The background image shows a wide-angle aerial view of the Denver city skyline at sunset or sunrise. The foreground is filled with a dense urban tree canopy, with many trees displaying vibrant autumn colors like orange, yellow, and red. In the distance, the city's modern skyscrapers are silhouetted against a bright sky.

URBAN TREE CANOPY ASSESSMENT

Spatial Analysis for the City of Denver

Aletha Spang and William Hitson

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College of Architecture and Planning
UNIVERSITY OF COLORADO DENVER

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BACKGROUND

Urban trees provide significant ecosystem services primarily through regulating and supporting mechanisms. First, trees play an important role in climate change mitigation and air pollution control by sequestering carbon and filtering pollutants. Second, they reduce the Urban Heat Island (UHI) effect by providing shade and by cooling air temperatures through evapotranspiration (Dobbs, Kendal, & Nitschke, 2014). Studies have shown trees can lower peak temperatures by two to nine degrees Fahrenheit (EPA, 2021b). Third, trees improve stormwater management through uptake of runoff, filtration of contaminants, and improvement of soil health (Dobbs, Kendal, & Nitschke, 2014; EPA, 2021a). Fourth, trees provide habitat for other organisms which supports biodiversity (Dobbs, Kendal, & Nitschke, 2014). Examples of other services urban trees provide include regulating noise, adding cultural and aesthetic value, improving psychological health, and provisioning of food, timber, or botanicals. The benefits provided by trees are extensive and well established.

Urban trees bring disservices with them as well. Two primary concerns are increased allergens and infrastructure damage (Dobbs, Kendal, & Nitschke, 2014). Increased allergens can drive up real health costs, while infrastructure damage may occur through root systems or in times of severe weather or poor tree health. Additionally, trees require investment to maintain. Planting, pruning, pest control, and watering trees all have financial and resource costs, particularly in climates less conducive to tree cover (EPA, 2021b). Despite these costs, a study of five cities indicated that for each dollar invested in the annual maintenance of urban trees, benefits of \$1.37 to \$3.09 were realized (McPherson et al., 2005). When considering both services and disservices, urban trees are widely viewed as net benefits to society (Schwartz et al., 2015).

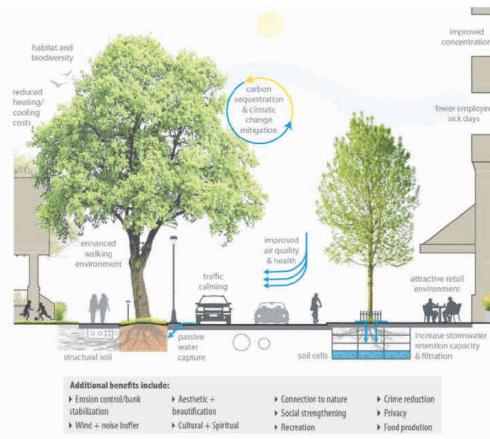


Figure 1: Benefits of urban tree canopy cover. Lefrançois et al. 2017.

While the benefits of urban trees are established, they are not equally realized by all. The distribution of Urban Tree Canopy Cover (UTCC or UTC) is a common concern within the movement and field of environmental justice (Schwartz et al., 2015). Both public

perception and evidence from literature suggest that UTCC is often negatively correlated with typical indicators of disadvantaged or marginalized communities (Schwartz et al., 2015; Riley & Gardiner, 2019). Typical indicators include measures of income, race, and education. This negative correlation in turn exacerbates inequities when ecosystem service benefits are disproportionately shared. However, research has also shown that these patterns of correlation are not universal. The relationship between UTCC and sociodemographic indicators can vary spatially and by context, especially as it pertains to each unique urban environment, and other factors may therefore be required to explain their relationship (Riley & Gardiner, 2019).

Accordingly, understanding the unique conditions of the City and County of Denver ('Denver' or 'the City') is critical to explaining its UTCC. In Denver, spatial distribution of inequity is frequently summarized as the "Inverted L" (Sachs, 2018). This shape is used to approximate and conceptualize patterns of race, education, income, UTCC, and numerous other factors with equity implications across the City, as seen in Figure 2 and 3 below.

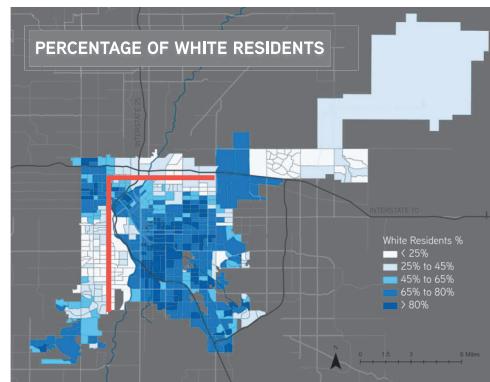


Figure 2: Map of white residents in Denver. Denver Open Data and US Census.

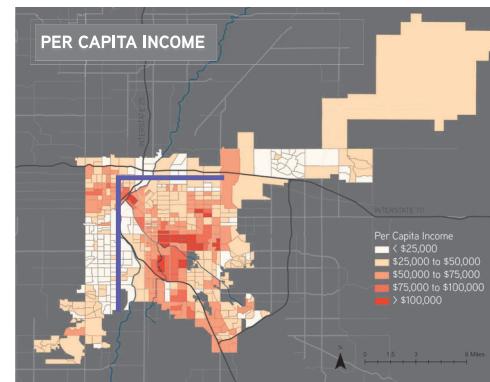


Figure 3: Map of per capita income in Denver. Denver Open Data and US Census.

In addition to sociodemographic data, development trends warrant consideration for their impacts on UTCC. Development in general is commonly perceived as one of the greatest threats to maintenance or expansion of the UTCC (EPA, 2021a; Finley, B. 2019). As an expanding urban center, Denver has experienced considerable development pressure over the last decade and should expect this pressure to continue (Figure 4 on next page).

Between 2010 and 2020, Denver's population grew by almost 20%, and the State Demography Office projects the statewide population to grow by 20% by 2040. (Colorado Parks and Wildlife, 2018; Hernandez, 2021).

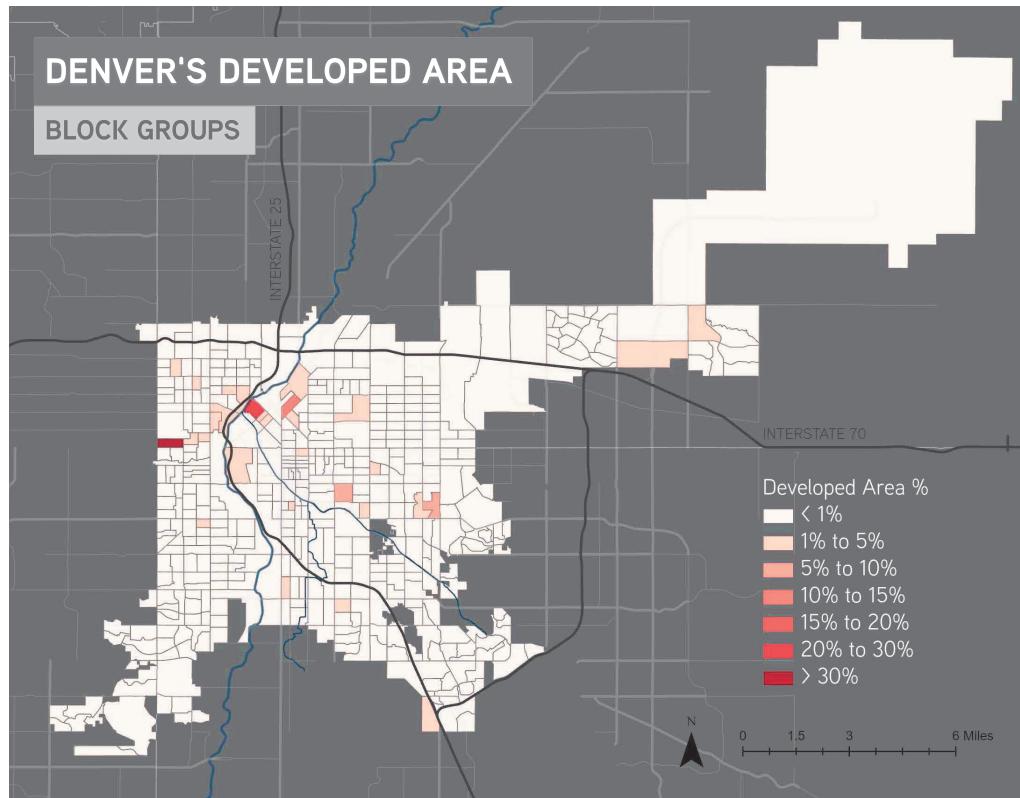


Figure 4: Total parcel development area summarized using census block groups. Denver Open Data.

Rising temperatures from climate change underscore the need for robust UTCC in Denver despite development pressure. Recent estimates from the National Oceanic and Atmospheric Administration show that Denver's average annual temperature for the period of 2011-2020 increased by 1.1 degrees Fahrenheit compared to the previous 10-year estimate (Stein, 2021). Current estimates for Denver's total tree canopy range from 10% to 13% while its explicit goal is to reach 20% coverage of the City (Denver Parks and

Recreation, 2019; Sachs, 2021). To achieve this goal in an equitable manner, it is important to first understand patterns that exist between UTCC, sociodemographic information, and development.

Visually, the tree canopy cover in Denver appears to follow the same 'inverted L' distribution of inequity (Figure 5 below). However, other explanations may exist for this visual pattern. For instance, the physical forms of major highways, such as Interstate-70 and Interstate-25, along with rail corridors may be limiting canopy growth in these block groups. Statistical support is necessary to validate the claim that the tree canopy distribution follows perceived patterns of inequity.

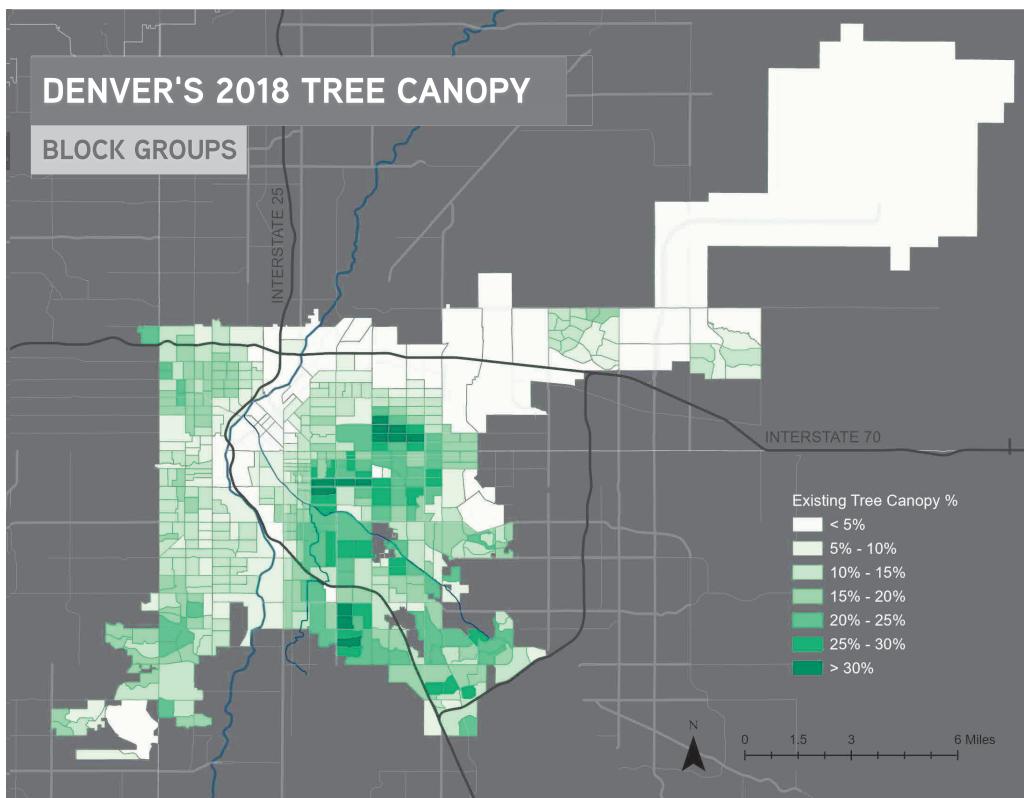


Figure 1: Existing tree canopy from 2018. Denver Open Data. Canopy area was summarized using census block groups and normalized by total block group area.

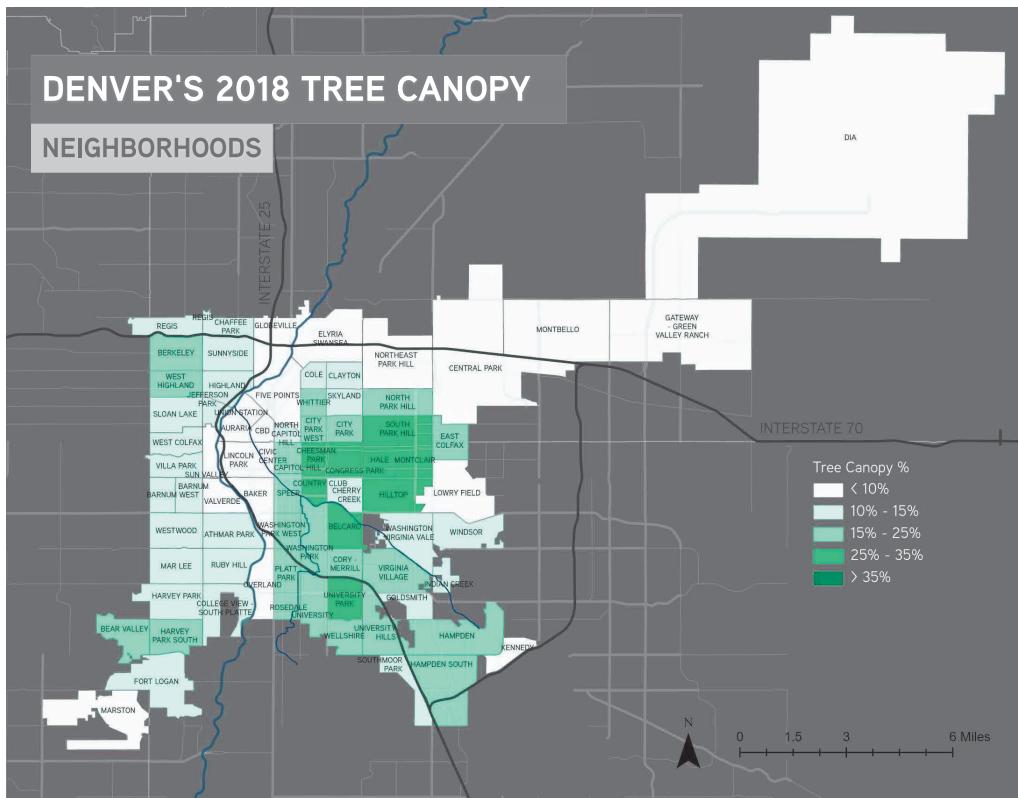


Figure 6: Existing tree canopy from 2018. Canopy area was summarized using statistical neighborhoods and normalized by total neighborhood area.

RESEARCH OBJECTIVES

The purpose of this investigation is to identify whether spatial distribution of UTCC in Denver follows patterns identified in literature with respect to sociodemographic data and development patterns. First we calculate tree canopy change and present a model to recreate our approach with subsequent years of tree canopy data. Next, we identify where canopy growth or loss is occurring in the city. We then examine where development has happened and calculate its area. Finally, we use this information to analyze whether canopy change is positively or negatively associated with sociodemographic data and with development.

Specifically, we ask:

- Which sociodemographic factors are positively and negatively correlated with UTCC in Denver?
- Which sociodemographic factors are positively and negatively correlated with UTCC change over time in Denver?
- Is development positively or negatively correlated with UTCC in Denver?
- Do residential and commercial developments have different correlations with UTCC in Denver?



Figure 7: Colorado Public Radio.

METHODS

Calculating Tree Canopy Change

ArcGIS Pro's Model Builder function was used to automate the comparison of shape areas for vector polygon data files from separate points in time while tracking additions or losses. Its function for this investigation was to track growth or loss in vector polygon representations of tree canopy from 2014 to 2018, but the model could be repurposed to compare future years against 2018 data. Similarly, the model could be used to compare other vector polygon files such as building footprints over time.

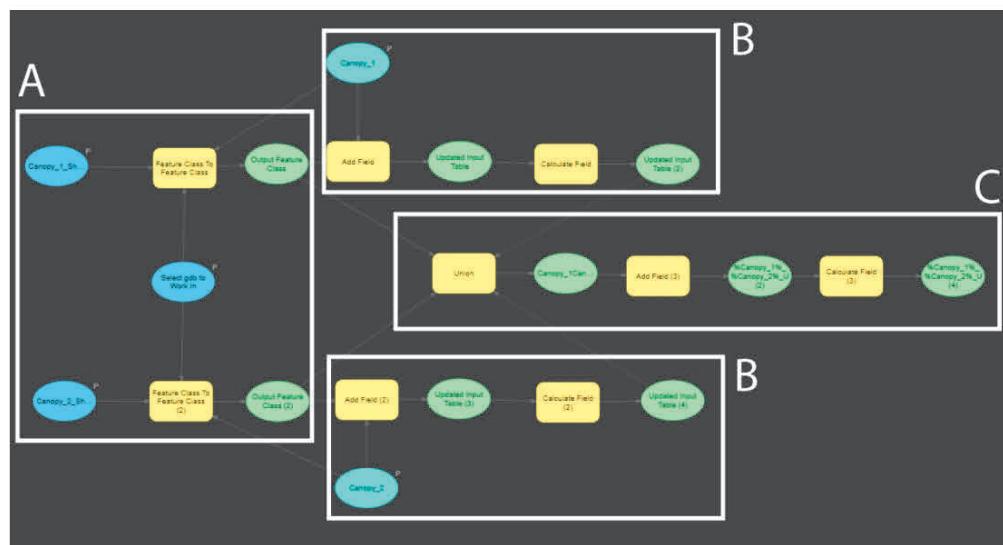


Figure 8: Model Builder for calculating tree canopy change over time, split into three phases.

The model can be summarized in 3 phases. In Phase A, the user selects two shapefiles for comparison. The shapefiles are converted to feature classes in the geodatabase of the user's choice, and the feature classes are projected using the current map's projection. For Denver, this projection was set to NAD 1983 UTM Zone 13N for maximum accuracy. In Phase B, each feature class is assigned a new attribute field which is named after the file itself. The field value, which will be used to track which file polygons originate from, is set to '1.' In Phase C, the 'Union' function is performed to compare the two vector polygon files. The difference is calculated between the fields created in Phase B to determine where canopy growth or loss has occurred, and is stored in a new data field. The single resulting file indicates which shapes are 'new' (canopy growth), 'old' (canopy loss), or maintained

between the two original files (no change). The outcome from this command can be seen in Figure 10 at right, where areas of growth are represented by green polygons, areas of loss are represented by red polygons, and areas of no change are represented by gray polygons.

The 'Select by Attributes' tool was used to find all areas of growth and loss and export them as separate feature classes that could then be aggregated for analysis.

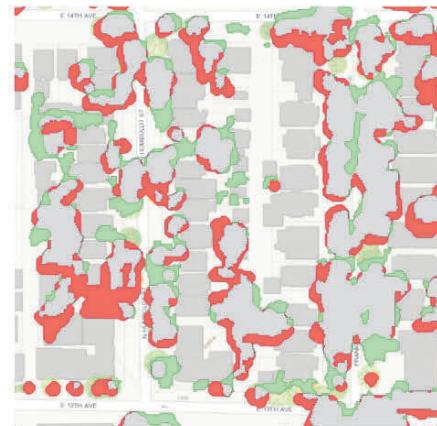


Figure 10: Model Builder outcome: polygons of growth and loss.

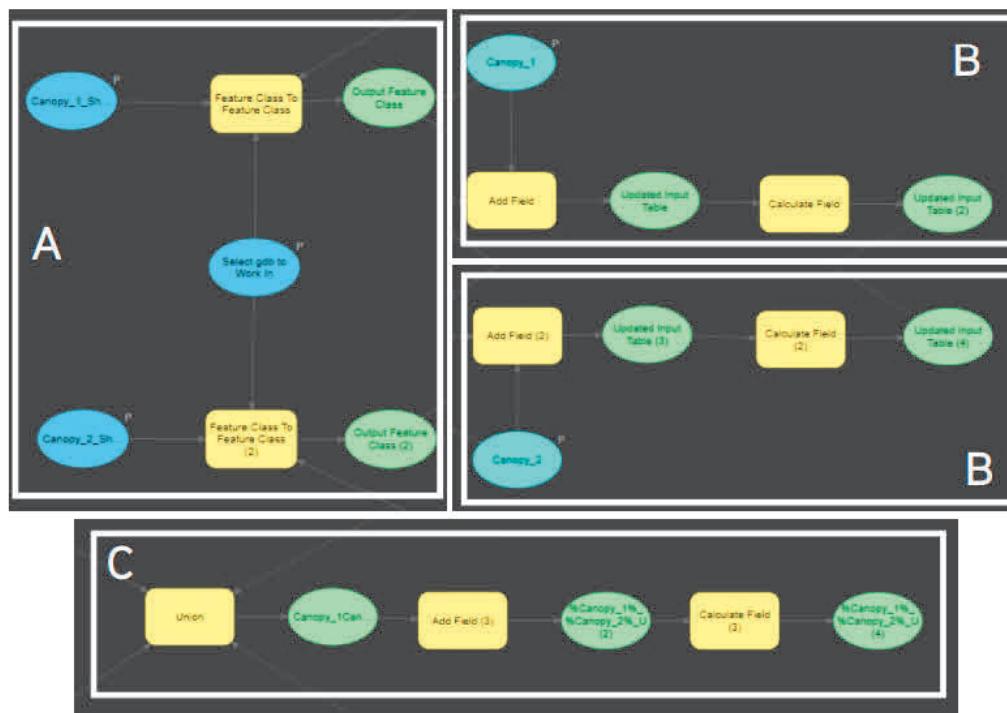


Figure 9: Closer look at Model Builder phases.

Calculating Denver's Development

Denver Parcel data was used as an indicator of general development across the city. The data layer was transformed and projected into the NAD 1983 UTM Zone 13N coordinate system. The file contains information on what year the physical improvements were constructed and whether the improvements are residential or commercial, located in the attribute fields labeled 'RES_ORIG_YR_BUILT' and 'COM_ORIG_YR_BUILT'. The 'Select by Attributes' tool was used to query parcels where the original build date for residential parcels was between 2014 and 2018, as these years aligned with the tree canopy datasets being examined. The selection was then exported as a separate feature class. The same process of 'Select by Attributes' was used to create a separate dataset for commercial parcel development. Finally, the two exported feature classes were combined to create a feature class that represents total development. For the three parcel datasets, total area was used as the metric for evaluation.

Aggregating Data into Block Groups

For the regression analysis, block group polygons were selected as the unit of analysis as they would provide the most granular sociodemographic data possible. When considering the specific conditions of Denver, it is important to recognize that the block group containing Denver International Airport may prove a unique case. Its size is an extreme outlier while its developed area is dominated by the airport itself. Because of this, it has the potential to skew the analysis. We therefore tested our research questions both with and without this census block in statistical tests.

The census block group dataset was taken from Denver Open Data's American Community Survey years 2014-2018 to align with the same years from the tree canopy datasets. From there, the 'Summarize Within' tool was used to aggregate the tree canopy and parcel development area within each block group. Within the tool panel, the field 'Shape_Area' was specified and the statistic 'Sum' was selected, as this appeared to give the most accurate summary results for total area. Each 'Summarize Within' calculation would only aggregate one dataset into the block group level, so the tool was run four separate times for tree canopy to account for the years of 2014 and 2018, total area of growth, and total area of loss. 'Summarize Within' was also calculated three times for parcel development to aggregate total development area, residential development area,

and commercial development area. This process resulted in seven separate datasets of block group polygons, each with demographic data and a single sum of area.

All of the block group datasets with areas of tree canopy and development were then joined together using the 'Union' tool. Any repeated fields were deleted, leaving only one copy of demographic data, canopy area numbers for 2014, 2018, total growth, total loss, total development, residential development, and commercial development. Additional fields were added: 'Net_Loss', which was calculated to be area of tree loss multiplied by -1, and 'Net_Change', calculated as the sum of net loss and growth areas that identified overall change in each block group.

Another field was added to find percent change and was calculated as the net change area divided by the original 2014 tree canopy area to find overall percentage of change in each area. The tree canopy areas from 2014 and 2018 were also normalized in additional fields, where they were divided by the total area of the block group. All of these areas were then converted from the default map units of square meters to square feet using the conversion factor of 10.7639.

Ordinary Least Squares Regression

Ordinary Least Squares regression tests were conducted in the program GeoDa, a free and open-source software with robust spatial statistic analysis capabilities. The aggregated census block group shapefile was exported from ArcGIS Pro. From this shapefile, the single .shp file was opened in GeoDa to run analyses. The regression was first conducted using the normalized static tree canopy area in each block group from 2018 to assess

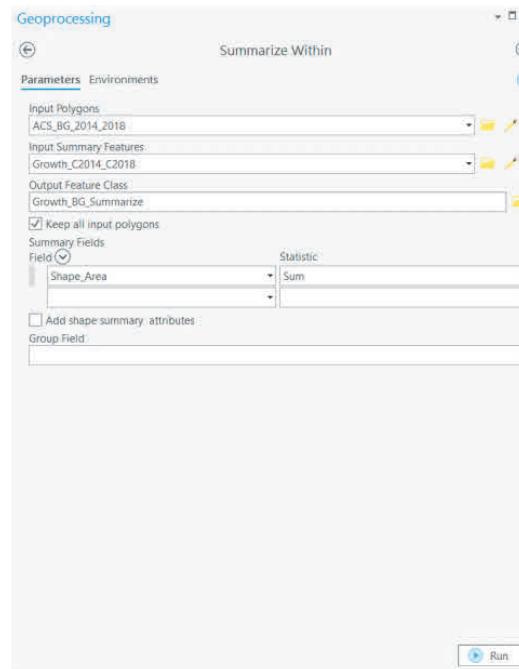


Figure 11: 'Summarize Within' tool parameters in ArcGIS Pro.

spatial relationships and confirm methodological validity. When the regression was conducted using all twenty-five variables of interest, it did not return significant results because the high number of variables obscured relationships. Instead, the socioeconomic variables were broken into five different smaller thematic groups that were analyzed together in the regression with more accurate results: race/ethnicity, identity, housing, income, and education.

Race	Identity	Housing	Income
Percentage of Hispanic Residents	Total Population	Percentage of Owner Occupied Units	Median Household Income
Percentage of White Residents	Population Density	Percentage of Renter Occupied Units	Average Household Income
Percentage of Black Residents	Median Age	Percentage of Vacant Units	Average Family Income
Percentage of Indigenous Residents	Percentage of Male Residents	Percentage of Family Households	Median Earnings
Percentage of Asian Residents	Percentage of Female Residents	Median Home Value	Per Capita Income
Percentage of Hawaiian Residents		Median Gross Rent	
Percentage of Residents with Other Race		Median Year Structure was Built	
Percentage of Two or More Races			

Figure 12: Independent variables included in Regression analyses.

A classic regression model was first conducted to determine if there would need to be correction for spatial error. Normalized tree canopy area was selected as the dependent variable, and independent variables were selected for each of the thematic groups, as seen in Figure 13 on the following page. The output report from this test (Figure 14) gave a probability or p-value for each of the independent variables. The variable was considered statistically significant if its p-value was less than or equal to 0.05, implying a 95% confidence that this relationship was non-random. The coefficient sign for each variable (whether positive or negative) determined the relationship of the independent variable to the

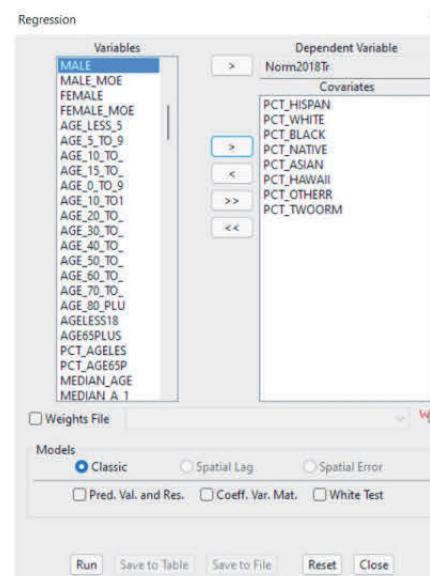


Figure 13: Classic regression test parameters in GeoDa.

dependent variable and whether it was positive or negative. From the first classic regression model test, the variables of percent white residents and percent Asian residents were considered significant with p-values less than 0.05.

Before these results could be assumed as accurate, the residual errors from the regression test first needed to be analyzed. A classic regression model requires the assumption that errors will be independent and will not have any correlation or relationship. In a spatial regression model, errors will often have autocorrelation that will affect the outcome and lead to false results. The residual errors from the regression test were then added to the attribute table and used as a variable for a Univariate Local Moran I's test.

The Moran's test first required a weights file before it could be conducted. To construct a weights file, a spatial correlogram was used to determine the point at which autocorrelation drops off in the normalized tree canopy field, identified as the point at which the upper line graph crosses the x-axis as seen in Figure 15 below to be around 5,000.

A Univariate Local Moran I's test was then conducted on the residual errors from the classic regression model. The test showed significant autocorrelation within the error terms, with clusters of high and low values across the city (Figure 16 below). Due to this autocorrelation, the

REGRESSION				
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION				
Data set : Tree_Canopy_Dev_BG_Summarize				
Dependent Variable : Sq010Tree Number of Observations: 481				
Mean dependent var : 758275 Number of Variables : 12				
S.D. dependent var : 658109 Degrees of Freedom : 469				
R-squared : 0.124750 F-statistic : 6.439895				
Adjusted R-squared : 0.114456 Prob(F-statistic) : 0.32912e-10				
Sum squared residual : 1.29536e+14 Log likelihood : -7012.44				
Sigma-square : 2.76405e+11 Akaike info criterion : 14049.5				
S.E. of regression : 525746 Schwarz criterion : 14099				
Sigma-square ML : 2.69513e+11				
S.E. of regression ML : 519147				
<hr/>				
Variable	Coefficient	Std Error	t-Statistic	Probability
CONSTANT	1.04005e+06	524682	2.00397	0.04391
TTL_POPULA	-189.139	130.142	-1.36916	0.17160
PCT_HISPAN	-8724.15	5392.42	-1.61786	0.10637
PCT_WHITE	-1971.55	5204.59	-0.373597	0.70927
PCT_BLACK	-9280.89	951.4	-9.58811	0.00006
PCT_NATIVE	-10000.4	10651.6	-0.922208	0.36741
PCT_ASIAN	-11758	7449.19	-1.57842	0.11114
PCT_HAWAII	15668.7	22844.1	0.694891	0.49746
PCT_OTHER	2786.6	270951.4	0.101753	0.91904
PCT_TWORR	-11873.2	10240.7	-1.13002	0.25908
MALE	132.761	256.482	0.67358	0.50080
FEMALE	563.449	268.217	2.17629	0.03011
<hr/>				
REGRESSION DIAGNOSTICS				
MULTICOLLINEARITY CONDITION NUMBER : 68.455041				
TEST ON NORMALITY OF ERRORS				
TEST	DF	VALUE	PROB	
Jarque-Bera	2	1472.6213	0.00000	
DIAGNOSTICS FOR HETEROGENEITY				
RANDOM COEFFICIENTS				
TEST	DF	VALUE	PROB	
Breusch-Pagan test	11	75.9048	0.00000	
Koenker-Bassett test	11	15.9011	0.14068	
END OF REPORT				

Figure 14: Regression test output report with areas of most interest highlighted.

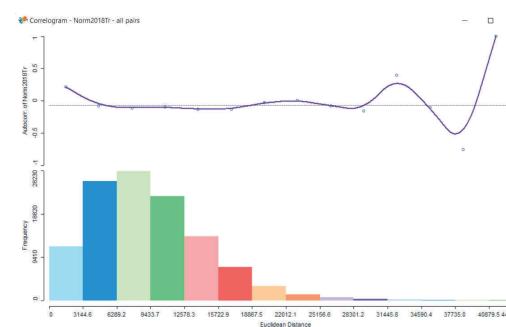


Figure 15: Spatial correlogram. Autocorrelation drops off where upper linear graph crosses x-axis around 5000.

the results from a classic regression could not be used for analysis. A spatial error model was created instead for a more accurate regression.

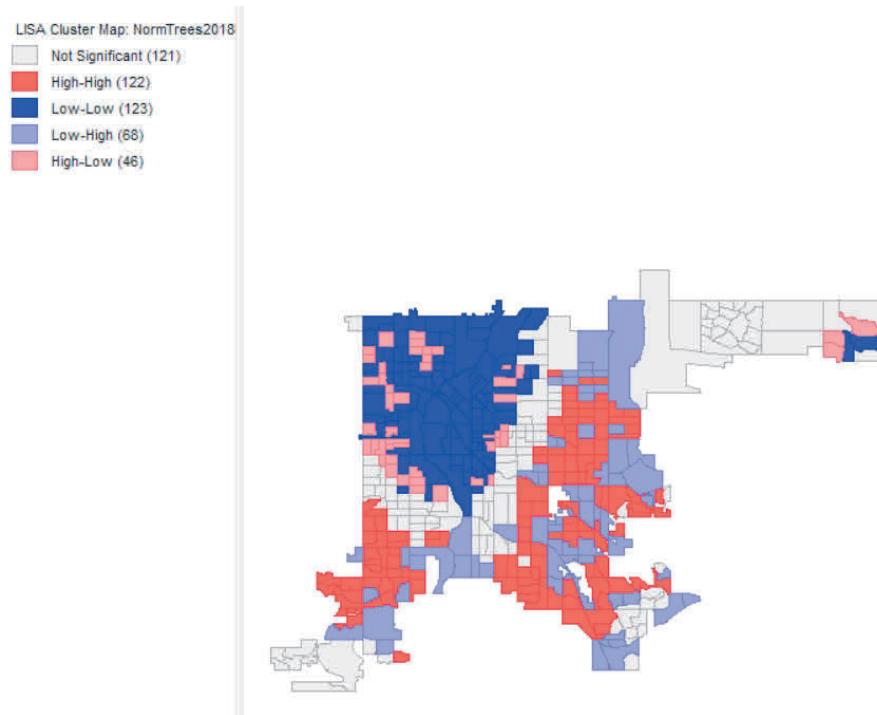


Figure 16: Univariate Local Moran's I test on residual errors. Autocorrelation is present, indicating a spatial error model must be run instead.

the results from a classic regression could not be used for analysis. A spatial error model was created instead for a more accurate regression.

A spatial error model regression was then conducted for normalized tree canopy area from 2018 both with and without the airport, and for tree canopy change with and without the airport (Figure 17). After the initial twenty-five variables were tested, non-significant variables with p-values of greater than 0.05 were removed and the regression was run until all remaining variables were significant with p-values of less than or equal to 0.05. Development percentages were only used in the regressions of tree canopy change because they also show change from 2014-2018 and would not be comparable to a static

number of tree canopy area. Spreadsheets were created to keep track of the variables, p-values, coefficients, and R-squared values. The R-squared values indicate the proportion of which the independent variables explained the dependent variables, where a value of 0 can be interpreted as no explanation for variation and a value of 1 can be interpreted as full explanation of variation.

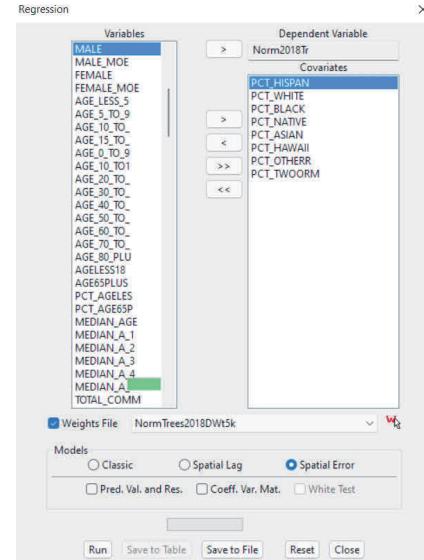


Figure 17: Spatial error regression model parameters.

RESULTS

Tree Canopy Change

Net percentage of tree canopy change was calculated and mapped on a census block group level and a neighborhood level (Figure 18 below and Figure 19 on the following page). Both visualizations show significant canopy loss concentrated around the downtown Denver area between the years of 2014 and 2018, with some canopy growth happening along the city edges and the airport corridor. Green Valley Ranch had the largest canopy growth with a 46.64% increase, followed by DIA, Wellshire, Kennedy, Hampden, Marston, and Hampden South (Figure 20 on page 19). Every other neighborhood in Denver had tree canopy loss instead. Central Business District had the most tree canopy loss with a 49.47% decrease.

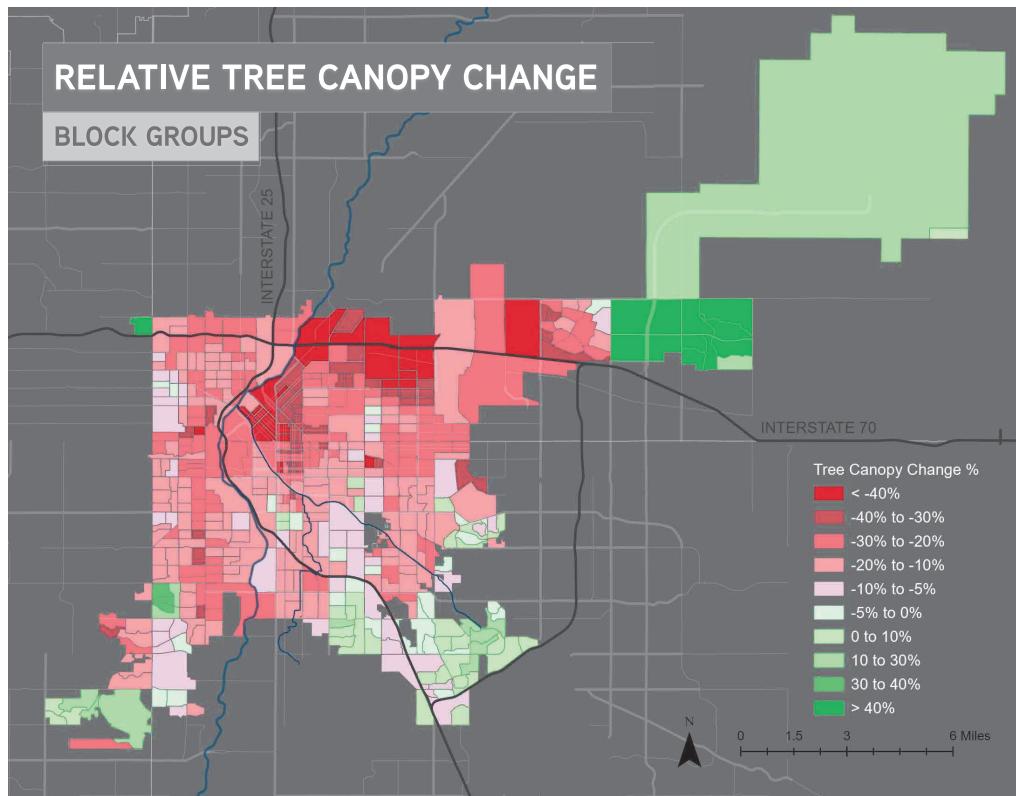


Figure 18: Net percentage of tree canopy from 2014 to 2018. Tree canopy area was summarized inside block groups and subtracted to find net change, and normalized over original tree canopy area from 2014.

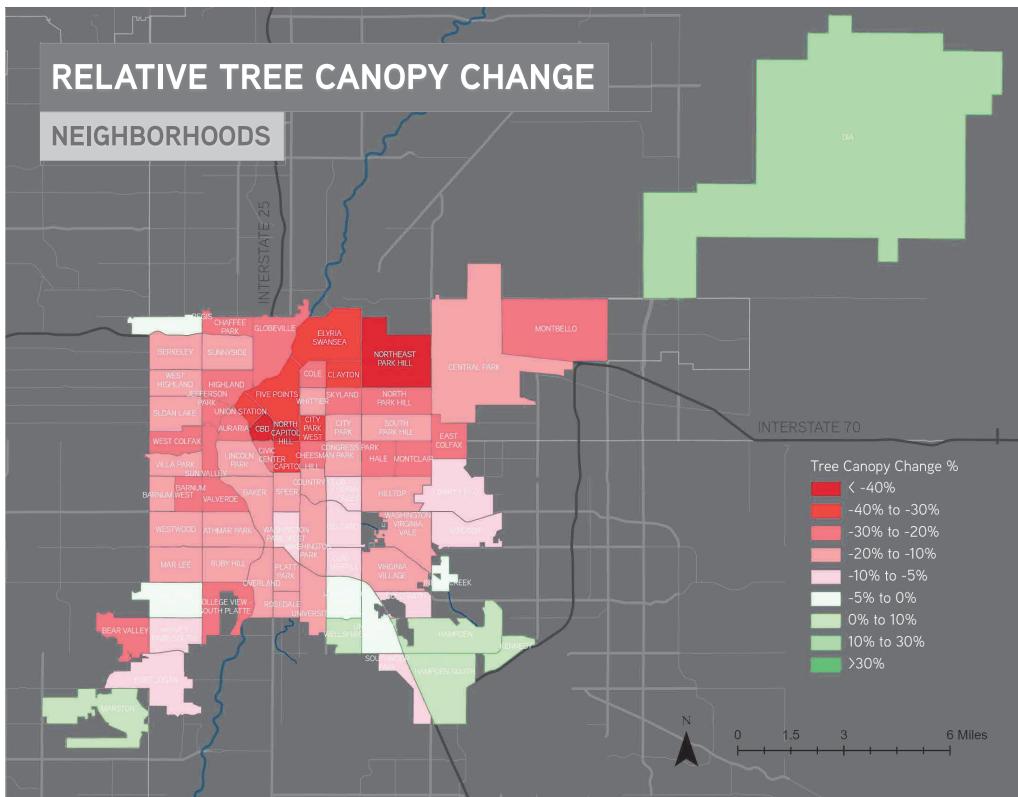


Figure 19: Net percentage of tree canopy from 2014 to 2018. Tree canopy area was summarized inside block groups and subtracted to find net change, and normalized over original tree canopy area from 2014. Data source: Denver Open Data.

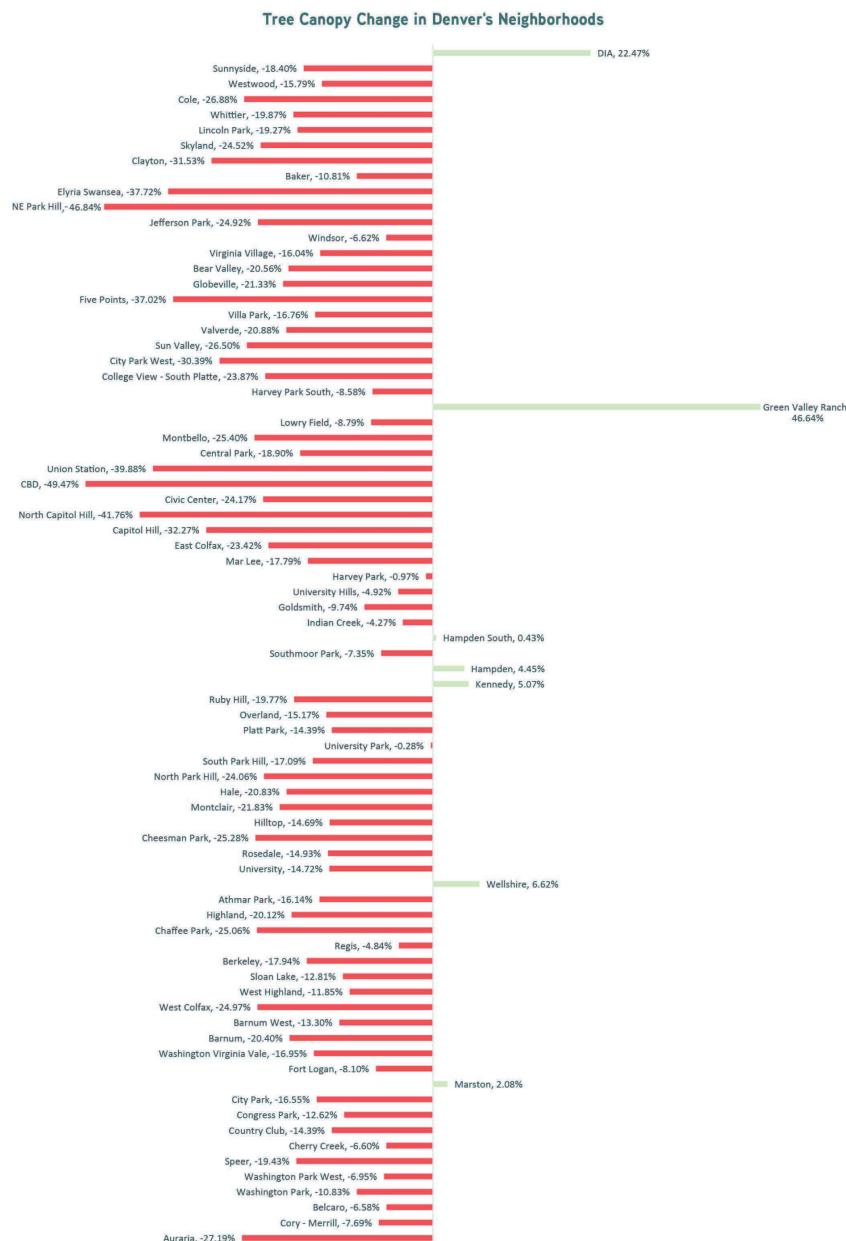


Figure 20: Tree canopy percent change for each neighborhood in Denver.

Regression Outcome: Normalized Tree Canopy Area from 2018 (Static) with Airport

	Independent Variables	P-Values	R-Squared	Significant?	Relationship
First Test	Percentage of Hispanic Residents	0.16	0.34	No	Positive
	Percentage of White Residents	0.001	0.34	Yes	Positive
	Percentage of Black Residents	0.73	0.34	No	Positive
	Percentage of Indigenous Residents	0.59	0.34	No	Negative
	Percentage of Asian Residents	0.09	0.34	No	Negative
	Percentage of Hawaiian Residents	0.01	0.34	Yes	Positive
	Percentage of Residents with Other Race	0.78	0.34	No	Negative
	Percentage of Two or More Races	0.57	0.34	No	Negative
	Total Population	0	0.32	Yes	Negative
	Population Density	0.34	0.32	No	Positive
	Median Age	0	0.32	Yes	Positive
	Percentage of Male Residents	0.07	0.32	No	Negative
	Percentage of Female Residents	0.01	0.32	Yes	Positive
	Percentage of Owner Occupied Units	0.002	0.51	Yes	Positive
	Percentage of Renter Occupied Units	0.08	0.51	No	Positive
	Percentage of Vacant Units	0.00001	0.51	Yes	Negative
	Percentage of Family Households	0.08	0.51	No	Negative
	Median Home Value	0	0.51	Yes	Positive
	Median Gross Rent	0.0005	0.51	Yes	Negative
	Median Year Structure was Built	0	0.51	Yes	Negative
	Median Household Income	0.41	0.39	No	Negative
	Average Household Income	0	0.39	Yes	Positive
	Average Family Income	0.47	0.39	No	Positive
	Median Earnings	0.15	0.39	No	Negative
	Per Capita Income	0	0.39	Yes	Negative
Second Test	Percentage of Residents with Less than High School Diploma	0.46	0.39	No	Positive
	Percentage of Residents with High School Diploma/Equivalent	0.14	0.39	No	Positive
	Percentage of Residents with Some College	0.02	0.39	Yes	Positive
	Percentage of Residents with Bachelor's or Higher	0	0.39	Yes	Positive
	Percentage of White Residents	0.00046	0.56	Yes	Positive
	Percentage of Hawaiian Residents	0.02	0.56	Yes	Positive
	Total Population	0	0.56	Yes	Negative
	Median Age	0.33	0.56	No	Positive
	Percentage of Female Residents	0.03	0.56	Yes	Positive
	Percentage of Owner Occupied Units	0.08	0.56	No	Positive
	Percentage of Vacant Units	0	0.56	Yes	Negative
	Median Home Value	0	0.56	Yes	Positive

Regression Outcome: Normalized Tree Canopy Area from 2018 (Static) without Airport

	Independent Variables	P-Values	R-Squared	Significant?	Relationship
First Test	Percentage of Hispanic Residents	0.16	0.34	No	Positive
	Percentage of White Residents	0.001	0.34	Yes	Positive
	Percentage of Black Residents	0.7	0.34	No	Positive
	Percentage of Indigenous Residents	0.55	0.34	No	Negative
	Percentage of Asian Residents	0.08	0.34	No	Negative
	Percentage of Hawaiian Residents	0.01	0.34	Yes	Positive
	Percentage of Residents with Other Race	0.75	0.34	No	Negative
	Percentage of Two or More Races	0.64	0.34	No	Negative
	Total Population	0	0.32	Yes	Negative
	Population Density	0.46	0.32	No	Positive
	Median Age	0	0.32	Yes	Positive
	Percentage of Male Residents	0.03	0.32	Yes	Negative
	Percentage of Female Residents	0.009	0.32	Yes	Positive
	Percentage of Owner Occupied Units	0.002	0.5	Yes	Positive
	Percentage of Renter Occupied Units	0.08	0.5	No	Positive
	Percentage of Vacant Units	0.000001	0.5	Yes	Negative
	Percentage of Family Households	0.06	0.5	No	Negative
	Median Home Value	0	0.5	Yes	Positive
	Median Gross Rent	0.0006	0.5	Yes	Negative
	Median Year Structure was Built	0	0.5	Yes	Negative
	Median Household Income	0.44	0.39	No	Negative
	Average Household Income	0	0.39	Yes	Positive
	Average Family Income	0.49	0.39	No	Positive
	Median Earnings	0.17	0.39	No	Negative
	Per Capita Income	0	0.39	Yes	Negative
Second Test	Percentage of Residents with Less than High School Diploma	0.56	0.39	No	Positive
	Percentage of Residents with High School Diploma/Equivalent	0.16	0.39	No	Positive
	Percentage of Residents with Some College	0.01	0.39	Yes	Positive
	Percentage of Residents with Bachelor's or Higher	0	0.39	Yes	Positive
	Percentage of White Residents	0.001	0.57	Yes	Positive
	Percentage of Hawaiian Residents	0.026	0.57	Yes	Positive
	Total Population	0	0.57	Yes	Negative
	Median Age	0.45	0.57	No	Positive
	Percentage of Male Residents	0.21	0.57	No	Negative
	Percentage of Female Residents	0.02	0.57	Yes	Positive
	Percentage of Owner Occupied Units	0.04	0.57	Yes	Positive
	Percentage of Vacant Units	0	0.57	Yes	Negative
	Median Home Value	0	0.57	Yes	Positive
	Median Gross Rent	0.02	0.57	Yes	Negative
	Median Year Structure was Built	0	0.57	Yes	Negative
	Average Household Income	0.06	0.57	No	Positive
	Per Capita Income	0.009	0.57	Yes	Negative
	Percentage of Residents with Some College	0.96	0.57	No	Negative
	Percentage of Residents with Bachelor's or Higher	0.42	0.57	No	Positive

Regression Outcome: Tree Canopy Change 2014-2018 with Airport

	Independent Variables	P-Values	R-Squared	Significant?	Relationship
First Test	Percentage of Hispanic Residents	0.26	0.384	No	Positive
	Percentage of White Residents	0.049	0.384	Yes	Positive
	Percentage of Black Residents	0.282	0.384	No	Positive
	Percentage of Indigenous Residents	0.9	0.384	No	Negative
	Percentage of Asian Residents	0.185	0.384	No	Positive
	Percentage of Hawaiian Residents	0.657	0.384	No	Positive
	Percentage of Residents with Other Race	0.767	0.384	No	Positive
	Percentage of Two or More Races	0.686	0.384	No	Negative
	Total Population	0.008	0.43	Yes	Positive
	Population Density	0.00004	0.43	Yes	Negative
	Median Age	0	0.43	Yes	Positive
	Percentage of Male Residents	0.592	0.43	No	Positive
	Percentage of Female Residents	0.018	0.43	Yes	Positive
	Percentage of Owner Occupied Units	0.08	0.433	No	Positive
	Percentage of Renter Occupied Units	0.31	0.433	No	Positive
	Percentage of Vacant Units	0.001	0.433	Yes	Negative
	Percentage of Family Households	0.697	0.433	No	Negative
	Median Home Value	0.004	0.433	Yes	Positive
	Median Gross Rent	0.874	0.433	No	Positive
	Median Year Structure was Built	0.068	0.433	No	Negative
	Median Household Income	0.088	0.4	No	Positive
	Average Household Income	0.087	0.4	No	Positive
	Average Family Income	0.362	0.4	No	Negative
	Median Earnings	0.258	0.4	No	Positive
	Per Capita Income	0.36	0.4	No	Negative
	Percentage of Residents with Less than High School Diploma	0.004	0.455	Yes	Negative
	Percentage of Residents with High School Diploma/Equivalent	0.56	0.455	Yes	Negative
	Percentage of Residents with Some College	0.95	0.455	Yes	Positive
	Percentage of Residents with Bachelor's or Higher	0.92	0.455	Yes	Negative
Second Test	Percentage Development Area	0	0.46	Yes	Negative
	Percentage Residential Development Area	0.02	0.46	Yes	Positive
	Percentage Commercial Development Area	0.03	0.46	Yes	Negative
	Percentage of White Residents	0.31	0.54	No	Negative
	Total Population	0.01	0.54	Yes	Positive
	Population Density	0.0008	0.54	Yes	Negative
	Median Age	0.0003	0.54	Yes	Positive
	Percentage of Female Residents	0.16	0.54	No	Positive
	Percentage of Vacant Units	0.012	0.54	Yes	Negative

Regression Outcome: Tree Canopy Change 2014-2018 without Airport

	Independent Variables	P-Values	R-Squared	Significant?	Relationship
First Test	Percentage of Hispanic Residents	0.26	0.38	No	Positive
	Percentage of White Residents	0.05	0.38	Yes	Positive
	Percentage of Black Residents	0.28	0.38	No	Positive
	Percentage of Indigenous Residents	0.89	0.38	No	Negative
	Percentage of Asian Residents	0.19	0.38	No	Positive
	Percentage of Hawaiian Residents	0.66	0.38	No	Positive
	Percentage of Residents with Other Race	0.76	0.38	No	Positive
	Percentage of Two or More Races	0.69	0.38	No	Negative
	Total Population	0.008	0.42	Yes	Positive
	Population Density	0.00004	0.42	Yes	Negative
	Median Age	0	0.42	Yes	Positive
	Percentage of Male Residents	0.6	0.42	No	Positive
	Percentage of Female Residents	0.02	0.42	Yes	Positive
	Percentage of Owner Occupied Units	0.083	0.42	No	Positive
	Percentage of Renter Occupied Units	0.3	0.42	No	Positive
	Percentage of Vacant Units	0.001	0.42	Yes	Negative
	Percentage of Family Households	0.66	0.42	No	Negative
	Median Home Value	0.003	0.42	Yes	Positive
	Median Gross Rent	0.88	0.42	No	Positive
	Median Year Structure was Built	0.06	0.42	No	Negative
	Median Household Income	0.08	0.4	No	Positive
	Average Household Income	0.09	0.4	No	Positive
	Average Family Income	0.37	0.4	No	Negative
	Median Earnings	0.25	0.4	No	Positive
	Per Capita Income	0.37	0.4	No	Negative
	Percentage of Residents with Less than High School Diploma	0.005	0.38	Yes	Negative
	Percentage of Residents with High School Diploma/Equivalent	0.55	0.38	No	Negative
	Percentage of Residents with Some College	0.96	0.38	No	Positive
	Percentage of Residents with Bachelor's or Higher	0.94	0.38	No	Negative
Second Test	Percentage Development Area	0	0.45	Yes	Negative
	Percentage Residential Development Area	0.027	0.45	Yes	Positive
	Percentage Commercial Development Area	0.045	0.45	Yes	Negative
	Percentage of White Residents	0.3	0.53	No	Negative
	Total Population	0.01	0.53	Yes	Positive
	Population Density	0.0005	0.53	Yes	Negative
	Median Age	0.00007	0.53	Yes	Positive
	Percentage of Vacant Units	0.01	0.53	Yes	Negative

Ordinary Least Squares Regression

Tree Canopy Area from 2018 with Airport:

After several regression tests, tree canopy area in 2018 was found to be positively correlated with percentage of white and Hawaiian residents, percentage of female residents, and median home value. Tree canopy area was found to be negatively correlated with total population, percentage of vacant units, median gross rent, median year the housing structure was built, and per capita income (Figure 21 on page 20).

Tree Canopy Area from 2018 without Airport:

Tree canopy area without the airport block group was found to be positively correlated with percentage of white and Hawaiian residents, percentage of female residents, percentage of owner occupied units, and median home value. Tree canopy area was negatively correlated with total population, percentage of vacant units, median gross rent, median year the housing structure was built, and per capita income (Figure 22 on page 21).

There was some significant difference between tree canopy area and sociodemographic factors with and without the airport. Without the airport, the additional variable of percentage of owner occupied units was found to be positively correlated to tree canopy area. The R-squared value was only slightly different with a 0.01 increase without the airport.

Tree Canopy Change with Airport

Change in tree canopy was found to be positively correlated with total population, median age, and percentage of residential development. It was negatively correlated with population density, percentage of vacant units, percentage of residents with less than a high school diploma, percentage of total development area, and percentage of commercial development (Figure 23 on page 22).

Tree Canopy Change without Airport

Change in tree canopy without the airport block group was found to be positively correlated with total population, median age, and percentage of residential development. It was negatively correlated with population density, percentage of vacant units, percentage of residents with less than a high school diploma, percentage of total development area, and percentage of commercial development (Figure 24 on page 23).

There was no significant difference between tree canopy change and sociodemographic factors with and without the airport. When the airport was removed, variable p-values decreased slightly but not enough to change their statistical significance. The R-squared value decreased from 0.54 to 0.53.

DISCUSSION

Results from our static canopy analyses showed mixed support for relationships suggested in literature between UTCC and sociodemographic data. In statistical tests with and without the airport block group, race was statistically significant (p -value = 0.05), with percentages of white and Hawaiian residents positively correlated with UTCC. However, data on education level showed no significant correlation. Interestingly, median home value was positively correlated with UTCC, while per capita income was negatively correlated with UTCC. A possible explanation for median home value positively correlating with UTCC could be the influence of UTCC on property values rather than the inverse. Nonetheless, the negative correlation between per capita income and UTCC was unexpected and suggests that traditional assumptions about income may not be useful in explaining Denver's tree canopy or that per capita income is an inappropriate choice of metric. It is possible that per capita income might be biased against block groups with large populations outside the typical workforce age. More accurate measures of income such as median household income per block group were not found to be statistically significant, indicating that per capita income may not be an explanatory factor. The positive relationship between percentage of female residents and UTCC was also a surprising finding. While several explanations could be hypothesized, further study might focus on the presence of single mother households. R-squared values of 0.56 and 0.57 with and without the airport, respectively, indicate that the sociodemographic data in these tests may not comprehensively predict UTCC in Denver.

Results from our regression of canopy change over time provided answers to our last three research questions. First, few sociodemographic factors correlated with canopy change. Population density, percentage of vacant units, and percentage of residents with less than a high school diploma all negatively correlated with canopy change. Together, these might indicate areas of population vulnerable to displacement from redevelopment. However, more support would be needed to validate this as a possible explanation. Total population was positively correlated with canopy change, but this does not account for block group size and is therefore likely a poor explanatory variable as population density was instead negatively correlated. Median age was also positively correlated with canopy change but neither supports or refutes any predictions in our model. Regressions with and without the airport block group produced nearly identical results with r-squared values of 0.54 and 0.53, respectively.

Assessing development's relationship with canopy change through parcel data provided clearer answers to our final two questions. Using this approach, we found statistically significant support for residential development positively correlating with canopy change, commercial development negatively correlating with canopy change, and the total development negatively correlating with canopy change. The negative correlations of commercial and total development support assumptions that development typically contributes to the degradation of our UTCC. However, using this model, the type of development matters. One possible explanation for the positive effect of residential development on tree canopy could be unique

to the type and location of residential development in Denver. Where redevelopment occurs in the urban core, it may negatively impact the UTCC through construction practices regardless of development type. Where it occurs in urban edge or suburban contexts, it maybe the first development of previously unforested prairie land. These open spaces are also typically where large-scale residential subdivisions are built, with street tree planting being a common component of the development. Relative tree canopy change around the perimeter of the county boundary illustrates this potential hypothesis.

This study has several limitations. The most significant limitation is the process we used to aggregate data at block group level for analysis against sociodemographic factors. In doing so, we lost the high level of granularity in canopy change provided by the tree canopy data files as well as the parcel data. Thus, we are unable to detect a more direct and localized effect of development on tree canopy changes. The choice of parcel data as an indicator of development may also impact our results. Original build dates for parcels may not be the most representative way of describing the general concept of development. Further, there is some level of bias in selecting dates recorded between the beginning of 2014 and the end of 2018 that may not accurately detail when the construction actually occurred. The parcel data must therefore be interpreted as an approximate estimate of development within a block group and not a definitive metric. However, our model and results suggest avenues for further study.

METADATA

Layer Name/Description	Coordinate System/Projection	Datum/Spheroid	Parent Scale/Resolution	Currency/ Publication Date	Data Type	Source
Tree Canopy 2014	Geographic	WGS1984	NA	2018	Vector Polygon	Denver Open Data
Tree Canopy 2018	UTM Zone 13N	NAD1983	1:5,000 and 1:150,000,000	2019	Vector Polygon	Denver Parks and Rec
American Community Survey Block Groups 2014-2018	Geographic	WGS1984	NA	2018	Vector Polygon	Denver Open Data
Parcels	Geographic	WGS1984	NA	2022	Vector Polygon	Denver Open Data
Denver Statistical Neighborhoods	UTM Zone 13N	NAD1983	NA	2022	Vector Polygon	Denver Open Data

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