Urban Forests and Environmental Equity in Calgary, Canada

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ABSTRACT
Environmental equity requires the fair and even distribution of environmental resources, and access to trees is one concern in urban environments. Two important components of the urban forest are the number of public trees on the right-of-way, or simply street trees, and the urban tree canopy (UTC) comprising all the trees in private and public lands within a city. Numerous studies have shown that street trees and UTC are unevenly distributed in many cities in Canada and the United States. Further, there are strong correlations showing the inequity of the distribution of both categories of trees and socioeconomic indicators such as income, education, and ethnicity.

This study identifies environmental inequities in Calgary by calculating global and local spatial autocorrelation on the distribution of street trees and UTC. Results from the global measure indicate that the overall pattern of the distribution of street trees and UTC are clustered, while the results from the local measure show that there are significant clusters in certain areas of the city. The two highest correlations, one moderate and one strong, are local bivariate relationships and show considerable inequity in the distribution of street trees and UTC concerning income and ethnicity respectively.

INTRODUCTION

Over the last 20 years, research on the environmental inequity of the distribution of green spaces, parks, playgrounds, and other environmental amenities within urban settings has received considerable attention (Astell-Burt et al., 2014; Potestio et al., 2009; Smoyer-Tomic et al., 2004; Tooke et al., 2010). An important environmental amenity within the urban environment is the urban forest. The urban forest can be defined as "all the trees in the urban realm – in public and private spaces, along linear routes and waterways and in amenity areas (Doick & Davies, 2016, p. 49).

As an environmental amenity, the urban forest provides several tangible and intangible benefits to urban dwellers. For example, trees reduce the damaging impact of stormwater runoff due to extensive impervious surfaces (Livesley et al., 2016). It also has an ameliorating effect on the impact of the warmer and drier microclimate associated with urban settings, thus reducing the heat island effect (Salmond et al., 2016; Tiwari et al., 2021). Proximity and accessibility to urban forests and green spaces have a beneficial impact on health risk factors such as increased physical activity and reduced child obesity rates (Takano et al., 2002; Potestio et al., 2009). Another important benefit is that an increased number of trees has a positive effect on the property values and rental prices of dwellings in residential areas (Donovan & Butry, 2011). In addition, there is a strong relationship between the percentage of urban tree canopy (UTC), an essential component of the urban forest, and crime rate reduction (Troy et al., 2012). There are also intangible benefits obtained from urban trees that may affect the mental well-being of urban dwellers. A study of urban forest values in Canada found that people appreciate urban trees because "they provide peacefulness, comfort, escape, beauty, naturalness, a connection to nature, biodiversity, a sense of history, and a preferred environment for family and community." (Peckham et al., 2013, p. 161).

In North America, the percentage of UTC varies significantly from city to city. In the United States, the percentage of UTC is documented as low as one percent, as it is in the city of Lancaster, California, and as high as 47 percent, as in the city of Atherton, California (Nowak, 1994). In Canada, the percentage of UTC can also vary significantly from city to city. For example, in the city of Halifax, in the province of Nova Scotia, the percentage of UTC is almost 40%; in the city of Toronto, Ontario, it is close to 30%; while in the city of Calgary, Alberta, it is just over 8% (Alexander et al., 2014; Lambert, 2021; McGovern et al., 2016). The relatively low percentage of UTC in Calgary is significant because it indicates that the areas benefitted are limited more than in more forested cities.

As well, the distribution of UTC within a city may vary considerably from one neighbourhood to the next. Several studies have examined the spatial distribution of UTC in different cities and have attempted to explain the uneven distribution that is often found by examining the connection between UTC and socioeconomic variables. For instance, some studies have looked at the uneven distribution of UTC and green spaces and used a single socioeconomic variable, such as median household income or a low-income threshold, as the main explanatory variable in their statistical analysis. These studies have found that lower-income neighbourhoods have less access to green space and a lower percentage of UTC (Astell-Burt et al., 2014; Greene et al., 2018). Other studies have used a multivariate approach, using income along with other measures of socioeconomic inequality, such as education level and home ownership, to explain the uneven distribution of UTC. These studies have also found that the relationship between uneven access to UTC and socioeconomic inequality is significant, but the strength of the statistical relationship varies substantially from city to city (Krafft & Fryd, 2016; Schwarz et al., 2015; Tooke et al., 2010). In some studies, the measure of socioeconomic inequality has been derived from several related variables, and a composite measure or an index has been used. For example, the Atkinson index, the Gini coefficient, and the Theil index determined that the distribution of environmental amenities is lower in areas that experience greater socioeconomic inequality (Luck et al., 2009; Nyelele & Kroll, 2020; Volin et al., 2020). In one of these studies, the inverse relationship between tree cover and socioeconomic inequality became stronger over time (Luck et al., 2009).

For many cities, the relationship between the distribution of trees and race is statistically significant. In studies carried out in the US, race and ethnicity have been used as potential explanatory variables for the uneven distribution of UTC, and there appears to be a strong and negative relationship between certain minority races and ethnic groups on the one hand and inequity in the distribution of UTC on the other hand. Neighbourhoods and census areas with a higher proportion of African-Americans and Hispanics tend to have a lower percentage of UTC (Koo et al., 2019; Landry & Chakraborty, 2009; Schwarz et al., 2015; Nyelele & Kroll, 2020). However, in at least one of these studies, the relationship between race and UTC became weaker over time (Koo et al., 2019).

In general terms, it would appear that indicators of economic status such as median household income, poverty, and household tenure (owned vs. rented), along with indicators of race and ethnicity (percentage of African-Americans and Hispanics), are the most significant variables in these types of studies. As stated by Nyelele & Kroll:

Racial and ethnic minorities and low-income neighbourhoods tend to have lower vegetation cover and associated ecosystem services relative to more affluent areas, yet these areas tend to be *underprivileged and the most vulnerable areas that rely more heavily upon these ecosystem services. (2002, p. 2)*

To determine the distribution of urban forests within a city, several methods have been used. Some studies have used high-resolution satellite imagery or aerial photography to estimate the percentage of UTC in each neighbourhood or census area (Greene et al., 2018; Volin et al., 2020; Walton et al., 2008). When estimating UTC, both private and public areas are usually included. However, in at least one study, the measure of greenness came from street trees that are on the public right-of-way (Landry & Chakraborty, 2009). This allowed the researchers to examine environmental equity by looking at the spatial distribution of trees that are on public lands and that are publicly financed.

In Calgary, detailed data on both street trees and UTC are available, allowing tree distribution to be assessed from two different spatial databases. As an assessment of environmental equity in the distribution of the urban forest has not been done for Calgary, the main objective of this study is to establish If the distribution of trees in Calgary are clustered and if these clusters can be spatially correlated with socioeconomic variables to show environmental inequity.

METHODS

Study Area and Enumeration Unit

The study area is the city of Calgary, in the province of Alberta, Canada. For Calgary, two acceptable levels of enumeration units for socioeconomic variables could be used: census tracts from the federal census and community districts from the municipal census. This study considered the most appropriate level of enumeration unit.

A community district, henceforth referred to as a "community," is a unit the municipal government uses to administer all the areas under its jurisdiction. Community boundaries also delineate the enumeration units used by the municipal government to collect census data. The province of Alberta is one of four provinces and territories in Canada where municipalities may conduct their annual civic census (Province of Alberta, p. 376). There are 306 communities in the city, with 212 classified as residential areas. In addition, there are 42 industrial areas, four major parks, and 48 undeveloped residential sub-areas set aside for future development (The City of Calgary, August 2016). The Municipal census units have more homogeneity in socioeconomic, historical, and geographic characteristics and are thus better suited for this study (Gauvin et al., 2007; Potestio et al., 2009). However, not all the residential communities were used; only 189 were considered, as 23 communities have insufficient data and have been omitted. Further, in many residential communities, areas of significant size are used for non-residential purposes such as commercial, recreational, school areas, urban nature reserves, etc. For instance, in one inner-city community, over 75% of its area has been designated for non-residential purposes. To focus strictly on residential areas, this study considers only the areas within a residential community classified by the municipal government as low-density, medium-density, and high-density residential. In addition to the community boundaries, the planning sectors used by the municipal government were also used to make reference to certain areas of the city. In total, there are nine sectors, including Centre, East, North, Northeast, Northwest, South, Southeast, and West. Each community falls entirely within a single city sector. The sector with the largest number of communities is the Centre sector (62), and the East has the smallest number (23) (The City of Calgary, September 2018). Figure 1 shows the study area with the community types and the city sectors.

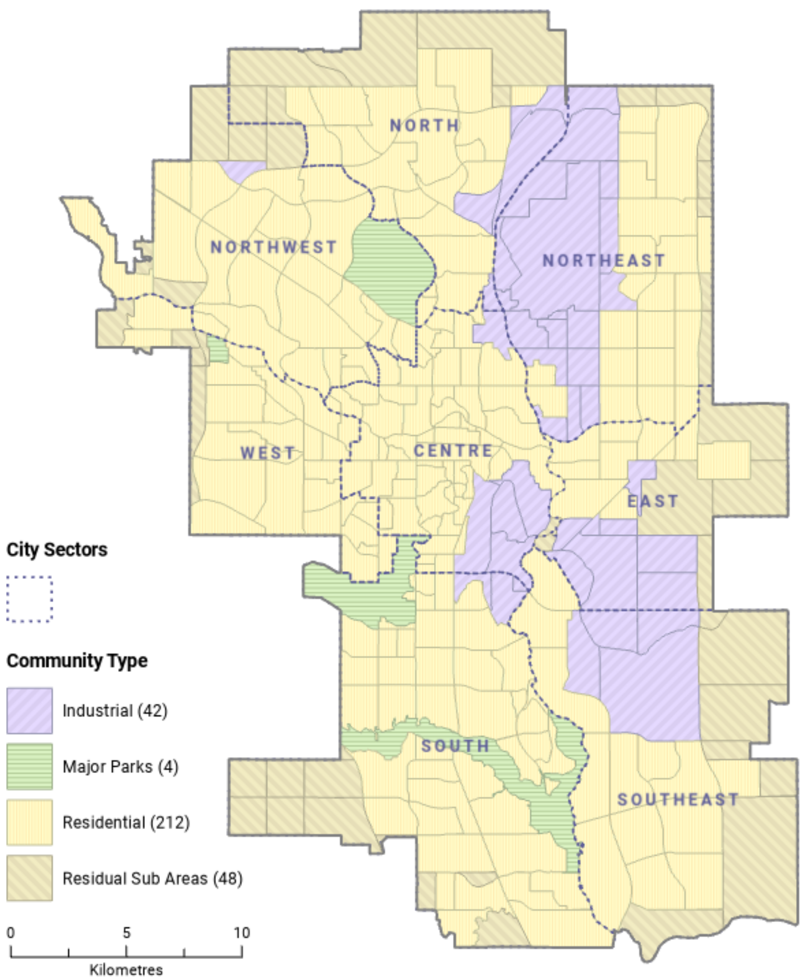

Figure 1: The study area, the city of Calgary and the various community types and city sectors.

The data source utilized is Open Calgary (https://data.calgary.ca/), the data portal of the municipal government. Shapefiles with all the communities and city sectors were downloaded from this portal and imported into an ArcGIS geodatabase. The shapefiles' original coordinate system, WGS 1984, was converted to a projected coordinate system based on the Transverse

Mercator projection, a central meridian of 114° west, and a scale factor of 0.9999. This projected coordinate system was used for every feature class.

Tree Data – Response Variables
This study considers two different aspects of the urban forest: the distribution of street trees and tree canopy cover, or UTC, in residential areas of the city. Street trees in this study are planted in public areas and mapped as individual points. UTC is the tree cover extent formed by the tree crown and visible from the air; it may include trees on public and private land, and serves as the basis for most analyses of social justice using urban tree density (Danford et al., 2014; Greene et al., 2018; Volin et al., 2020).

The street trees are from a dataset named Public Trees, and it was downloaded from Open Calgary (https://data.calgary.ca/). This point dataset has the location of all the public trees owned by the municipal government, includes over 500,000 point features (The City of Calgary, January 2018), and does not include trees on private property. This dataset was used to obtain a count of the number of street trees in the residential land-use areas within each residential community. Only the points classified as trees were included in the analysis (86.79%). Points classified as shrubs and stumps (13.20%) were excluded. Also, only trees that are adjacent to the public right-of-way within a residential land use zone were included. This operation was deemed necessary to limit the count of trees to areas within a community classified as residential. This filtered the final count of street trees in this analysis down to 230,495.

To normalize the count of trees in each community, the total number was divided by the number of dwellings. The resulting measure, trees per dwelling, avoids issues with other normalization approaches, such as tree density. Since street trees occur only along the right-of-way, normalizing by area would not be appropriate, as only the area immediately adjacent to the right-of-way is affected. The number of trees per dwelling is one of the variables used to examine if the distribution of the urban forest is evenly distributed, and it represents the density of street trees.

The second dataset, Tree Canopy 2020, was also downloaded from the data portal. This dataset has polygon features that delineate the extent of tree canopy for the entire city. The municipality used remote sensing techniques to extract the tree canopy polygons from orthophotos and Lidar data. After deriving the tree canopy polygons, the municipality edited and checked the data for quality using different photogrammetric processing tools (The City of Calgary, January 2021). The original dataset has over 1.6 individual polygons, but not all the polygons were necessary for this project as a significant proportion falls outside the residential areas. ArcGIS Pro was used to perform map overlay operations to retain only the polygons or portions of polygons inside residential land use areas. The tree canopy area and the area of the residential land use zones were used to compute the percentage of canopy cover for each residential community. Normalizing by area was not an issue as with the previous dataset, as the canopy cover is distributed over the entire area and not just along the right of way. This variable, the percentage of residential UTC, was also used to examine the distribution of the urban forest.

Demographic Data – Explanatory Variables

The demographic data was obtained from several sources, including The City of Calgary, The Calgary Real Estate Board (CREB), and Environics Analytics (EA), an analytical service company in Canada and an Esri partner. Demographic data from the municipality included variables such as the total number of dwellings, household tenure - the number of dwellings owned versus number of dwellings rented, the number of residents, population density, the age of the community, etc. The data from CREB included a benchmark value for the median house price in each residential community. The data from EA included socioeconomic variables such as education level, with several attributes ranging from the number of adults with high-school level education to those with an education level above a bachelor's degree. EA data also included other variables such as median income, average household income, and percent of visible and non-visible minorities. Table 1 shows the main variables and the corresponding data source.

VARIABLE	DATA SOURCE
Number of residents	The City of Calgary
Number of dwellings	The City of Calgary
Mean and median income	Esri - Environics Analytics
Dwellings owned or rented	Esri - Environics Analytics
Education level (high school, no college, etc.)	Esri - Environics Analytics
Visible and non-visible minority population	Esri - Environics Analytics
Median house price	The Calgary Real Estate Board - CREB

Table 1: Demographic and socioeconomic variables and the corresponding data source.

In Canada, the term "visible minority" is used to identify non-Caucasian population segments. Statistics Canada defines a visible minority as "persons, other than Aboriginal peoples, who are non-Caucasian in race or non-white in colour." The visible minority designation includes the following ethnic groups: South Asian, Chinese, Black, Filipino, Arab, Latin American, Southeast Asian, West Asian, Korean, Japanese, and Other (Statistics Canada, 2021). All the data obtained from Environics Analytics is at the community level. The data was obtained using the ArcGIS Enrich tool and an ArcGIS Online organizational account. Obtaining the required variables was part of the first significant step in the methodology workflow (Figure 2, step A).

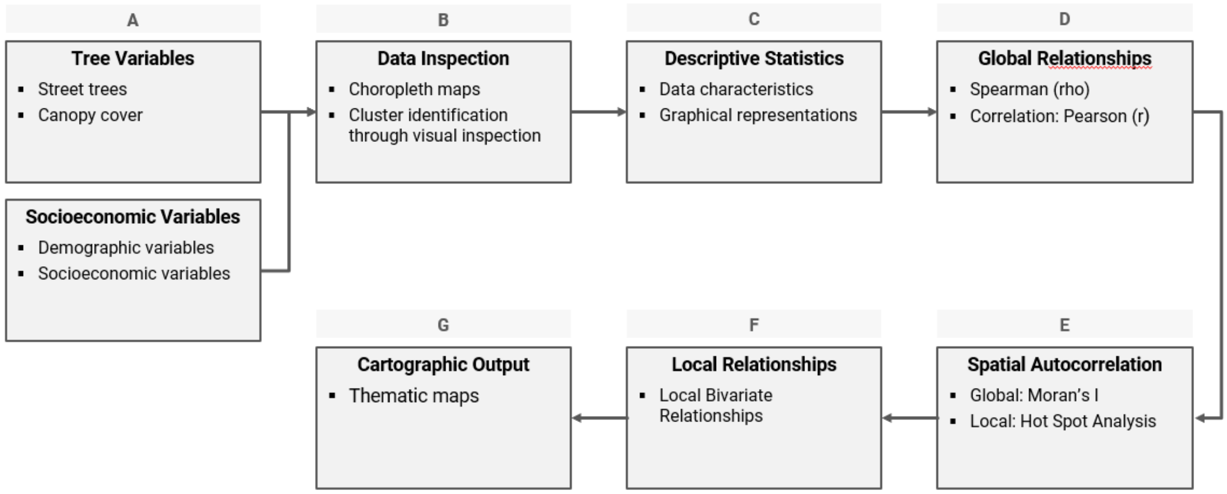

Figure 2: Depiction of the methodology workflow used in this project

Statistical and Spatial Analysis

The first analytical objective was to determine if the distribution of urban forest is evenly distributed. To achieve this objective, thematic choropleth maps were created to examine the distribution of each tree variable (Figure 2, step B). An attempt was made to use an appropriate and valid classification method for each choropleth. An assessment index called the goodness of variance fit (GVF) was employed to evaluate the validity of the classification method used. The GVF produces an index ranging from zero to one. Dent recommends using index values greater than 0.80 (2009, p. 93). After the choropleth maps were designed, descriptive statistics were used to better understand each variable's numerical characteristics (Figure 2, step C).

The next step in the methodology workflow was to correlate street trees and UTC with different demographics and socioeconomic indicators (Figure 2, step D). Considering the highly skewed nature of the tree variables, it was determined that the most appropriate approach would be to use non-parametric methods. Thus, the Spearman correlation coefficient was selected as the primary correlation method. However, as the tree variables were based on total tallies of street trees and tree canopy and not based on sample data, the Pearson correlation coefficient was also used descriptively to compare the two correlation coefficients (McGrew et al., 2014; Rogerson, 2020). Initially, a correlation matrix was used to identify the strongest correlation coefficients. Any relationship with a moderate or strong correlation was selected for further analysis. In the subsequent analysis, a scatterplot was used to examine each selected relationship in more detail. The goal was to identify the strongest relationship and the relationship with the least amount of scatter. The relationship with the strongest correlation coefficient was selected for each tree variable. Based on the results, only two socioeconomic variables were selected for spatial analysis, along with the corresponding urban forest variables.

The next major step was to assess the degree of clustering in each tree variable (Figure 2, step E). To accomplish this, global and local methods of spatial association were used. The Spatial Autocorrelation tool (Global Moran's I) and the High/Low Clustering tool (Getis-Ord General G) in ArcGIS Pro were used for the global methods (Anselin, 2014; Grekousis, 2020; Wu & Kemp, 2019). The reason for using two global methods is that the General G statistic can detect the presence of low and high-value clusters, whereas the Global Moran's I cannot (Grekousis, 2020). Both methods provided a statistically significant measure of spatial autocorrelation for the entire study area. Using these methods helped determine if the overall pattern of the distribution was dispersed, random, or clustered (Moran's I) and if low, random, or high clusters characterized the distribution. The Cluster and Outlier analysis tool (Anselin Local Moran's I) and Hot Spot Analysis tool (Getis-Ord Gi*) were used for the local methods (Grekousis, 2020; Livings et al., 2020). The Cluster and Outlier analysis tool helped identify the residential communities with statistically significant clusters. These are residential communities in close proximity and with similar attribute values - high-high clusters or low-low clusters. Also, the tool identified outliers, which are residential communities in close proximity but with different attribute values – high-low and low-high outliers (Grekousis, 2020; Livings et al., 2020). The Hot Spot analysis tool helped identify residential communities in a spatial cluster of low values (cold spots) and communities in a spatial cluster of high values (hot spots). Before the local measures could be used, it was necessary to check for locational outliers and to use incremental autocorrelation to determine an appropriate scale of analysis and to develop a spatial weights matrix file (SWM). The SWM file was used for the parameter "Conceptualization of Spatial Relationships" whenever tools for estimating local methods, such as hot spot analysis, were employed. Hot spot analysis was also carried out on the socioeconomic variables with the highest correlation with canopy cover and trees per dwelling. These variables are the percentage of visible minorities and median household income, correspondingly (Figure 2, Step D).

The penultimate step in the methodology involved the use of the ArcGIS tool Local Bivariate Relationships (Figure 2, step F). This tool uses entropy to identify local relationships that are statistically significant. In information technology, entropy is the amount of uncertainty in a given variable (Guo, 2010). Further, entropy can be used in multivariate analysis to detect statistically significant relationships without assuming a regression model (Guo, 2010), as the characteristics of the data did not permit the development of a properly specified regression model). To analyze local bivariate relationships, the variable trees per dwelling was paired with median household income. In contrast, the variable percentage of UTC was paired with the variable percentage of visible minorities.

A separate analysis was conducted for each set of paired variables, UTC with visible minorities and street trees and median household income. Using the Local Bivariate Relationships tool, each residential community was classified into six types of relationships: positive linear, negative linear, curvilinear concave, curvilinear convex, undefined complex, and not significant. The positive and negative relationships can be interpreted the same way as in linear regression. In a positive relationship, as the values of the explanatory variable increase, the values in the dependent variable also increase linearly. In a negative relationship, as the values of the explanatory variable increase, the values in the dependent variable decrease linearly. Concave relationships are characterized by the dependent variable changing into a downward-bending curve as the independent variable increases. Convex relationships are characterized by the dependent variable changing into an upward-bending curve as the independent variable increases. Undefined complex relationships have statistically significant relationships between the independent and dependent variables but cannot be represented as linear (positive or negative) or curvilinear (concave or convex). The last type, not significant relationships, occurs when the relationship between the two variables is not statistically significant (ESRI, n.d.).

From the results obtained, the type of relationship (positive linear, negative linear, etc.) and the corresponding linear R-squared value were used to map and analyze the relationships between tree variables and socioeconomic variables. Two choropleth maps were designed (Figure 2, step G) to summarize the local bivariate relationships.

RESULTS AND DISCUSSION

Descriptive Statistics

The results show that the mean canopy cover is 14.62%, with a standard deviation of 7.95%. The community with the lowest percentage, 0.12% (Carrington), is in the North sector of the city, while the community with the highest percentage, 34.87% (Roxboro), is in the Centre sector. The distribution for this variable has a small, positive skewness value of 0.08. In terms of trees per dwelling, the mean is 0.65, with a standard deviation of 0.67. The minimum value is 0.01, while the maximum value is 5.44. The distribution for this value is positively skewed, with a value of 3.56.

Correlation Analysis

The results of correlation analysis show that some demographic and socioeconomic variables were moderately or strongly correlated with canopy percentage and trees per dwelling, meriting special consideration. Tables 2 and 3 show the correlation between each of the tree variables and the demographic or socioeconomic variables where the strength of the relationship is moderate (greater than 0.25 or less than -0.25) or strong (greater than 0.60 or less than -0.60).

VARIABLE NAME	RELATIONSHIP STRENGTH	SPEARMAN – rho
Visible minority (%)	Strong	-0.68
Mean household income	Moderate	0.24
Bachelor's degree & above (%)	Moderate	0.38

Table 2: Correlation between canopy cover and selected demographic and socioeconomic variables.

VARIABLE NAME	RELATIONSHIP STRENGTH	SPEARMAN – rho
Median household income	Moderate	0.50
Population density	Moderate	-0.46
Visible minority (%)	Moderate	-0.57
Bachelor's degree & above (%)	Moderate	0.28

Table 3: Correlation between trees per dwelling and selected demographic and socioeconomic variables.

The results show that the demographic variable with the most significant correlation with canopy cover is the percentage of visible minorities in each community (Table 2). Also, the socioeconomic variable with the most significant correlation with trees per dwelling is median household income (Table 3).

Global Measures of Spatial Association

For the canopy percentage, the global Moran's I shows that the overall pattern is clustered, with a z-score of 3.96. This indicates less than a 1% likelihood that the clustered pattern is due to chance. The high/low clustering analysis (Getis-Ord General G) shows the presence of high clusters (a concentration of significantly high positive values) and a high z-score value of 4.68, which indicates a less than 1% likelihood that the high clusters in the study area are due to chance. Thus, the null hypothesis of complete spatial randomness for this variable can be rejected.

For the trees per dwelling variable, the spatial autocorrelation analysis using Moran's I shows that the pattern is clustered with a z-score of 4.68. Similarly, the high/low clustering analysis shows a z-score of 6.41. This indicates a probability greater than 99.99% that the clustering and presence of high clusters in the overall distribution are real and not due to chance. The null hypothesis of complete spatial random for this spatial variable can also be rejected.

Local Measures of Spatial Association

Cluster and Outlier Analysis

The cluster and outlier analysis for the tree canopy shows there are 71 out of 188 communities classified as high-high clusters, primarily in the Centre sector. This indicates that a community with a high clustering of tree canopy is near other similarly clustered communities. In the Centre sector, 43 out of 49 residential communities are classified as high-high clusters. The rest of the high-high clusters occurred mainly in communities adjacent to or near the Centre sector, and the south sector has the second largest number, with a total of 13 out of 37. Hence, approximately 61% of all high-high clusters are in the Centre sector and 18% in the South sector. The East, Northeast, and Southeast sectors of the city have no high-high clusters (Figure 3a), and 43 out of 188 communities are low-low clusters. The North sector has 12, the Northeast sector 14, the Southeast sector seven, and the Northwest and South sectors have five each. In terms of the proportion of low-low clusters within each sector, the North, Northeast, and Southeast sectors have the greatest proportion, with 12 out of 18 (67%), 14 out of 19 (74%), and 7 out of 11 (64%), respectively. There are a few low-high outliers (10) located primarily in the Centre and West sectors, but there are no high-low outliers.

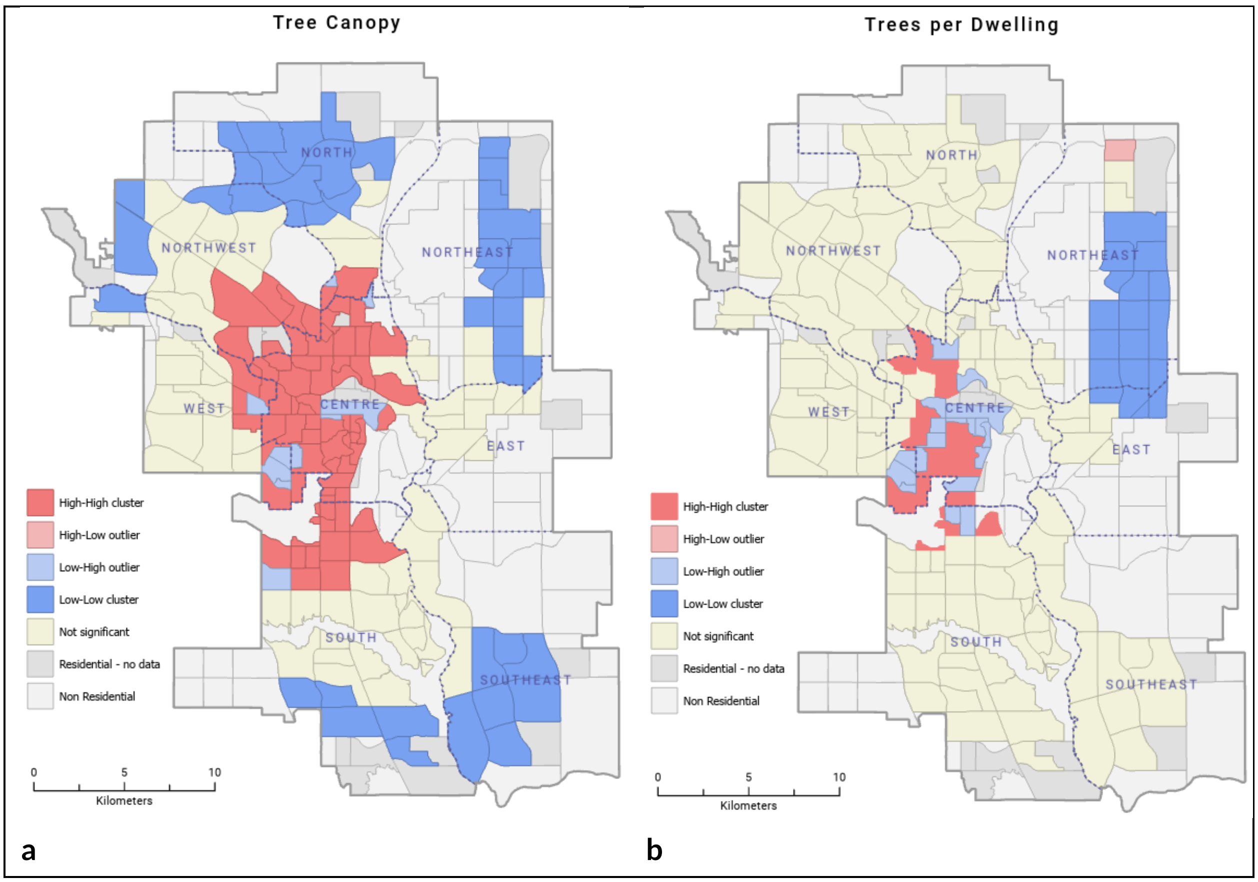

Figure 3: The cluster and outlier analysis results for the variables tree canopy and trees per dwelling.

For the variable trees per dwelling (Figure 3b), the cluster and outlier analysis showed a total of 23 out of 188 residential communities classified as high-high clusters located in the Centre (17), the South (4), and the West (2) sectors. On the other hand, there are 18 residential communities classified as low-low clusters, with 14 located in the Northeast and 4 in the East sectors. Regarding the proportion of these clusters within these two sectors, the Northeast has 14 out of 19 (74%), and the East sector has 4 out of 9 (44%). In total, 18 communities are classified as low-high outliers, with 13 occurring in the Centre, 3 in the West, and 2 in the South sectors. Only one community in the Northeast sector is classified as a high-low outlier.

Hot Spot Analysis

A hot spot analysis was carried out for visible minorities and median income. For visible minorities, the North and Northeast were the sectors with the largest number of communities classified as hot spots with 99% confidence, and the Centre, West, and South sectors were predominantly cold spots with 99% confidence (Figure 4a). For median income, only the Centre, South, and West sectors had hot spots with 99% confidence. The vast majority of these hot spots were in the Centre sector. The cold spots with 99% confidence occurred only in the Northeast and East sectors (Figure 4b).

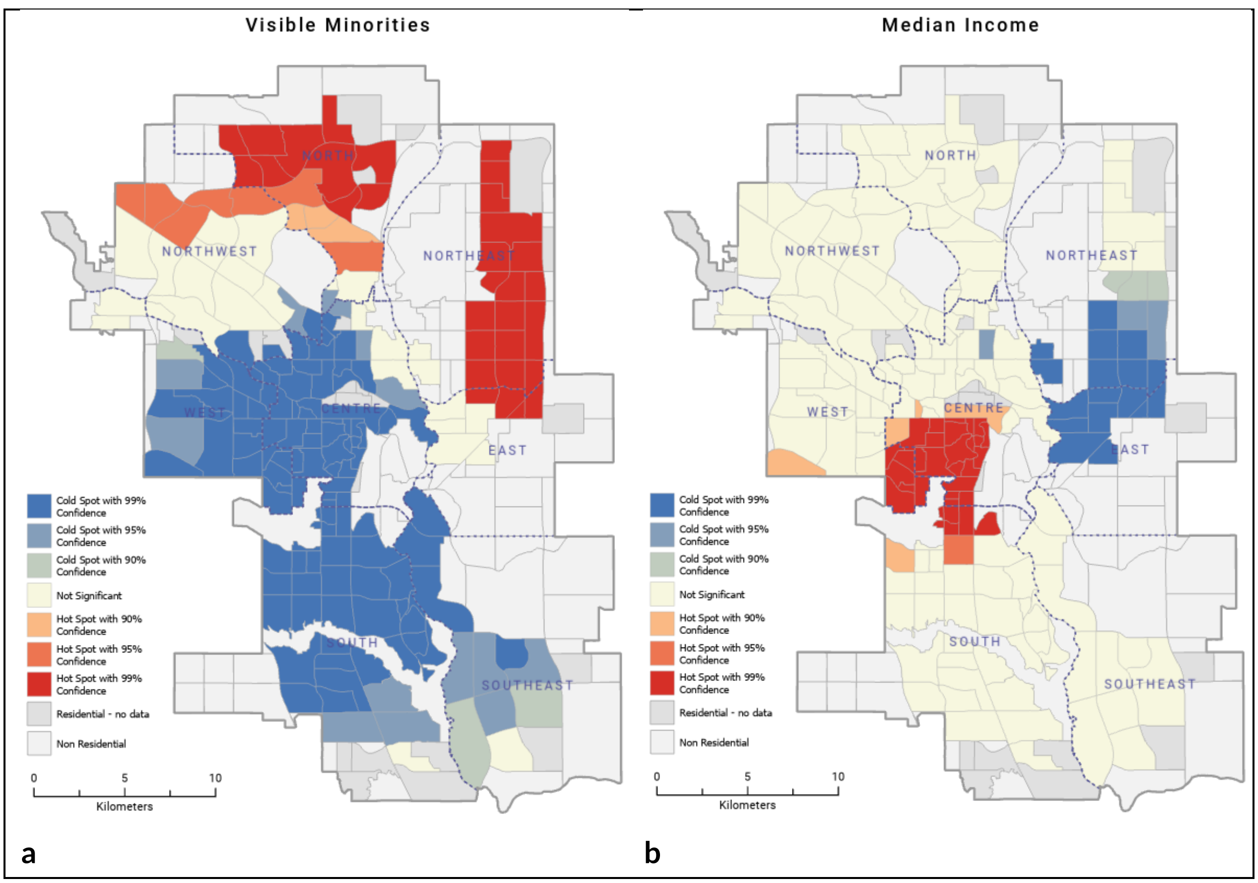

Figure 4: The hot spot analysis results for the variables tree visible minorities and median income.

The results of the hot spot analysis for both tree variables are similar to the cluster and outlier analysis in the sense that areas classified as high-high clusters are typically hot spots with 99%

confidence, and areas classified as low-low clusters are cold spots with 99% confidence. Only a very small portion of the communities classified as hot or cold spots are at the 95% or 90% confidence level. For instance, 43 communities are classified as high-high clusters in the Centre sector, and 44 sectors are classified as hot spots with 99% confidence. As well, the sectors with the highest proportion of low-low clusters, the North, Northeast, and Southeast sectors, are also the sectors with the largest numbers of cold spots communities with 99% confidence.

As observed from the results of the hot spot analysis, the greatest concentration of hot spot communities for canopy cover is in the Centre sector, where almost 90% of the communities are hot spots with 99% certainty, as shown in Figure 5a.

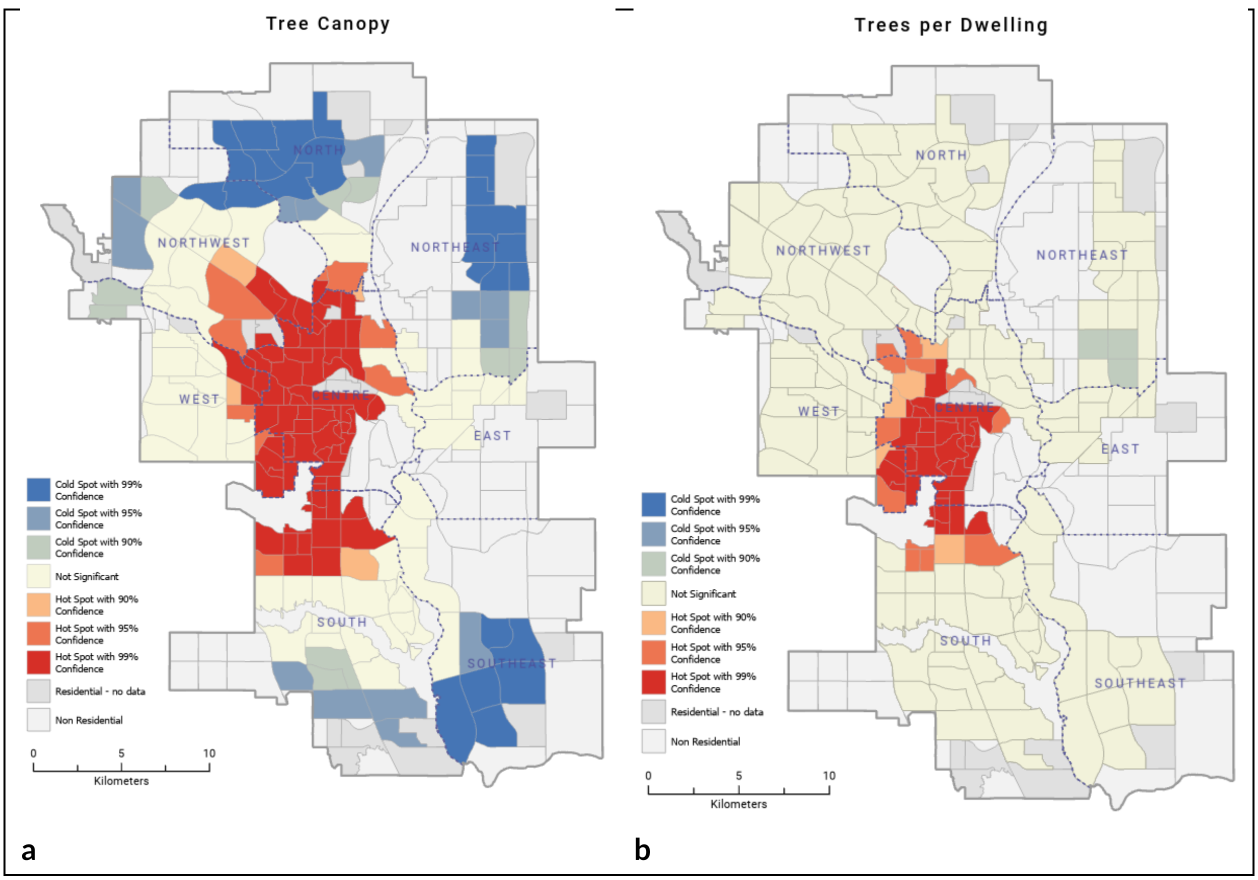

Figure 5: The hot spot analysis results for the variables tree canopy and trees per dwelling.

In the South, Northwest and West sectors, a relatively small percentage of district communities are hot spots with 99% confidence. It is important to note that the hot spot communities in the South, Northwest, and West are either adjacent to the Centre sector or near it. This area in the city's core is the only area with canopy-cover hot spots. Another important characteristic of this area is that it is primarily a cold spot area for visible minorities (Figure 4a). In fact, over 85% of the communities in this area are cold spots with 99% confidence.

In terms of cold spots for canopy cover, the greatest concentration is in the city's periphery, with the largest number of communities in the North, Northeast, and Southeast sectors. over 44% of the communities in the North sectors, over 47% in the Northeast, and over 54% in the Southeast, all are cold spots with 99% confidence. The North and Northeast sectors also have the largest number of hot spots for visible minorities. In the North sector, over 55% of the communities are hot spots with 99% confidence, while in the Northeast, more than 89% of all communities fit this category. Based on the hot spot analysis for both variables, it is evident that as the percentage of visible minorities increases, the percentage of canopy cover decreases, and vice versa. This relationship is more significant in the Centre sector, with significant canopy cover, and in the North and Northeast sectors, with significant visible minorities (see Figure 5a).

The hot spot analysis for the variable trees per dwelling showed that most of the communities were in the western half of the Centre sector (Figure 5b). Approximately 53% of all communities in the Centre sector were hot spots with 99% confidence. Also, a small number of hot spots communities adjacent to or close to the Centre sector were in the South and West sectors. Compared with the hot spot result for median income, only the areas in the southwest part of the Centre sector and the northwest part of the South sector coincided. In total, only 34 residential communities, or 18%, were hot spots for both variables. The only significant relationship between the two variables occurred in this part of the city. Most communities in the city were classified as "not significant" for either variable, and only the median income variable had cold spots with 99% confidence, and only three communities were classified as cold spots with 90% confidence for trees per dwelling. The cold spots in median income, located primarily in the Northeast and East sectors, coincided with "not significant" communities in the trees per dwelling layer. Thus, when comparing the relationship between these two variables, there was no observable significant relationship between cold spots in either variable.

Local Bivariate Relationships (LBR)

This study uses local bivariate relationships to look at the strong relationship between tree canopy and visible minorities, and the moderate relationship with the highest value of Spearman – rho between trees per dwelling and median household income to illustrate where moderate positive relationships may reveal patterns in local areas. As well, the above interpretation of hot spot analysis and corresponding correlation is supported by the LBR analysis results described here.

As shown in Figure 6a, most communities with a negative linear relationship are in the periphery of the city, in the North, Northeast, South, and Southeast sectors. However, only the North and Northeast sectors are hot spots for visible minorities. Further, if only the communities with a linear R-squared value of greater than 0.5 are considered, the vast majority in this category are in the North and Northeast sectors where the distribution is primarily visible minority hot spots and canopy cover cold spots. If the R-square value is increased to 0.6, the communities are almost exclusively in these two sectors, except for a couple of communities in the East sector. Additionally, all the residential communities in the North sector had an R-squared value greater than 0.4, and all the residential communities in the Northeast sector had an R-squared value greater than 0.5, indicating that in these communities, a moderate to strong negative relationship between visible minorities and canopy cover is predominant. On the other hand, in the Centre sector, the majority of communities have LBR classified as "not significant," where the majority of communities are hot spots for canopy cover (Figure 5a) and cold spots for visible minorities (Figure 4a). In the East sector, a few communities were classified as having a "convex" relationship; in the Northeast sector, four communities were classified as having a "concave" relationship. In the Centre and Northwest sectors of the city, most communities are classified as having a "not significant" relationship (Figure 6a).

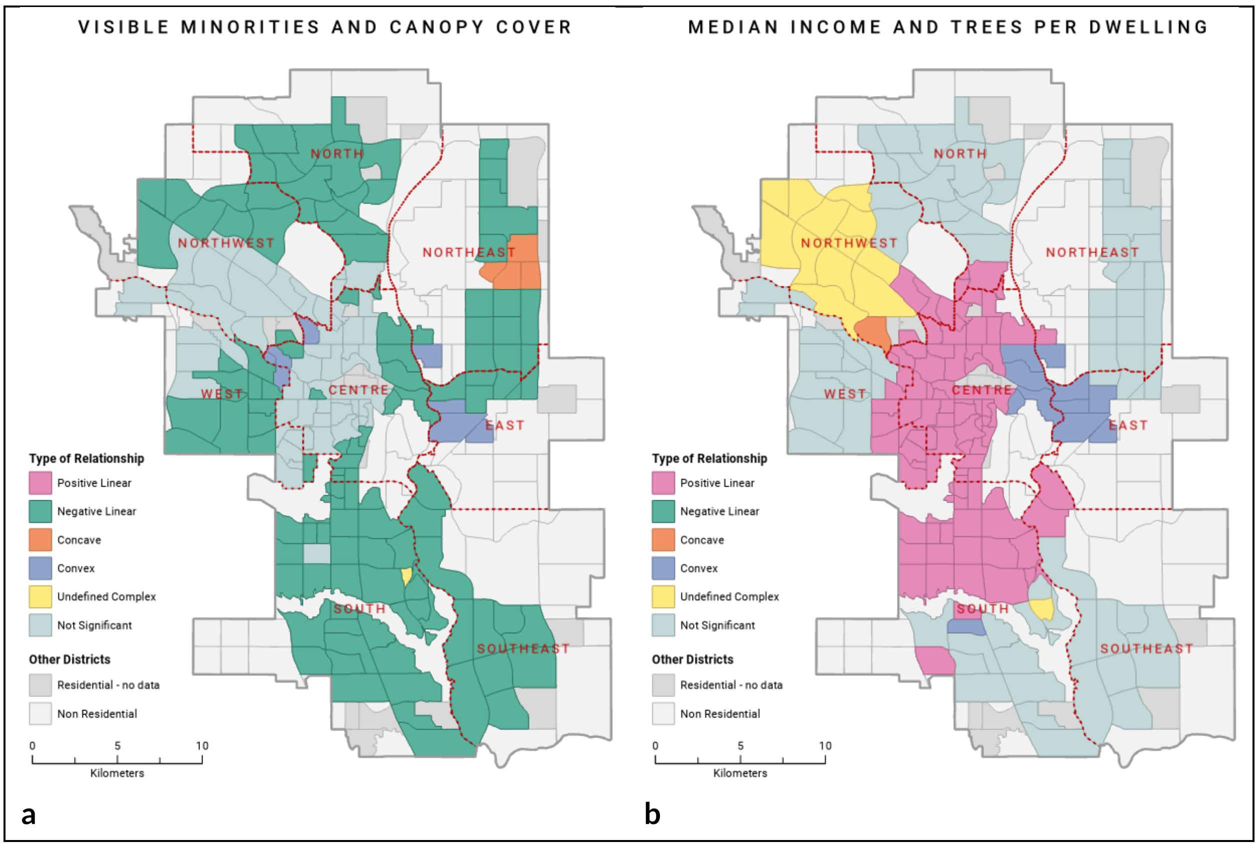

Figure 6: The LBR between visible minorities and canopy cover, and median income and trees per dwelling.

However, if only those city communities with a linear R-square value greater than 0.50 are considered, then, the city sectors with the largest number of communities in this category are the North and Northeast. The negative relationship between these two variables is most significant in these two sectors.

The results of the local bivariate relationship analysis between trees per dwelling and median household income showed that in most communities, the relationship between these two variables is moderate but not significant (Figure 6b). However, in the center and the north portion of the South sector, a substantial number of communities have a "positive linear" relationship. In the Centre sector, 42 out of 49 communities fall in this category, and in the South sector, 20 out of 37 communities are also in this category. Seven communities have a convex relationship; four are in the Centre sector, and three are in the East sector. Three communities in the Northwest sector have an "undefined complex" relationship. Again, if we were to limit the city sectors where the adjusted linear R-squared is greater than 0.50, the two sectors in the city with the largest number of communities are only the Centre and South sectors.

CONCLUSION AND FUTURE WORK

Based on the analysis of street trees, it can be determined that there is some inequality in the distribution of street trees in the urban forest in Calgary. However, this inequality is limited to two city sectors only, where the Centre sector has most of the high clusters of street tress, and the Northeast sector has most of the low clusters of street trees. For the rest of the city, the level of inequality appears to be insignificant. Future work could be done on this dataset to see to what extent the policies of the municipal government have contributed to reducing the inequality of street trees. Other work may involve an examination of tree species diversity and their relationship to demographic and socioeconomic variables.

The distribution of tree canopy shows a greater degree of inequality. In general, neighbourhoods with a higher percentage of visible minorities tend to have less canopy cover. This is an important inequality that needs to be addressed, as the benefits of the urban forest to local populations are well-documented. Future work could include other socioeconomic variables that may be strongly correlated with canopy cover distribution. For example, poverty levels, the percentage of households spending more than 30% on rent, and residents' attitudes toward residential trees could be used in future studies.

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