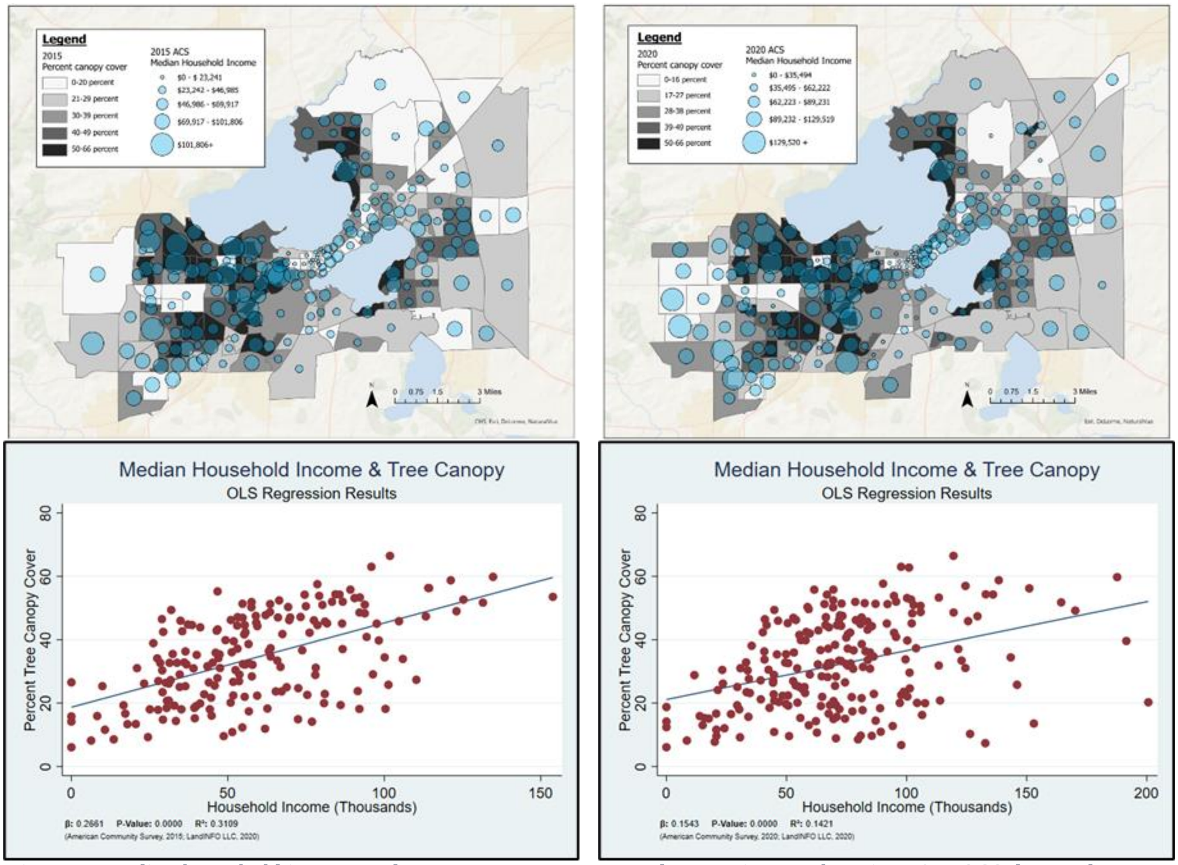

Figure 5: Median household income and tree canopy cover map and regression results using 2015 ACS data and 2020 tree canopy data (left). Median household and tree canopy cover map and regression results using 2020 ACS data and 2020 tree canopy data (right).

The statistical results for 2015 median household income produced a beta coefficient of 0.5575, R^2 of 0.311, and p-value of 0 compared to the 2020 results with a beta coefficient of 0.377, R^2 of 0.142, and p-value of 0. Although it decreased in significance, it is still highly important, with very large rate of change and explanatory value. In addition to median household income, we analyzed the relationship between income brackets. The brackets were broken into \$5,000 increments and range from less than \$10,000 to \$200,000+, each measured as a percent of the total census block group population earning within the bracket. We found that the lower income brackets had strong negative relationships with canopy cover whereas higher income brackets had a strong positive relationship with canopy cover. The change in relationship from negative to positive relationship noticeably occurs between the \$60-\$75,000 range. The change in the beta coefficients across income brackets reveals this pattern extremely well (see Table 4). Canopy cover and income have been shown to be very closely related in other studies, but the brilliantly clear manifestation of this relationship in our results is remarkably straightforward. Finally, the proportion of the population living in poverty is a variable that had a strong predictive quality, rate of change, and was statistically significant between 2015 and 2020, producing a strong negative relationship between the variable and canopy cover. The statistical results for 2015 population in poverty produced a beta coefficient of -0.4466, R^2 of 0.1995, and p-value of 0.000, while 2020 produced a beta coefficient of -0.3247, R^2 of 0.105 and p-value of 0.000.

Results: Education Demographic Factors (25+ years of age)

The education demographic variables we used represent the highest level of education attained by adults older than 25 years, each measured as a percent of the total census block group population. Our results indicate that higher levels of education generally lead to positive relationships with tree canopy. Doctorate, Professional, and Master's degrees all enjoy positive relationships with tree canopy (see Figure 6).

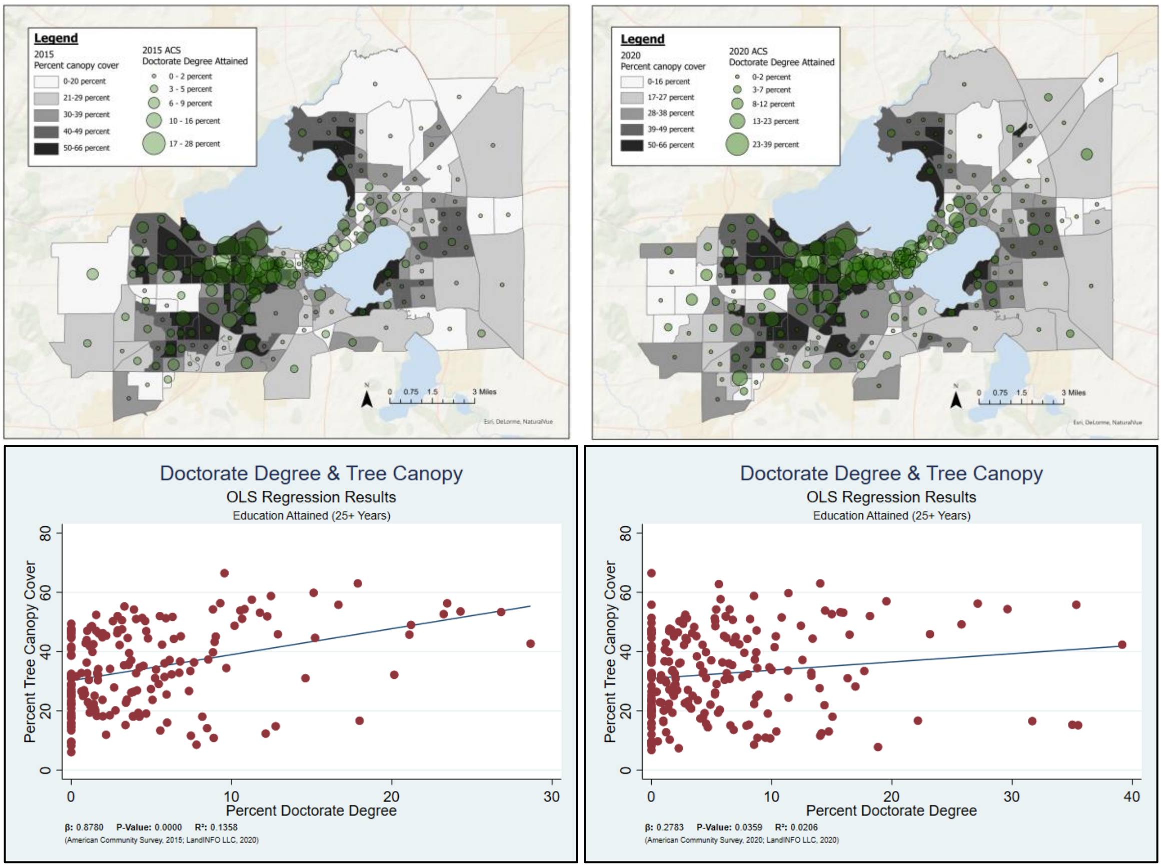

Figure 6: Percent of people with doctorate degrees and tree canopy cover map and regression results using 2015 ACS data and 2020 tree canopy data (left). Percent of people with doctorate degrees and tree canopy cover map and regression results using 2020 ACS data and 2020 tree canopy data (right).

Terminal degrees (Doctorate, Professional) maintained the strongest positive relationships with tree canopy across 2015 and 2020, with statistically significant P-values (< .05), moderate to high R^2 values (between .02 - .13), and relatively large Beta coefficients. Master's degrees in 2015 experienced positive relationships with moderate R^2 and Beta coefficient values (0.058 and 0.241, respectively), and a statistically significant p-value (0.001). These values dropped in 2020 with significantly lower R^2 values (0.009), lower Beta coefficient (0.093) along with an increase in P-value (0.175). Most educational attainment demographics had negative relationships with tree canopy, including “Some College” and Bachelor’s degree attainment. Notably, relationships among education demographics less than a high-school diploma were particularly tenuous, characterized by high P-values and low R^2 likely due to small sample sizes; however, a combined variable collapsing all educational attainment less than a high school diploma yielded far greater statistical certainty. Non-high school graduates experienced a moderate negative relationship with tree canopy in 2015, with a moderate negative beta coefficient (-0.261) a moderate R^2 (0.068) and a statistically significant p-value (0.000). In 2020, the relationship between non-high school graduates and tree canopy weakened significantly, producing a low Beta coefficient and R^2 (-0.086 and 0.007, respectively) and a moderately large p-value (0.212). This follows the greater trend in our educational attainment results: all levels of attainment besides Professional degree and GED experienced significant drops in explanatory value from 2015 to 2020.

Results: Racial & Ethnic Demographic Factors

Racial and ethnic demographics were measured as the percentage of the population in each census block group. White and Asian populations yielded the strongest relationships with tree canopy, producing statistically significant results and relatively high R^2 values. The White population had a moderate Beta coefficient in 2015 (0.257), a moderate R^2 value (0.066), and a statistically significant p-value (0.000). This relationship weakened somewhat but remained positive and significant in 2020 with a Beta coefficient of 0.173, an R^2 value of 0.030, and a statistically significant p-value of 0.011 (see Figure 7). The

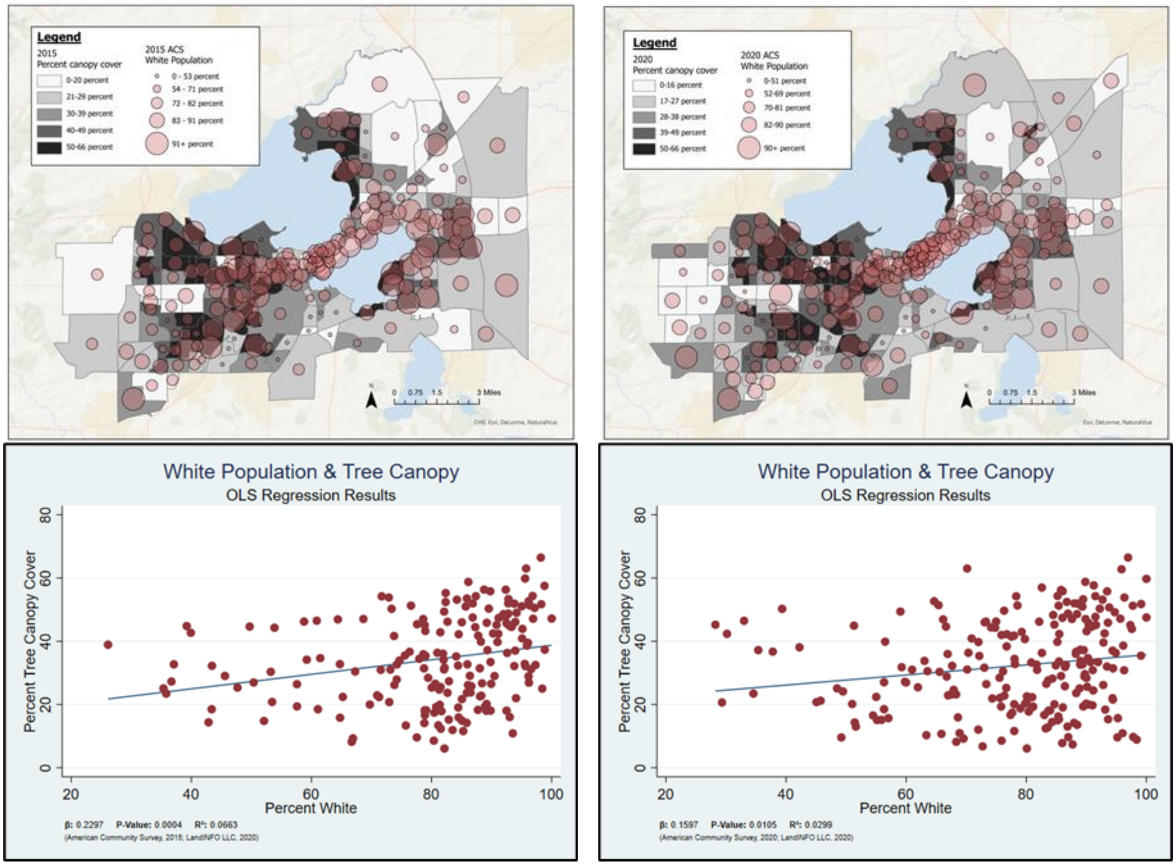

Figure 7: Percent of people who identify as White and tree canopy cover map and regression results using 2015 ACS data and 2020 tree canopy data (left). Percent of people who identify as White and tree canopy cover map and regression results using 2020 ACS data and 2020 tree canopy data (right).

Asian population had a moderate negative Beta coefficient in 2015 (-0.217), a moderate R^2 value (0.047), and a statistically

significant p-value (0.003). This relationship remained nearly the same in 2020 with a negative Beta coefficient of -0.212, an R^2 value of 0.045, and a statistically significant p-value of 0.002.

Black, Hispanic, and the "Other Race" demographics all had negative relationships with tree canopy, although the strength of those relationships decreased from 2015 to 2020. The "Other Race" population had a moderate relationship with tree canopy in 2015, with a moderate negative Beta coefficient (-0.154), a moderate R^2 value (0.024), and a statistically significant p-value (0.037). This relationship weakened in 2020 with a low negative Beta coefficient (-0.095), a low R^2 value (0.009), and a moderate p-value (0.162). The Hispanic population had a moderate relationship with tree canopy in

2015, with a moderate negative Beta coefficient (-0.142), a moderate R^2 value (0.020), and a low p-value (0.055). This relationship weakened in 2020 with a low negative Beta coefficient (-0.074), a low R^2 value (0.006), and a moderate p-value (0.274). The Black population had weak relationship with tree canopy, with a low negative Beta coefficient in 2015 (-0.076), a low R^2 value (0.006), and a large p-value (0.305). This relationship weakened further and remained negative in 2020 with a Beta coefficient of -0.050, an R^2 value of 0.003, and a large p-value of 0.460.

American Indian / Alaskan Native and Native Hawaiian / Pacific Islander populations had very weak negative relationships with very high p-values, likely due to an incredibly small population size within the study area. The American Indian / Alaskan Native population had a practically non-existent relationship with tree canopy in 2015, with a Beta coefficient of (-0.006), an R^2 value of 0.000, and a p-value of (0.937). This persisted in 2020 with a Beta coefficient of -0.016, an R^2 value 0.000, and a p-value of 0.815. Native Hawaiian / Pacific Islander populations has a marginally stronger relationship with tree canopy. In 2015, the Native Hawaiian / Pacific Islander had a Beta coefficient of -0.049, an R^2 value of 0.002, and a p-value of 0.507. This relationship weakened further in 2020 with a Beta coefficient of -0.031, an R^2 value of 0.001, and a p-value of 0.650.

Perhaps the most interesting change in relationships from 2015 to 2020 is that of the multi-Racial population. The relationship changed from a moderate negative relationship in 2015 to a practically non-existent yet positive relationship in 2020. In 2015, the "multi-Racial" population had moderate negative Beta coefficient (-0.201, a moderate R^2 value (0.040), and a statistically significant p-value (0.006). This relationship became very weakly positive in 2020 with a low negative Beta coefficient (-0.021), an R^2 value of 0.000, and a large p-value (0.755). The large change between these years is likely due to increased self-identification as multi-Racial or more precise survey methodology (US Census Bureau, 2021).

Analysis

Our results show that housing and economic factors are the greatest predictors of tree canopy in both 2015 and 2020. Housing tenure was clearly the dominant predictor within the analyzed data, explaining 37% of the variance in tree canopy in 2015 and 28% in 2020. Structure age was also an incredibly strong predictor, explaining 16% and 23% of the variance in tree canopy in 2015 and 2020, respectively, and these variables likely influence each other. Madison grew six percent over the five years, from a population of 287,000 in 2015 to 305,000 in 2020, and an increase in apartment construction to meet this demand is likely responsible for much of this age and tenure-related disparity. However, an examination of the Madison Code of Ordinances reveals that an abutting property is responsible for the costs of all initial tree plantings within the publicly maintained terrace (MCO, 2022, sec. 10.10). This cost to plant new street trees may disincentivise landlords of smaller apartment dwellings from doing so, and potentially exacerbate these disparities. Household income and property value were also strong predictors of tree canopy, and act as a counterpoint to the importance of newly constructed apartments. The relationship with household income and property value suggests that high-income earners reside in the outskirts of the city, with higher tree canopy percentages, likely in single-family homes and not in the many new luxury apartment buildings being constructed within the city proper. Median resident age was also a strong predictor and seems to accentuate this point that young, moderate earning residents live in low tree canopy areas, while older residents live in older, more valuable properties with greater levels of tree canopy.

Although the social demographic variables we analyzed were comparatively less predictive, they remain significant identifiers of extant disparities. Though White and Asian populations are the strongest predictors of tree canopy, these proportions may be inverted to find alternate meanings. Most importantly, while an increase in proportion of the White population indicates a likely increase in tree canopy, the inverse is also true: an increase in proportion of the non-White population indicates a likely decrease in tree canopy cover. While other racial demographics had negative relationships of various strength, this inversion produces a concrete and statistically significant fact which can be used to motivate corrective action. Similarly, highly educated people are more likely to enjoy greater tree cover than less educated people. However, it is somewhat surprising at what level of education this occurs, as any education level below a Master's degree almost uniformly has a negative relationship with tree canopy.

Overall, our results show a decrease in the predictive quality of many of the variables from 2015 to 2020. However, there are a few exceptions to this trend. First, structure age increased in significance likely due to the rapid development in Madison. Lower income levels, specifically $25,000-$35,000 and $40,000-$45,000, became more significantly negative, increasing the R^2 and Beta coefficient and decreasing the p-value. Educational attainment at the GED level had a similarly strengthened negative relationship. Median rent gained in positive significance, which is interesting due to the increasing numbers of luxury apartment buildings in the city. Finally, the multi-Racial population reversed the sign of its relationship from negative to positive, possibly due to increased levels self-identification.

Discussion

We believe that our analyses of 2020 tree canopy data with 2015 and 2020 American Community Survey demographic data show small shifts towards decreasing tree canopy inequalities. Although our results are encouraging, prioritizing tree canopy equity and growth in Madison remains very important and must be a focus of future city planning. The City of Madison's Urban Forestry Task Force report from 2019 recommends actions to decrease tree canopy inequality and promote public and private tree plantings in underserved areas (Kane et al., 2019). However, these initiatives remain vulnerable to budgetary constraints and competition with other governmental initiatives. Additionally, they may not address tree canopy deficiencies on small-scale private rental properties, and further incentivisation may be necessary. Our analyses pinpoint specific areas of inequality with numerical precision and will not only enable the City of Madison to address these issues, but also provide quantitative evidence for the need of corrective action and resources.

Our analyses have additional implications outside of Madison and can be generalized to other studies of geographically distributed amenities. By controlling for parks and golf courses, our methodology removes non-residential areas which inflate tree canopy percentages within census block groups. This generates a more accurate analysis of tree canopy distribution within neighborhoods, and thus a stronger argument for the remediation of any identified disparities. Furthermore, using demographic data from 2015 and 2020 gives our analysis a useful temporal dimension. This adds insight into ongoing trends in demographic distributions and allows us to see how these distributions change over time in relation to tree canopy. The largest barrier to the methodological generalizability of our study is the acquisition of high-resolution LiDAR vector data; our data was provided for non-commercial use by Land INFO Worldwide Mapping and was originally intended to inform 5G cellular network transmitter placement.

Our time-based analyses would be more precise with the addition of 2015 tree canopy cover data to our dataset. Although this was not possible, we were able to effectively compare 2015 and 2020 demographic data against one year of tree canopy data. With the addition of 2015 tree canopy data, the research would be more finely tuned, with each year of demographic data having the corresponding year of tree canopy cover data. Future research could incorporate this data for further comparison and provide greater understanding of the relationship between demographics and urban tree canopy. Additionally, future research may incorporate a stratified random sample community survey to provide the resident's view of current canopy cover levels. The addition of community viewpoints would inform corrective action and future urban planning of community desires.

Inequities in tree canopy produce disparate mental and physical health outcomes which effect whole communities. The elimination of these inequities must be a priority of local government, including the City of Madison. This study provides quantitative evidence of tree canopy disparity, as well as precise methodology for measurement. Additionally, it provides temporal analysis of demographic shifts in relation to tree canopy. Public and private planting programs and incentives, such as those recommended by the Urban Forestry Task Force would help to improve tree canopy and reduce unequal distribution. If such initiatives are prioritized, we believe that they may begin alleviating some of the existing environmental justice issues in Madison and elsewhere, ultimately making cities a better place for all people to reside.

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Declaration of Interest Statement

Both authors declare that there are no conflicts of interest in the publication of this article. The study and research done were solely for the educational purposes of both authors attending the University of Wisconsin-Madison. This material has not been duplicated or published elsewhere.

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