# Health and Environmental

# Impacts of Tree Equity in Los Angeles, CA

(6386)

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# Introduction

A map of tree coverage is too often a map of race and income in any given city in the United States. As climate change intensifies, people of color and low-income communities become more vulnerable to climate impacts. Often, these communities are underserved by local governments, lacking in funding to improve living conditions, and disproportionately at risk for harm due to environmental racism. Tree equity score, which is derived from many factors including the percent of people of color, percent of unemployed people, health index, average temperature, percent of people in poverty, tree canopy gap, percent of senior citizens (65+) and percent of children (0-17), is increasingly becoming a metric by which local governments and urban planners can measure equity and justice in their communities. A lower tree equity score indicates an increased priority for wealth generation, economic development, and increased tree canopy. Our study seeks to identify a relationship between tree equity score and health and environmental issues affecting residents of Los Angeles County. Our research question is as follows: is there a higher risk of health and environmental issues for residents in areas with low tree equity scores? How might we understand the relationship between tree equity score, neighborhood demographics, and urban health?

The sources for the data used throughout the study came from the United States Census and American Forests non-profit organization. All census data was imported from the U.S. Census Bureau via the American Community Survey while the American Forests non-profit provided the tree equity score data for the state of California, separated by county.

The results for the regression model on Physical Health showed that there are statistically significant associations between physical health and tree equity score, median household income, average temperature, age with insurance, unemployment rate, percent of people of color, and tree canopy gap. The R-squared score for this model was 0.861, indicating that these independent variables account for roughly 86% of the physical health explanation.

A second regression model was used to test if certain variables such as Tree Equity Scores, Median Household Income, Physical Health, Asthma, Coronary Challenges, Percent People of Color, and Tree Canopy Gap, would predict Urban Heat in the city of Los Angeles. The results demonstrated that there were statistically significant associations between all variables. Additionally, the R-squared score was 0.540, which indicates these independent variables account for roughly 54% of the urban heat explanation. In this model, tree equity scores and urban heat are negatively correlated, indicating that as tree equity increases, urban heat decreases, which is what the group hypothesized.

It was hypothesized that more trees would positively impact all aspects of health, including physical health. Therefore a Statistical Hypothesis Test was conducted in order to find out if

there existed a statistically significant correlation between physical health and tree equity score in census block groups. However, the null hypothesis that tree equity score does impact physical health was rejected. These results were counter to our general intuition and it appears to be that a tree equity score does not necessarily impact a block group's overall mental health.

As our study confirmed significant impacts of low tree equity scores and high average temperatures, a policy suggestion would be for a city to invest in green spaces such as green rooftops, parks, and community gardens. This would allow for an increase in vegetation which could help lower temperatures and combat urban heat island effect. A second suggestion would be to include environmental development as a topic for NGOs and governmental organizations to consider when it comes to discussing social issues and social justice. Our findings showed a statistically significant correlation between high temperatures and the majority of residents being people of color, with Black communities facing some of the highest disparities. Thus, we decided to focus on white versus Black communities for our analysis.

## Background

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With our group's understanding of the disparities that people of color face within planning, we assumed the patterns of tree equity would highlight those disparities. Therefore, we wanted to address, more precisely, the implications of tree equity across block groups in the county of Los Angeles. Our group wanted to understand how tree coverage, amongst other factors, impacts communities, and more specifically, our research question wanted to understand how communities' health and well-being were impacted by tree equity. We chose to use the county of Los Angeles as our area of focus due to the scale and diversity of the region. Furthermore, Los Angeles has struggled with issues caused by the segregation of racial and ethnic groups for many years. One example is the distinct lack of green space in low-income areas like South and East Los Angeles, which is not usually a problem in more affluent neighborhoods that tend to have more open, green space such as West Los Angeles. Our preconceived notion is that green space provides health benefits to communities and, therefore, a lack of green space may cause harm to a population's health led to the research topic being addressed. Given that our study focuses on tree equity score, we chose to use the same variables that form the derivative of American Forests' calculation for tree equity score. Although we do not know their exact calculation and methodology, we attempted to perform our own analysis using the same data. They include different categories for health, including "physical health," "mental health," "coronary problems," and "asthma." The physical health, mental health, and asthma data were the self-reported health challenges of the people within the block group as a percentage of the residents within a block group that experience these challenges. Further, they use data on the percentage of a block group that is covered in trees, known as tree canopy percentage in tandem

to a multitude of sociological factors to generate a tree equity score. These include variables such as race, poverty rate, and unemployment rate.

## Methodology

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We attempted to answer our primary research question by conducting a statistical analysis on a number of datasets to help us better understand tree equity in the Los Angeles area as it relates to mental and physical health. More specifically, we looked for what characteristics are present in block groups that have a higher tree equity score such as race, income, and mental and physical health quality. Although the tree equity score is calculated through an accumulation of social characteristics, our research sought to establish a statistically significant correlation that might suggest a causal relationship between factors we deemed to be related to tree coverage in theory. We gathered quantitative data provided by demographic and social characteristics data from the United States Census and tree equity score data provided by American Forests non-profit. We treated our data as population data given that both our data sources collect information from every household and census block group rather than sampling only a portion of the population. Further, we recognize that establishing a causal relationship from quantitative data is reliant on characteristics that are measurable alone and that qualitative data might create a better picture in congruence to quantitative data. Information that might come from a survey or questionnaire of very specific relationships in a block group would surely be important to include, but such data was not able to be included in this study.

Our data was prepared in Jupyter Lab Notebook Interface using Python language to clean and organize our data. Our group was able to write code to import our data sets and perform a number of functions that allow us to perform a statistical analysis. We were able to pick and choose which data categories we deemed important to our research question before removing null or missing values. Next, we merged our data sets together with geospatial areas along each block group's fips code. Once together, we used a number of python packages to create descriptive statistics, descriptive models, statistical tests, and map visualizations that help us observe patterns within the Los Angeles area. Our descriptive statistics include the average value, medium value, and standard deviation. We would then visualize the data including histograms, scatter plots, and box and whisker plots. We also looked at our datasets spatially to identify where exactly some behavior occurs as it relates to demographic factors. Once we found some phenomena worth exploring, we ran a difference of means one tailed statistical-test to identify the likelihood that we observe the phenomena by random chance. Finally, we prepared a multi-factor regression model in an attempt to determine what factors affect physical health and average temperature by how much of an impact they make.

Our project is structured around common practices in statistical analysis research found in public policy studies. At a general level, our analysis begins with observations found in our dataset that relates to our research question. We identify a pattern within our dataset and we hypothesize why such a pattern exists. Finally we run statistical tests to formulate a theory. As such, our analysis is centered around abductive reasoning in that we began our research with a preconceived hypothesis on what we expect our data to look like given a general understanding of society and American history. We recognize that the preconceived hypothesis may open the door to biases in how we select our data. We may overly value some data that may not accurately answer our research question or we might exclude data that is important and should be included. We believe that by working with a 95% confidence interval, we account for variance between a true underlying value within our data. We are willing to accept a 5% chance that we may be wrong about the data we collect, and we are willing to accept our results as is even if they may be counter to our original hypothesis. We feel confident that our methodology allows us to reach conclusions that effectively support an answer to our research question.

# Results

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### Self Reported Physical Health and Tree Equity Score

Our first analysis compares physical health and tree equity score. We wanted to see any statistically significant correlation between physical health and tree equity score in census block groups, as an integral part of our original hypothesis was that a higher tree equity score would positively impact all aspects of health. Our general theory was that there would be a positive correlation to tree equity score and physical health such that a higher tree equity score would correlate with better physical health.

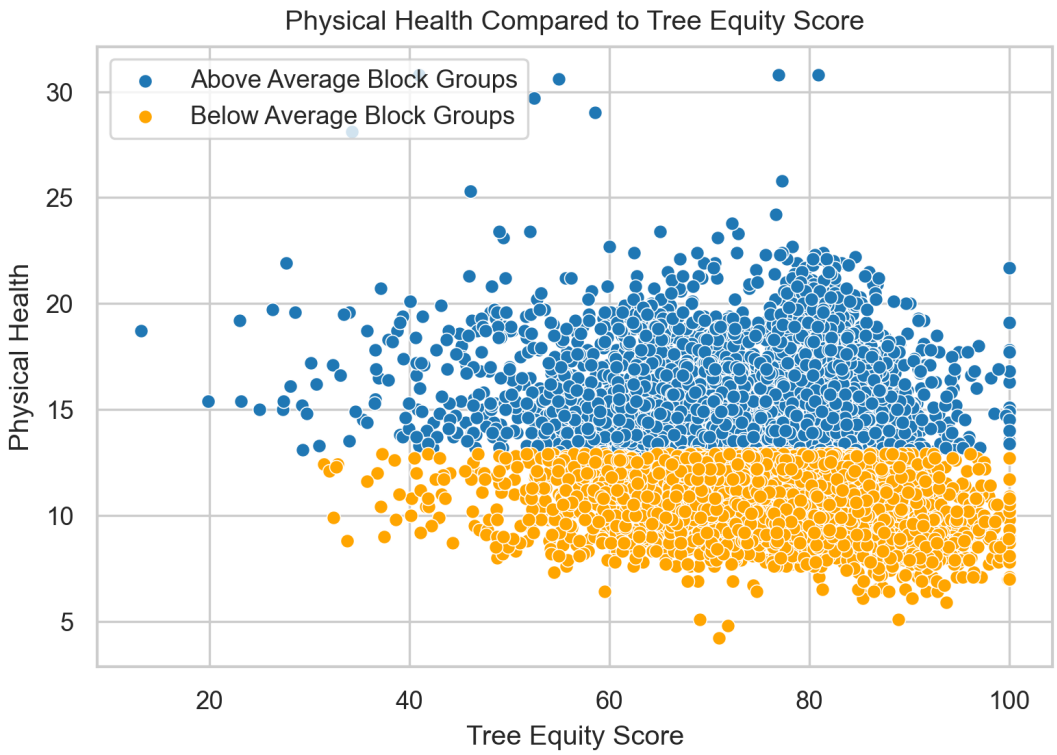


Figure 1.1: Tree Equity and Physical Health

When divided between groups above and below the physical health average (12.96) of individual block groups and using a scattergram to visualize any correlation because we are only comparing between 2 factors (tree equity and physical health). We find no meaningful correlation between the two variables. Given the observed results, we formulate our null hypothesis to be that Tree Equity Score does impact physical health and our alternative hypothesis is that the tree equity score does not impact Physical health.

Assuming a 0.05 alpha value, we ran a difference of means test and got a p-value of $2.51 \times 10^{-64}$. Thus, we reject the null hypothesis that tree equity score impacts physical health. This means that it is statistically significant that there is no meaningful difference between physical health given a block group's tree equity score. These results are counter to our general intuition that tree coverage affects physical health. It appears to be that a tree equity score does not necessarily make that big of a difference in a block group's overall physical health, and we must be cognizant of other factors that might influence physical health besides tree coverage.

**Tree Equity Scores and Race**

This second analysis compares race groups and tree equity scores. We wanted to see any statistically significant correlation between tree equity score and race in census block groups. An integral part of our hypothesis was a correlation between one's race and physical health. Our general theory prior to running a statistical test is that block groups that are majority black would

have lower tree equity scores than majority white groups based on our understanding of Los Angeles' history with segregation and red lining..

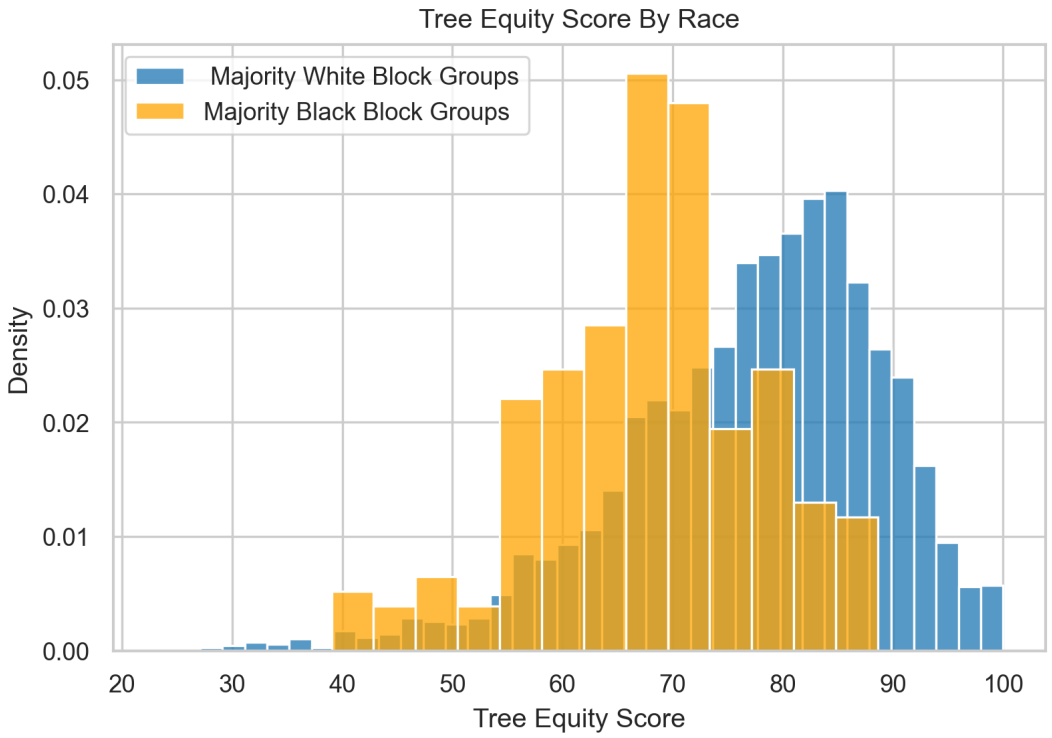


Figure 1.2: Majority White vs. Black block groups and Tree Equity

We used a histogram in this analysis to identify a difference in physical health between majority white and majority-black census block groups. This data suggests a difference between the average physical health between block groups that are majority White and groups that are majority Black. Majority White groups averaged a tree equity score of 77.30, and majority Black groups averaged a score of 68.01. Thus, our null hypothesis is that there is no difference in tree equity score between white and black groups, while the alternative hypothesis is that there is a difference.

Assuming a 0.05 alpha value, we got a p-value of $2.65 \times 10^{-28}$. Thus, we reject the null hypothesis that there is no statistically significant difference between the average physical health of majority White block groups and majority Black block groups. This result suggests that there is indeed a statistically significant difference – that Black groups have lower tree equity scores than White groups by a margin of 9.28. This may be a result of a number of different factors; perhaps Black groups have lower median household incomes, or perhaps they are undereducated.

**Self Reported Physical Health and Race**

This last analysis compares physical health and race. We wanted to see any statistically significant correlation between physical health and race in census block groups. An integral part of our hypothesis was a correlation between one's race and physical health. Our general theory was that groups of color would report a higher frequency of physical health problems predicated on a notion that Black groups would have less robust health insurance coverage and may be living in poor living conditions.

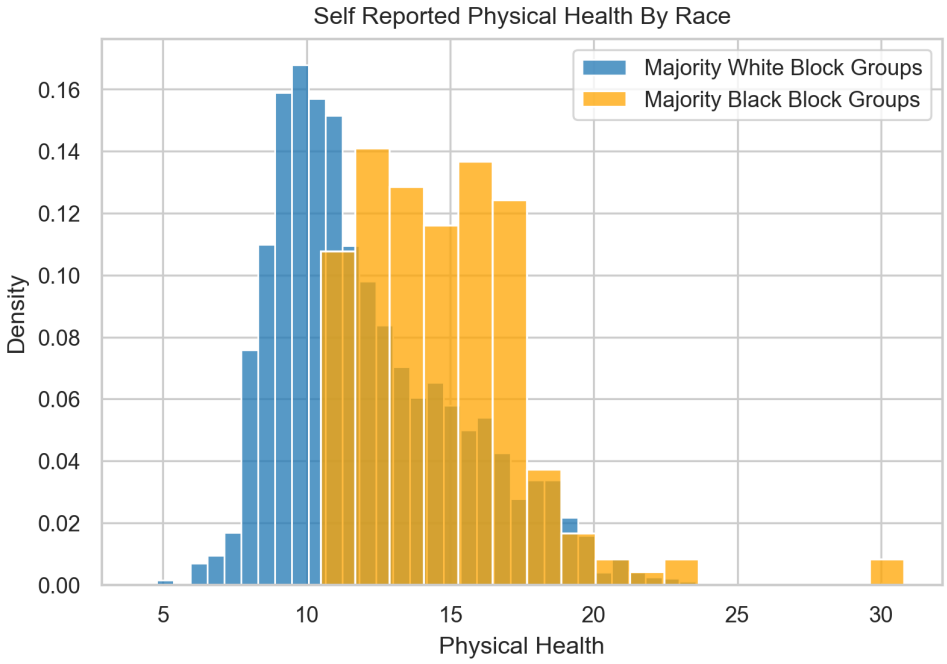


Figure 1.3: Majority White vs. Black and physical health

We used a histogram in this analysis to identify a relationship between physical health and majority White and majority-Black census block groups. This data suggests that there is a difference between the average physical health between block groups that are majority White and groups that are majority Black. Majority white groups have an average of 12.08% of residents experiencing physical health issues, whereas majority black groups average 14.73%. Thus, our null hypothesis that there is no difference, while the hypothesis is there is a difference.

Assuming a 0.05 alpha value, we got a p-value of $2.69 \times 10^{-27}$. Thus, we reject the null hypothesis that there is no statistical difference between the average physical health of majority White block groups and majority Black block groups. This result suggests that there is a statistically significant difference between the physical health of these two races and that it is not by random chance. Black groups experience physical health issues 2.65% more than White groups.

**Physical Health Regression Model**

We ran a regression model on physical health to try to further flesh out how the data we collected correlates with each other to determine what impacts the presence of physical health problems.

OLS Regression Results

| | | | |
|---|---|---|---|
| Dep. Variable: | Physical Health | R-squared: | 0.861 |
| Model: | OLS | Adj. R-squared: | 0.861 |
| Method: | Least Squares | F-statistic: | 5440. |
| Date: | Wed, 08 Dec 2021 | Prob (F-statistic): | 0.00 |
| Time: | 00:50:40 | Log-Likelihood: | -10101. |
| No. Observations: | 6161 | AIC: | 2.022e+04 |
| Df Residuals: | 6153 | BIC: | 2.027e+04 |
| Df Model: | 7 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| const | -1.1208 | 0.771 | -1.454 | 0.146 | -2.632 | 0.391 |
| Tree Equity Score | -0.0094 | 0.002 | -6.059 | 0.000 | -0.013 | -0.006 |
| Estimate Median Household Income | 1.622e-06 | 5.97e-07 | 2.719 | 0.007 | 4.53e-07 | 2.79e-06 |
| Average Temperature | 0.0309 | 0.007 | 4.141 | 0.000 | 0.016 | 0.045 |
| Has_Insurance | -0.0003 | 2.46e-05 | -11.551 | 0.000 | -0.000 | -0.000 |
| Percent POC | 1.9879 | 0.092 | 21.554 | 0.000 | 1.807 | 2.169 |
| Coronary Challenges | -0.7727 | 0.082 | -9.374 | 0.000 | -0.934 | -0.611 |
| Mental Health | 0.8151 | 0.008 | 105.322 | 0.000 | 0.800 | 0.830 |

| | | | |
|---|---|---|---|
| Omnibus: | 1373.832 | Durbin-Watson: | 1.385 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 43475.882 |
| Skew: | -0.368 | Prob(JB): | 0.00 |
| Kurtosis: | 15.993 | Cond. No. | 4.25e+06 |

Figure 2.1 Physical Health Regression Model

The regression model on physical health we ended up with has the following variables: Tree Equity Scores, Median Household Income, Average Temperature, having Insurance, Percentage of People of Color, and Coronary Challenges, and Mental Health would predict average physical health. Setting Physical Health as the response (dependent variable) and the other variables identified as the predictors (independent variables), the regression model identified that there were statistically significant associations between all variables with a P-value < .05. Additionally, the R-squared score was 0.861, which indicates these independent variables explain roughly 86% of the physical health data.

**Average Temperature Regression Model**

OLS Regression Results

| | | | |
|---|---|---|---|
| Dep. Variable: | Average Temperature | R-squared: | 0.540 |
| Model: | OLS | Adj. R-squared: | 0.539 |
| Method: | Least Squares | F-statistic: | 901.9 |
| Date: | Tue, 07 Dec 2021 | Prob (F-statistic): | 0.00 |
| Time: | 22:26:25 | Log-Likelihood: | -13111. |
| No. Observations: | 6161 | AIC: | 2.624e+04 |
| Df Residuals: | 6152 | BIC: | 2.630e+04 |
| Df Model: | 8 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| const | 106.3964 | 0.509 | 208.964 | 0.000 | 105.398 | 107.395 |
| Tree Equity Score | -0.0482 | 0.004 | -11.189 | 0.000 | -0.057 | -0.040 |
| Estimate Median Household Income | -1.441e-05 | 9.61e-07 | -14.987 | 0.000 | -1.63e-05 | -1.25e-05 |
| Physical Health | 0.1407 | 0.021 | 6.819 | 0.000 | 0.100 | 0.181 |
| Mental Health | 0.3984 | 0.027 | 14.923 | 0.000 | 0.346 | 0.451 |
| Percent POC | 3.7069 | 0.150 | 24.753 | 0.000 | 3.413 | 4.001 |
| Asthma | -1.1217 | 0.047 | -24.020 | 0.000 | -1.213 | -1.030 |
| Coronary Challenges | 0.9318 | 0.144 | 6.452 | 0.000 | 0.649 | 1.215 |
| Tree Canopy Gap | -2.5711 | 0.509 | -5.055 | 0.000 | -3.568 | -1.574 |

| | | | |
|---|---|---|---|
| Omnibus: | 1095.644 | Durbin-Watson: | 1.251 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 3408.066 |
| Skew: | -0.912 | Prob(JB): | 0.00 |
| Kurtosis: | 6.154 | Cond. No. | 2.25e+06 |

Figure 2.2 Average Temperature Regression Model

The regression model on Average Temperature uses the following variables: Tree Equity Scores, Median Household Income, Physical Health, Asthma, Coronary Challenges, Mental Health, Percentage of People of Color, and Tree Canopy Gap would predict Urban Heat. Setting Urban Heat as the response (dependent variable) and the other variables identified as the predictors (independent variables), the regression model identified that there were statistically significant associations between all variables with a P-value < .05. Additionally, the R-squared score was 0.540, which indicates these independent variables explain 54% of the average temperature data.

**Map Visualizations**

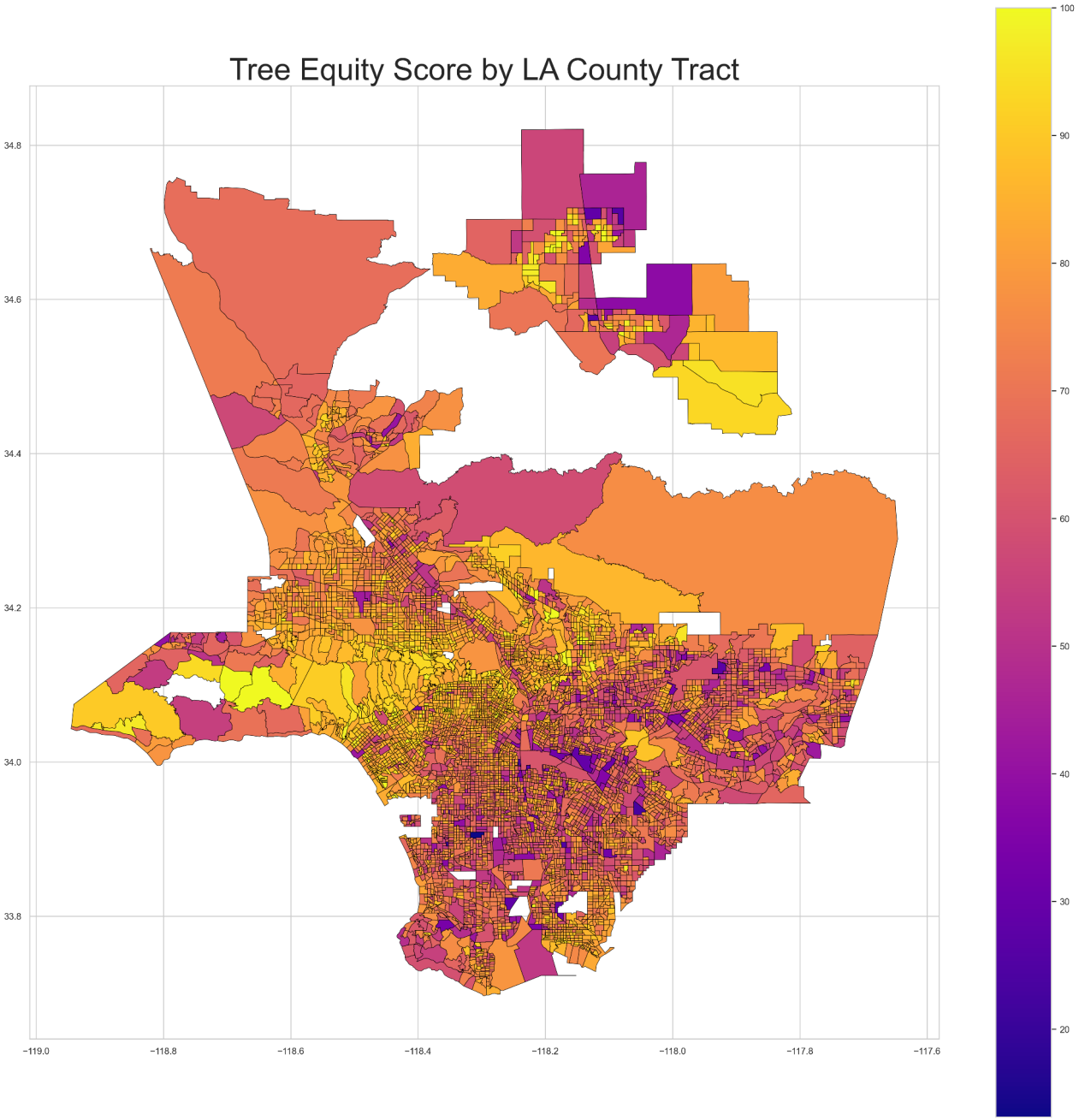


Figure 3.1 Tree Equity Score, where 100 (yellow) is the highest and best score.

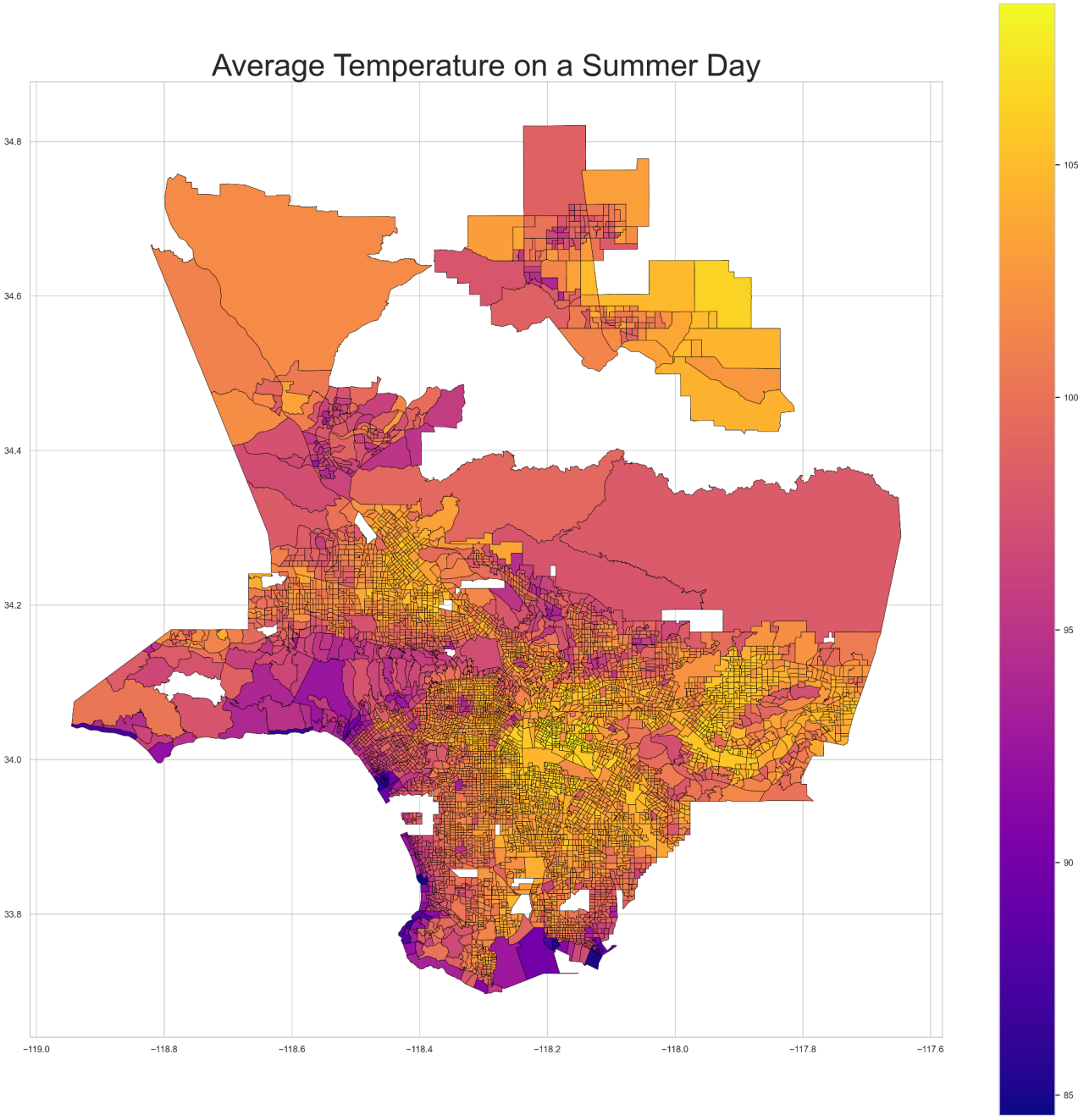


Figure 3.2 Average Temperature on a hot Summer day, ranging from 85°F to >105°F.

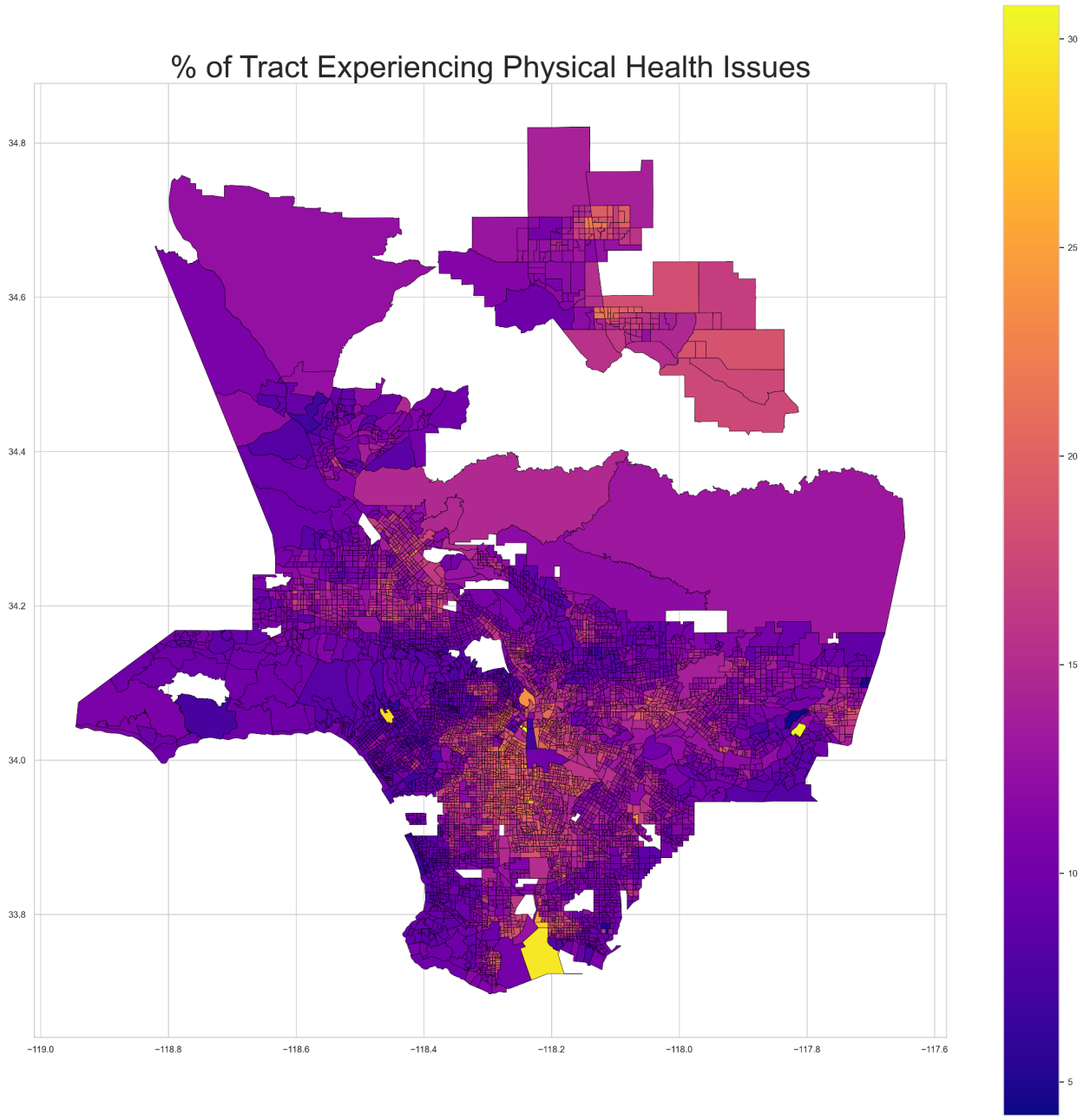


Figure 3.3 Physical Health, where 5 (purple) indicates less frequent physical health problems and 30 (yellow) indicates more physical health problems.

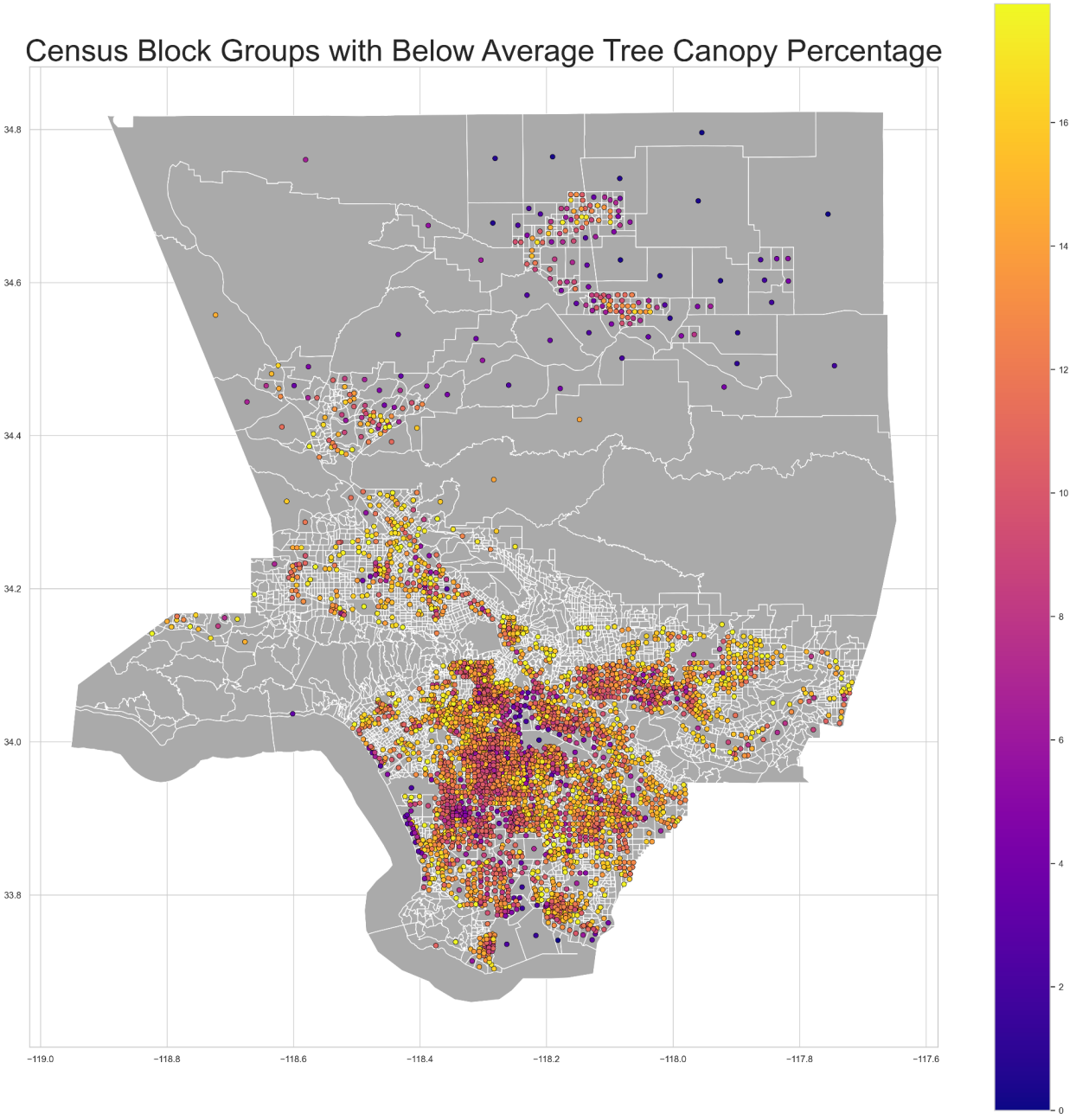


Figure 3.4 Tree Canopy, where each dot represents a census block group with below average tree canopy coverage.

# Discussion

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**Tree Equity and Physical Health**

Figure 1.1 analyzes two variables: tree equity score and physical health. According to the data source, the Tree Equity Score mapping project by American Forests, the physical health variable

is “the self-reported physical health challenges of the people in the block group.” Tree equity score is an overall score based on the following factors: percent of people of color, percent unemployed, health index, temperature, percent of people in poverty, percent of senior citizens (65+), and percent of children (0-17). Based on the data visualization, it appears that there is no obvious relationship between physical health and tree equity score. There are groups with poor tree equity scores that have good and poor self-reported physical health, just as there are groups with excellent tree equity scores that report good and poor physical health. Because the physical health variable is self-reported health concerns, as opposed to data from hospitalizations or doctor’s visits, the input that dictates the physical health variable values are relative to each individual’s experience. Whereas some individuals may feel that they have little to no physical health concerns, someone else may consider themselves to have many physical health concerns. However, there is no definitive indicator that the experiences of these two individuals is drastically different, despite what their differing physical health values indicate. Thus, using self-reported physical health concerns can involve biases, different injury and pain tolerances, and varying lived experiences that can influence how individuals report health concerns.

**Tree Equity and Race**

Figure 1.2 displays tree equity scores for majority Black (defined as greater than 50% Black residents) as well as majority white (defined as greater than 50% white residents) block groups. Majority Black block groups tend to have lower tree equity scores than majority white block groups, as can be seen in the histogram. Whereas the majority Black block group histogram peaks at an approximate tree equity score of 65, the majority white block group histogram peaks at an approximate tree equity score of 85. In addition, it is important to note that there are a few outlying majority white block groups that have tree equity scores between 40 and 25, approximately. Based on analyses of income, race, and tree equity scores, it can be inferred that these majority White block groups are most likely low income. Overall, these findings indicate that majority White block groups, on average, have higher tree equity scores than majority Black block groups. Having a lower tree equity score “indicates a greater priority for closing the tree canopy gap” (American Forests). Thus, it is of the utmost importance that majority Black block groups are prioritized when new policies are formed to increase tree cover and green space as well as wealth creation and economic development. By prioritizing majority Black block groups, planners and policymakers can begin to undo historic inequities in majority Black communities.

**Self Reported Physical Health and Race**

Figure 1.3 displays the physical health variable for majority Black (defined as greater than 50% Black residents) as well as majority white (defined as greater than 50% white residents) block groups. As stated in reference to Figure 1.1, the physical health variable is based on self-reported health concerns of individuals within the block groups. Based on the histogram, majority Black block groups reported greater physical health concerns, whereas majority white block groups reported less physical health concerns relative to the majority Black block groups. In the first

data visualization, Figure 1.1, the statistically significant p-value indicated that the null hypothesis be rejected, indicating that tree equity score does not impact physical health. In this visualization, the null hypothesis, which stated that there is no statistical difference between the average physical health of majority white block groups and majority Black block groups is rejected. Thus, there is a statistically significant difference between the self-reported health concerns of majority white and majority Black block groups. However, when looking at the findings of Figures 1.1 and 1.3 side by side, it seems to indicate that statistically significant discrepancies in self-reported physical health concerns are not correlated with differing tree equity scores. Due to historical inequities between Black and white people, it is possible that the statistically significant differences in self-reported physical health concerns are other factors such as discrimination in healthcare and racist placing of polluting landfills and factories in majority-Black areas. In addition, as is mentioned previously, because physical health concerns are self-reported, the values yielded are inherently subjective, biased, and experiential. Because majority Black block groups report higher physical health concerns, though, providing quality, affordable, and accessible health care as well as prioritizing these communities in health and environmental policies are important in decreasing health disparities across racial groups.

**Physical Health Regression Model**

Figure 2.1 illustrates that the independent variables: Tree Equity Scores, Median Household Income, Average Temperature, having Insurance, Percentage of People of Color, and Coronary Challenges, and Mental Health help predict physical health. Based on our research question, there are a couple of factors that may describe this phenomenon, including low-income households, the percentage of people of color, insurance, and lack of affordable and accessible transportation. As shown in the regression model, low-income households are connected to having less self-reported physical health concerns. This may be because low-income households may not own an automobile and may depend on public transportation and walking, resulting in better physical health overall. Los Angeles County does not have accessible transportation throughout the region and has been historically disinvested in communities that are predominantly low-income and communities of color, while white communities have witnessed more investment in public transportation. The lack of accessible and affordable transportation in predominantly low-income neighborhoods and communities of color such as South Central Los Angeles may result in low-income residents having to walk more than affluent residents, which results in less self-reported physical health challenges. In addition, having health insurance results in decreased physical health. Residents in Los Angeles County that do not have health insurance, may have better physical health because they cannot afford health insurance, and must exercise to stay healthy. These findings are useful for city planners and policymakers to help evaluate the underlying inequalities present across Los Angeles County. Planners must examine how low-income communities and communities of color navigate the city and where they can make transportation more accessible by prioritizing disadvantaged communities. In addition, policymakers must assess who in the community has access to insurance and how they can make

insurance programs more accessible and affordable. The Physical Health Regression model allows us to answer our research question by revealing that there is a connection between demographics and physical health, but there may be other inequalities present in the city aside from low tree equity scores that explain this relationship.

**Average Temperature Regression Model**

Figure 2.2 assesses if Tree Equity Score, Estimate Median Household Income, Physical Health, Mental Health, Percent POC, Asthma, Coronary Challenges, and Tree Canopy Gap are predictors of urban heat, otherwise referred to as "Average Temperature". The associated R-squared score, 0.540, indicates that the indicators contribute to approximately 54% of the urban heat response. There are many factors that might contribute to the results illustrated in this regression model. The "Average Temperature" variable is defined by the data source as "the average temperature of the block group on a hot summer's day" (American Forests). There are a number of predictor variables of note in this regression analysis. First, physical health has a coefficient value of 0.1407. The positive coefficient and the p-value less than the alpha value of 0.05 indicates that as the average temperature, otherwise referred to as urban heat, increases, self-reported physical health concerns also increase. There are many potential reasons for this relationship including heat-related illness, such as hyperthermia and heat stroke, as well as other afflictions such as sunburn, skin damage, and dehydration. Second, mental health has a coefficient value of 0.3984. Once again, this positive coefficient and the statistically significant p-value indicates that an increase in average temperature is correlated with increased self-reported mental health concerns. Some potential explanations for this relationship include increased stress and anxiety due to heat, which could be attributed to lack of insulation of a structure or no access to air conditioning. Third, the percent of people of color has a coefficient value of 3.7069 as well as a statistically significant p-value. Thus, the percent of people of color is positively correlated with average temperature. As the percent of people of color in a block group increases, so does the average temperature. Based on the findings illuminated in Figure 1.2, which shows the discrepancies in tree equity score between majority Black and majority white block groups, it is likely that this average temperature differential is due, at least in part, to the urban heat island. With less trees and vegetation, surface temperatures are higher, and there are often lower tree equity scores in majority Black block groups. Last, estimate median household income has a coefficient value of -1.441e-05. Although this may appear to be a small negative correlation, because the scale of income is vastly different than the scale of temperature, it indicates a relationship worth exploring further. Because the p-value is statistically significant, the regression indicates that as the average temperature increases, estimate median household income decreases. The compounding factors seem to indicate that majority Black block groups, which are often lower income than majority white block groups, have lower tree equity scores and higher average temperature. Thus, it makes sense that the regression would show a negative correlation between average temperature and estimate median household income.

**Tree Equity Score Map**

Figure 3.1 displays a higher tree equity score in yellow and a lower tree equity score in purple. We can see that there is a low tree equity score in areas that are low-income and predominantly people of color, such as South Los Angeles. This correlation helps us answer our research question by demonstrating that race and income are correlated with tree equity. Similar to the Tree Canopy Point Map, it demonstrates that there are spatial disparities present across Los Angeles County such as lack of investment and homeownership in communities that have a lower tree equity score. These findings are useful because they demonstrate that there is an inequitable investment in areas across Los Angeles County. Areas with more people of color and low-income residents have a lower-tree equity score that creates healthy conditions for residents. To reduce the negative impacts associated with a lower tree equity score, city planners and policymakers must invest in these communities by providing cooling shelters, more green spaces, and providing maintenance assistance to reduce any burden placed on the renter and the residents living in these communities.

**Average Temperature Map**

Figure 3.2 displays a distribution of average temperatures across Los Angeles County. The map illustrates that there are higher temperatures in low-income communities and communities like South Los Angeles, compared to white communities like West Los Angeles. This map allows us to answer our research question by demonstrating that there is a correlation between urban heat, tree equity score, tree canopy percentage, and neighborhood demographics. The Average temperature map resembles the tree equity score map, tree canopy point map, and findings from our regression analysis, which indicate that there is a disparity present in Los Angeles county associated with community demographics. Low-income communities and communities of color face higher urban heat than those that are living in areas with a higher tree equity score. This correlation creates public health concerns and unbearable heat for vulnerable residents. These findings are useful because they demonstrate that city planners and policymakers must invest in these communities to reduce any negative impact associated with high average temperatures. As climate change continues to increase average temperatures, low-income communities and communities of color will face the biggest burden. To reduce these negative impacts, Los Angeles County must begin investing in these communities by providing cooling centers, planting more trees, and landscaping programs to reduce the burden faced by low-income residents and people of color.

**Physical Health Map**

Figure 3.3 reveals that low-income communities and communities of color in South Los Angeles have a higher level of physical health compared to high-income areas. Similar to the Physical Health Regression Model, the Physical health map indicates that there is a connection between people of color, income, and access to health insurance. This may be due to multiple factors such as lack of dependence on cars and more walking. Communities living in these areas may have

higher physical health because they rely on public transportation and walking to get to their destination. In addition, low-income communities and people of color in South Los Angeles may not have access to affordable health care and may have to take better care of their physical health compared to more affluent communities in Los Angeles County. Communities with better physical health may also be working blue-collar jobs that require more physical labor than residents who are more affluent. While this map reveals that physical health is better in areas where there is a lower tree equity score and higher average temperature, it makes us question what other inequalities are present within these communities that allow residents to have better physical health. This relationship allows us to question how reliant low-income residents are on public transportation, their occupation, and their ability to afford health insurance.

**Census Block Groups with the Below Average Tree Canopy Percentage point map**

Figure 3.4 displays a low tree canopy percentage in the color purple and more trees in the yellow. At a glance, this map does not show a clear correlation between tree canopies and community demographics. However, when we look closely in the South LA region, we can see that there are more clusters of purple points than in West Los Angeles which suggests that there may be a below-average tree canopy percentage in areas that are predominantly people of color such as South Los Angeles, while there is a higher tree canopy percentage in areas that are predominantly white such as West Los Angeles. The point map reveals evidence that helps answer our research question by illustrating that census blocks in Los Angeles may have varying access to resources and in low-income communities, there may be less access to funding for tree maintenance. There may be many factors that cause this relationship, including disinvestment and a gap in homeownership. Communities that have a below-average tree canopy percentage as seen in the color purple have been historically disinvested, and lack the resources to produce community beautification projects such as the planting and maintaining of trees. However, in areas that have yellow dots, there has been more investment in cities through public infrastructure, transportation, and landscaping. In addition, low-income communities in California tend to be made up primarily of renters, who oftentimes do not have the capability to plant and maintain trees because they are unable to keep up with the costs associated with maintaining trees in a space they do not own. This map is helpful in understanding the inequalities present across Los Angeles county census blocks, specifically by highlighting areas that have been disinvested and not seen much investment in green space and public infrastructure as well as a homeownership gap that leaves many low-income renters living in areas with few trees and green spaces.

# Conclusion

**Primary Takeaways**

The results of our study find that there are racial disparities between groups in Los Angeles in a variety of different factors such as physical health and tree coverage. We find statistically significant differences in self reported physical health issues and tree equity scores as seen in figure 1.2 and figure 1.3 between majority white and Black block groups. We can identify this trend visually as well through the maps in figure 3.1 and 3.3 – there are concentrated patches of lower tree equity scores and higher physical health issues in parts of Los Angeles that are known to be primarily non-White. Identifying a reverse trend proved to be effective at identifying statistically significant indicators of physical health and average temperature. Tree equity score could reasonably predict the variables that derive itself – there was a statistically significant trend in figures 2.1 and 2.2 when Tree Equity scores were used in our regression analysis. As the Tree equity score increased, we saw a decrease in average temperature and physical health issues.

**Limitations of the Study**

We believe that our regression analysis, although it matches our general theory, can be improved to address mistakes within the setup. For instance, we believe that our regression analysis may have issues of multicollinearity in the physical health and mental health variables. Both are highly concentrated along the same slope within the same scale suggesting an implicit feedback loop behavior. Our regression model may not be able to easily distinguish between whether or not mental health issues affect average temperature or whether it should be physical health issues because both variables describe a similar pattern. We may be experiencing issues of heteroskedasticity too. Some variables seem to have data points that stray further and farther from a central trend line that violates classical assumptions necessary for a regression analysis: that the data be linear in nature. Further research and strategies to handle heteroskedasticity would be necessary to improve our model.

Further inclusion of a race dummy variable to distinguish between majority white block groups and majority Black block groups would most likely dramatically improve our regression model as well. In order to explicitly draw out differences between races, a dummy variable would ascribe an exact impact on our regression model. Due to time limitations, we had to use percent POC as an imperfect replacement given that percent POC and majority white/Black block groups are slightly different measurements.

**Policy Implications and Recommendations**

Our research suggests that because there is a discrepancy between races in Los Angeles, that policymakers have a responsibility to promote equity in living conditions and health. Sociological factors are implicit in one's day to day lives, but they dramatically affect one's lifestyle in the long run. They are not easy to quantify nor describe, but we believe that our report has successfully identified a few variables of difference between groups of race. We also believe that we have identified ways that sociological factors build off of each other – that small

improvements in one category can lead to improvements in others. We suggest that policy makers prioritize block groups that are majority people of color by increasing investments in these areas. We wish to see plans that increase green space, vegetation, and tree planting. We wish to see an increase in participatory planning so that these historically underserved communities can gain autonomy in their lives, not have their lives be dependent on their economic status.

## Contributions

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|---|---|
| Rose An | Rose wrote the results section of the written portion. |
| CJ Chow | CJ compiled and edited all of the code, found the dataset for and created the point map, wrote the methodology and conclusion sections, and made general edits and revisions. |
| Sam Ellman | Sam wrote the discussion sections for the data visualizations and the average temperature regression model, helped CJ with the conclusion section, and made final edits. |
| Natalie Ikhrata | Natalie wrote the background section of the written portion. |
| Mayra Garcia | Mayra wrote the discussion sections for the maps and the physical health regression model. |
| Vanessa Ramirez | Vanessa wrote the introduction of the written portion. |

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