# A STUDY OF URBAN FOREST AND GREENSPACE INEQUALITY IN MISSISSAUGA AND BRAMPTON USING REMOTE SENSING AND NDVI

by

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**Abstract**

This study aims to analyse the relationship between urban forests and greenspaces, and income levels. It aims to evaluate how trees and greenspaces are distributed amongst the census tracts in Brampton and Mississauga, Ontario. This study utilizes the Normalized Difference Vegetation Index (derived from Sentinel-2 imagery) to distinguish vegetation and non-vegetated land covers. A supervised classification system was used, and three information classes were created: non-vegetation, vegetation cover, and water. Then two choropleth maps were created for each municipality to show the median household income across census tracts. These were divided into four ranges: ≤$60,000, $60,000 to $80,000, $80,000 to $100,000, and >$100,000. Then three census tracts with the lowest income were compared to the three census tracts with the highest income in each municipality. The results showed that high-income areas had more vegetation cover compared to low-income census tracts in both Brampton and Mississauga. The census tracts in the >$100,000 range had an average vegetation cover of 38.2% in Mississauga, and 22.7% in Brampton. The census tracts in ≤$60,000 range had an average vegetation cover of 22.7% in Mississauga and 17.9% in Brampton. In Mississauga, the three census tracts with the highest incomes had percentage vegetation cover ranging from 65.3% to 76.2%, whereas vegetation cover in low-income census tracts ranged from 15% to 30.5%. In Brampton, the highest-income CTs had a vegetation cover of 28.4% to 38.5%, whereas the lowest-income CTs had a vegetation cover of 9.2% to 29.7%.

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## Table of Contents

**List of Figures**

**List of Tables**

**List of Acronyms**

CBG: Census Block Group

CICC: Canadian Institute for Climate Change

CMA: Census Metropolitan Area

CT: Census Tract

GEE: Google Earth Engine

GNDVI: Green Normalized Difference Vegetation Index

GTA: Greater Toronto Area

MHI: Median Household Income

NASA: National Aeronautics and Space Administration

NDVI: Normalized Difference Vegetation Index

NDWI: Normalized Difference Water Index

NIR: Near-Infrared

UF: Urban Forest

USGS: United States Geological Survey

UTC: Urban Tree Canopy

VC: Vegetation Cover

## CHAPTER 1: INTRODUCTION

In Canada, approximately 73.7 percent (%) of the population live in one of the Census Metropolitan Areas (CMAs), and this trend continues to increase (Statistics Canada, 2022a). Approximately, 18.1% of Canadians live in the Greater Toronto Area (Statistics Canada, 2022a). Urban forests (UF) and greenspaces have become increasingly important in Canadian cities, particularly in the Greater Toronto Area (GTA), to counteract the effects of deforestation and climate change due to continuing development and urbanization. According to the Canadian Institute for Climate Change (CICC) (2021), UF are defined as trees, forests, and greenspaces within and around cities. This includes trees and vegetation across urban spaces, such as institutional and commercial areas, along streets, in residential backyards, and surrounding urban periphery (CICC, 2021). Greenspaces are defined as green infrastructure, natural spaces, open spaces, and engineered greenspaces (Kingsley and EcoHealth Ontario, 2019). They include public parks, conservation areas, greenways, trails, gardens, school grounds, and golf courses (Kingsley and EcoHealth Ontario, 2019). Trees and greenspaces provide a range of environmental benefits, including cooling the air, reducing greenhouse gas emissions, providing clean air, and supporting wildlife (CICC, 2021). However, trees and greenspaces also provide a range of social and economical benefits as well. Researchers have found that trees and greenspaces have a profound effect on an individual's mental health (Carrus et al., 2015).

It is vital that trees and greenspaces are accessible for everyone within a city regardless of their household income or the neighbourhood they reside in, so they can reap the benefits provided by trees. However, studies have shown that urban environmental inequality is an increasingly growing problem in Canadian cities (Pinault et al., 2021). Researchers found that neighbourhoods with higher household incomes and higher property values typically have higher urban tree canopy cover compared to neighbourhoods with lower household income and lower property values (Landry et al., 2020). They also found that wealthier neighbourhoods not only had a higher tree cover, but also a greater diversity of species (Lin et al., 2021). Wealth has shown to be a factor that affects the quantity and diversity of trees within a neighbourhood. In the U.S., tree inequality between low- and high-income neighbourhoods has resulted in low-income neighbourhoods having higher average temperatures (McDonald et al., 2021). The uneven distribution of trees puts individuals in lower income neighbourhoods at a greater disadvantage (Pinault et al., 2021).

There is a need to analyse the distribution of trees within cities and remote sensing can facilitate in that analysis. Remote sensing is the process of analysing physical characteristics of an area through measuring the radiation reflected from an object from a distance (USGS, 2022b). It provides a valuable tool for studying the composition of UF within large, urbanized cities using satellite imagery and satellite-derived measurements. The Normalized Difference Vegetation Index (NDVI) (which is based on red and near-infrared reflectance) is a good measure of vegetation greenness and density of vegetation (USGS, 2022a). This allows researchers to examine the distribution and abundance of vegetation around a city as well as the different types of vegetation (i.e., trees versus grasslands) (NASA, 2000).

### 1.1 Study Objectives

The aim of this paper is to examine UF and greenspaces in Census Tracts (CT) within Mississauga and Brampton using remote sensing technology and NDVI, to evaluate the correlation between wealth and environmental inequality. As such, this research aims to answer one question: *Does median household income influence the distribution of urban forests and greenspaces between high-income and low-income census tracts in Mississauga and Brampton, resulting in* *environmental inequality within the cities?* Two main objectives will be examined to answer the research question:

1. To assess the relationship between income levels, and urban forests and greenspaces across Brampton and Mississauga census tracts, using Sentinel-2 images and NDVI analysis.
2. Study the characteristics of high-income and low-income census tracts in Brampton and Mississauga and how they differ.

### 1.2 Study Area

When selecting study areas, factors such as population size, land area, population density and number of census tracts were considered. It was also important that the cities were relatively developed and were experiencing continuous development and urbanization to analyse how trees are distributed in urbanized areas. Previous studies also focused primarily on large urban cities (Landry et al., 2020; MacDonald et al., 2021; Marshman, 2018). Therefore, municipalities with large portions of rural or undeveloped land, or municipalities with too few census tracts were not considered. Furthermore, the study areas were limited to municipalities within the GTA, and that had little prior research done on this topic. Toronto was not selected, as there have been prior research done on the relationship between wealth and UF and greenspaces (Greene et al., 2018; Landry et al., 2020). Therefore, Brampton and Mississauga were selected as the focus for this research paper (Figure 1.1). These cities are similar in population size, land area, population density, and have a similar number of census tracts (Table 1.1). Despite Brampton and Mississauga being the $9^{th}$ and $7^{th}$ most populous cities in Canada (Statistics Canada, 2022b), and their continuous growth, there is little research done on the relationship between vegetation density and income in the two municipalities.

**Table 1.1:** City census data from the 2021 census profile (Statistics Canada, 2022b).

| City | Population | Land Area (sq. km.) | Population Density (people per sq. km.) | Number of CTs |
|---|---|---|---|---|
| Mississauga | 717,961 | 292.7 | 2452.5 | 147 |
| Brampton | 656,480 | 265.9 | 2469.0 | 122 |


**Figure 1.1:** Sentinel-2 Images of City of Brampton (a) and City of Mississauga (b) (Copernicus Open Access Hub, 2022).

Mississauga is a suburban city with a population of 717,961 and covers an area of 292.7 $km^2$ (Table 1.1). The city borders the Town of Milton (West), Oakville (South-West), Toronto (East), Brampton (North) and Halton Hills (North-West). It is surrounded by Lake Ontario to the south. It has approximately 19% urban forest canopy cover (Plan-It Geo, 2014). Homeowners and tenants own the largest percentage of the City's urban forest, and more than half of the existing tree cover is within residential areas (TRCA, 2011). The city has approximately 500 parks, ranging from small community parks to large destination parks (City of Mississauga, 2021). The Credit River runs through the city, and most of the vegetation is concentrated along natural conservation areas. The north side of the city contains most of the industrial land areas and the northeast of the city contains Toronto Pearson Airport.

Brampton is a suburban city with a population of 656,480 and covers an area of 265.9 $km^2$ (Table 1.1). Unlike Mississauga, Brampton is surrounded by land on all four sides. The city borders the Town of Halton Hills (West), Mississauga (South), Vaughan (East), and Caledon (North). Brampton has a canopy cover of approximately 18% (City of Brampton, 2019). A small portion of the Credit River runs through the west side of the city, while the Etobicoke Creek runs through the east side of the city. These areas have a concentration of parks and conservation areas that contain an abundance of vegetation and greenspaces. The south side of the city contains majority of the industrial and commercial land areas.

## CHAPTER 2: LITERATURE REVIEW

The literature review of this research paper examines three topics. The first topic focuses on prior studies regarding the relationship between socioeconomic factors and urban tree canopy (UTC), and their overall conclusions. There are very few studies that examine the relationship between a neighbourhood's socioeconomic conditions and the UTC. Most studies on this topic primarily focus on U.S. cities (Chuang et al., 2017; Lin et al., 2021; McDonald et al., 2021; Schwarz et al., 2015). The second topic will examine the academic usage of NDVI for estimating tree cover. NDVI is one of the most popular methods of estimating vegetation cover through remote sensing (Huang et al., 2021). The last topic will focus on the environmental, health and social benefits of UF and greenspaces.

### 2.1 Socioeconomic factors and urban tree cover (UTC)

One good example of research studying the relationship between socioeconomic factors and UTC is Chuang et al. (2017). They conducted a comparative analysis of the effects of socioeconomic factors, primarily wealth, on UF distribution in wealthy and low-income neighbourhoods, between Washington, D.C. and Baltimore, Maryland. The study divides each of the cities into five wealth categories: remained relatively impoverished (NB1), decreasing wealth (NB2), remaining above poverty (NB3), increasing wealth (NB4), and remaining relatively wealthy (NB5) (Chuang et al., 2017). They also examined other socioeconomic factors such as socioeconomic status (median household income and education level), race and ethnicity, age, and housing and development characteristics (variables of housing ownership, vacancy rate, median housing value and rent, population density, and median age of built structure). There were three findings: (1) Stable-wealthy (NB5) neighbourhoods were more likely to have higher and more consistent tree coverage compared to other neighbourhoods, particularly impoverished (NB1) neighbourhoods; (2) decreases and increases in income were negatively associated with UTC in Washington, but not Baltimore, where income stability in both wealthy and impoverished neighbourhoods was a significant predictor of UTC; and (3) the relationship between other socioeconomic factors with UTC varied between both cities and needed further study (Chuang et al., 2017). Researchers found that in NB1 neighbourhoods in Washington the UTC was 21.90%, whereas in Baltimore it was 13.17%. Overall, this study found that wealth affected the percentage of tree cover in each of the neighbourhoods (Chuang et al., 2017).

Another more recent study analysed the UTC and temperature disparity, due to income inequality, in the 100 largest urbanized areas in the U.S. (McDonald et al., 2021). Overall, 92% of urbanized areas were shown to have less tree cover in lower-income neighbourhoods, which had a 19.7% median tree cover, compared to higher-income neighbourhoods, which had a 34.9% median tree cover (McDonald et al., 2021). In fact, researchers found that an increase in income by 5% resulted in an increase in tree cover by 1.2%. In addition to income, this study also specified density as a factor that played a role in tree cover. Neighbourhoods with higher density (4000-8000 people/km$^2$), typically had lower percent tree cover than lower density neighbourhoods (<2000 people/km$^2$). This is presumably because higher density neighbourhoods had less area to fit trees as more area was used for buildings and impervious surfaces. However, based on their research, it seems that income once again played a role in population density, as a majority (56%) of the less affluent individuals lived in these higher density neighbourhoods (McDonald et al., 2021).

A third paper that examines the relationship between socioeconomic factors and tree disparity in the Canadian context is Landry et al. (2020). This study examines four of the largest cities in Canada: Toronto, the urban agglomeration of Ottawa and Gatineau, Montreal, and Quebec

City. A total of 17 social, economic, and demographic parameters were examined for the study. They found that variables associated with wealth positively correlated with tree and grass cover. A possible explanation for this pattern is the aesthetic appeal of trees and their positive impact on property value (Landry et al., 2020). Wealthier individuals can afford homes in more aesthetically pleasing and expensive neighbourhoods. This effect of vegetation on property value creates a "green gentrification" which results in the displacement of lower income individuals to neighbourhoods with low UTC (Landry et al., 2020). They also found that variables of social vulnerability, such as proportion of people renting, under the low-revenue threshold, elderly and living alone, using active transportation, moving at high rate, and living in high density areas, show a positive correlation with built cover class (Landry et al., 2020). An interesting finding of this study showed that neighbourhoods with socio-economic vulnerability also have fewer species and functional diversity (Landry et al., 2020). Therefore, low functional diversity potentially results in UF that are less resilient to foreign pests, diseases, and varying climate conditions, such as droughts and high winds (Landry et al., 2020). This could affect the UTC in low-income neighbourhoods.

Overall, research has shown that wealthier neighbourhoods have more tree cover, compared to lower income neighbourhoods. Since trees have been shown to increase property value and aesthetics, wealthier people tend to gravitate towards these communities that have more UTC, thus further increasing property values (Escobedo et al., 2015). The studies have also shown how socioeconomic factors, such as ethnicity, age, and housing tenure, play a role in the uneven distribution of UTC within cities. However, many of these socioeconomic factors correlate with wealth and therefore have similar UTC within neighbourhoods.

### 2.2 Environmental, Health and Social Benefits of Urban Forests and Greenspaces

Trees and greenspaces provide a multitude of environmental, health and social benefits. UF and greenspaces can help cities adapt to climate change, cool the air temperature, and reduce flooding by managing water runoff (CICC, 2021; Turner-Skoff and Cavender, 2019). One study found that urban parks were 1°C cooler than non-green sites (Bowler et al., 2010). They also found that larger parks, especially with trees, were cooler throughout the day (Bowler et al., 2010). Although McDonald et al. (2021) research also focused on the effects of wealth on UTC, they also examined how tree cover affected the overall temperature of a neighbourhood (McDonald et al., 2021). On average, the results showed that low-income neighbourhoods had 15.2% less tree cover and were 1.5°C warmer than higher income communities. In the northeast of the U.S., urbanized areas had a greater temperature difference. Low-income neighbourhoods in these areas had 30% less tree cover and were 4.0°C warmer. This increase in temperature is a potential result of having less tree cover in less affluent neighbourhoods (McDonald et al., 2021).

Multiple studies have also shown that UF and greenspaces provide health and social benefits. Turner-Skoff and Cavender (2019), discuss the health benefits associated with UF and greenspaces. One of the most important health benefits that UF and greenspaces provide is the reduction of air pollution (Turner-Skoff and Cavender, 2019). Chronic exposure to air pollution can result in health cardiovascular and respiratory health problems (Atkinson et al., 2018). Urban trees can remove 711,000 metric tons of air pollution a year (Turner-Skoff and Cavender, 2019). They suggest that having more trees with the right mature species can reduce air pollution and reduce mortality in urban centers (Turner-Skoff and Cavender, 2019). Additionally, Carrus et al. (2015), studied the positive effects of UF and greenspaces on an individual's mental health and well-being. They selected four different types of green areas varying in the level of biodiversity richness (low vs. high), and location (urban vs. peri-urban) (Carrus et al., 2015). They then selected 569 respondents to fill out questionnaires outlining their experiences at these locations. The results showed biodiversity in urban and peri-urban areas had a positive effect on individuals' mental health and well-being (Carrus et al., 2015). Furthermore, UF and greenspaces have been found to reduce stress and promote relaxation (Grilli and Sacchelli, 2020).

### 2.3 Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index has an abundance of academic literature surrounding its usage to measure canopy growth and strength, as it is one of the most widely used and implemented vegetation indices (Huang et al., 2021). NDVI is calculated by taking the near-infrared (NIR) band minus the red band, then dividing the difference by the sum of the red and NIR band (Huang et al., 2021). It is often used in regional and global vegetation assessments (Xue and Su, 2017). However, despite the benefits of the NDVI, it is sensitive to the effects of soil brightness, atmosphere, clouds and cloud shadows, and leaf canopy shadows, as it uses near-infrared (NIR) radiation to determine vegetation density (Xue and Su, 2017).

Some of the previously discussed literature in this review also utilized NDVI, or some variation of the index, in their analysis of UTC in wealthy and lower income neighbourhoods. Landry et al. (2020) emphasises the usefulness of the NIR band in distinguishing between vegetated and non-vegetated ground cover. McDonald et al. (2021), used NDVI in combination with the entropy texture function in Google Earth Engine (GEE) to distinguish trees from other green areas, such as pastures, baseball fields, or golf courses. Then, they created a binary layer where pixels with high NDVI threshold and high texture values were given a value of one, and the other pixels were given a value of zero (McDonald et al., 2021).

Another research paper used NDVI to examine the effects of socioeconomic factors on UTC (Szantoi et al., 2012). Their research had two objectives: (1) study the distribution of UF cover in Miami-Dade County, and (2) study the relationship between ethnicity, age, income, education, and housing tenure, and NDVI of the UTC. They classified 1000 random points into five categories: UF cover (e.g., trees, palms, and shrubs), buildings, pervious (i.e., bare soil and herbaceous vegetation), impervious (e.g., concrete or asphalt), and water). The UF cover was then analysed using NDVI, where relatively high NDVI values (0.5 or greater) indicated healthy green vegetation (i.e., UF) and a low NDVI values (less than 0) indicated a lack of vegetation (Szantoi et al., 2012). Socioeconomic subclasses were created for each census block group (CBG), while NDVI mean values were calculated for each CBG and were analyzed relative to each of the CBG socioeconomic subclasses.

Overall, it seems that the NDVI is useful in determining tree and vegetation cover. However, it seems that there are factors, such as soil brightness, atmosphere, clouds and cloud shadows, and leaf canopy shadows that can affect its accuracy. Additionally, NDVI is less effective in distinguishing different types of vegetation as it measures the amount of green biomass. Overall, NDVI is still a suitable method in determining vegetation coverage.

# CHAPTER 3: DATA AND METHODS

## 3.1 Data

### 3.1.1 Socio-economic and Demographic Data

Census data were extracted at the census tract level from the 2021 Canadian Census. Census tracts are small geographic areas with a population less than 7,500 people located in census metropolitan areas (CMA) that have a core population of 50,000 (Statistics Canada, 2022c). The CT shapefile for the two municipalities (Figure 3.1) was obtained from Statistics Canada. After-tax median household income (MHI) from the 2021 Canadian Census was used to determine wealth. MHI was obtained from "Table 98-10-0058-01 Household income statistics by household type: Census metropolitan areas, tracted census agglomerations and census tracts" (Statistics Canada, 2022b). MHI was selected as the wealth determining factor as it reflects economic status closer to the reality in contexts where every adult in the household might be earning money (Landry et al., 2020). Typically, wealthier individuals can afford more expensive houses in higher income neighbourhoods (Landry et al., 2020).


**Figure 3.1:** Census Tracts for Brampton (a) and Mississauga (b) (Statistics Canada, 2022).

### 3.1.2 Canopy and Geographic Data

The image data used was collected by the Sentinel-2A satellite using the Copernicus Open Access Hub (https://scihub.copernicus.eu/dhus/#/home). They are Level-1C satellite tiles T17TPJ and T17TNJ. The data were collected on June 25, 2022, at 16:09:11.024Z UTC. Since the purpose of the study is to examine the UF and greenspaces within a municipality, it was important to select images where the tree canopy was at its greenest. Therefore, only data from June, July, and August was considered. Due to clouds, cloud shadows and other aerosols, there were a limited number of images to select. When selecting data, only images with 10% or less cloud cover, were considered. The data used for this study had 3.95% cloud cover. Additionally, the analysis was done using Catalyst Professional and ESRI ArcGIS Pro 3.0.0 (ESRI, 2022; PCI Geomatics, 2022).

## 3.2 Methods

### 3.2.1 Choropleth Map of MHI

To evaluate the distribution of wealth across Mississauga and Brampton, choropleth maps were created that showed the MHI across CTs. The following classes were used to evaluate MHI in both municipalities:

1. Lesser than or equal to \$60,000
2. \$60,001 - \$80,000
3. \$80,001 - \$100,000
4. Greater than or equal to \$100,000

These income ranges were based on Statistics Canada's distribution of employment income table (Statistics Canada, 2023b). These were later used to illustrate the average vegetation cover for each range.

### 3.2.2 Normalized Difference Vegetation Index Analysis

A NDVI analysis was conducted for each municipality, using the Vegetation Index tool in Catalyst Professional. The NDVI is calculated as a ratio between the red (R) and NIR bands within a satellite image (NASA, 2000). The NDVI is calculated in accordance with the following formula:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \qquad (1)$$

Since Sentinel-2 images were used for this study, the following formula was used:

$$NDVI = \frac{(Band\ 8 - Band\ 4)}{(Band\ 8 + Band\ 4)} \qquad (2)$$

When sunlight hits vegetation, the pigment in plant leaves, chlorophyll, absorbs visible light for photosynthesis, but reflects NIR, allowing for researchers to analyse vegetation density and quantify vegetation greenness, using NDVI (NASA, 2000; USGS, 2022a). If there is more reflected radiation in NIR wavelengths compared to visible wavelengths, the vegetation in that pixel within the image is most likely dense and contains some type of forest. However, if there is little difference in intensity of visible and NIR wavelengths reflected, then the vegetation is most likely sparse and contains grassland (NASA, 2000). For this study, NDVI was used to analyse the distribution of UF within a municipality.

### 3.2.3 Image Classification

A supervised classification was then completed for each municipality after the NDVI analysis was completed using Catalyst Professional. A supervised classification is the process of classifying spectral classes into information classes using training areas (homogenous samples of different land use covers) that are manually selected by the analyst (Government of Canada, 2013). Spectral classes are a group of pixels that have uniform (or similar) brightness values, whereas information classes are the category of land uses the analyst is interested in analysing (Government of Canada, 2013). The training areas are used by the computer to recognize pixels that have similar spectral characteristics as the areas. These pixels are then grouped into spectral classes, which represent each information class (Government of Canada, 2013). One of the advantages of using a supervised classification is that it allows the analyst to have full control over the spectral classes that are assigned to the information classes of interest (Ederle and Weith, 2005). This means that the analyst does not need to match spectral classes to information classes as this is addressed during the selection of training areas (Ederle and Weith, 2005).

Since the aim of this study was to analyse the discrepancy in urban forests between high- and low-income census tracts, it was decided to classify each image into three informational classes:

1. Non-Vegetation (urban and agricultural land uses)
2. Vegetation Cover (includes greenspaces, parks, conservation areas, smaller vegetation, and trees)
3. Water

The classification scheme used was based on reference data in the form of Google Maps image. Bands 2 (blue), 3 (green), 4 (red), and 8 (NIR), as well as the NDVI band, were used as input channels for the classification of each municipality. Furthermore, a minimum of 20 training areas were created for each informational class. When running the classification, the Maximum Likelihood algorithm was selected, as it provided the most accurate results. Lastly, an accuracy assessment was conducted for each municipality to evaluate the quality of the classification information.

### 3.2.4 Vegetation Cover Analysis

The analysis was divided into two sections. The first part examines the entire municipality to see the overall trend in all the CT. The second part compares three low-income CT with three high-income CT. A GRD file was created for each municipality and transferred to ESRI ArcGIS Pro. To analyse the vegetation cover (VC) for all the CT in the municipality, the Zonal Statistics tool was used to obtain the total pixel count within each CT, and the pixel count for the VC. Once the pixel counts were obtained, the following formula was used to calculate the VC percentages for each CT within a municipality:

$$\% = \left(\frac{VC\ Count}{Total\ Pixel\ Count}\right) * 100 \qquad (3)$$

Once the % VC was calculated, a choropleth map was created using the natural breaks (Jenks) data classification method with five classes. This classification method creates groups of similar values and maximizes the difference between each group (ESRI, 2023). It is best used for data that are unevenly distributed, like the % VC (ESRI, 2023). By clustering similar values and separating different groups, the natural breaks method, made it easier to see patterns within the VC data between CT, which in turn, made it easier to compare VC and MHI. The VC and MHI choropleth maps were placed side-by-side to show the patterns between the two variables. Additionally, two bar charts were created to illustrate the average VC in each MHI range for the two municipalities. The following formula was used to calculate the average VC for each range:

$$Avg\ \% = \left(\frac{Sum\ of\ VC}{Number\ of\ CTs\ in\ MHI\ range}\right) \quad (4)$$

The second part of the analysis consisted of selecting three low-income CT and comparing them to three high-income CT. The CT were selected based on MHI. The three CT with the lowest MHI in a municipality, were compared to the three highest CT in the municipality. The vegetation class was clipped for each CT in ArcGIS Pro and placed above a satellite image. Lastly, the vegetation cover was calculated for each CT using equation 3.

# CHAPTER 4: RESULTS AND ANALYSIS

## 4.1 NDVI Results

Figure 4.1 represent the results of the NDVI analysis for Brampton and Mississauga. The images are shown in a grayscale. The white areas within the images represent areas with high vegetation density. The light gray areas represent greenspace (i.e., parks, fields, grass), farmland, and neighbourhoods with more vegetation and greenspace. The medium gray areas represent suburban neighbourhoods with houses closer together. Lastly, the dark gray or black areas represent areas that are industrial and commercial areas. Dark gray or black areas can also represent residential neighbourhoods that have more mid-rise and high-rise buildings, and water. These areas tend to have little to no vegetation, and therefore appear dark gray.

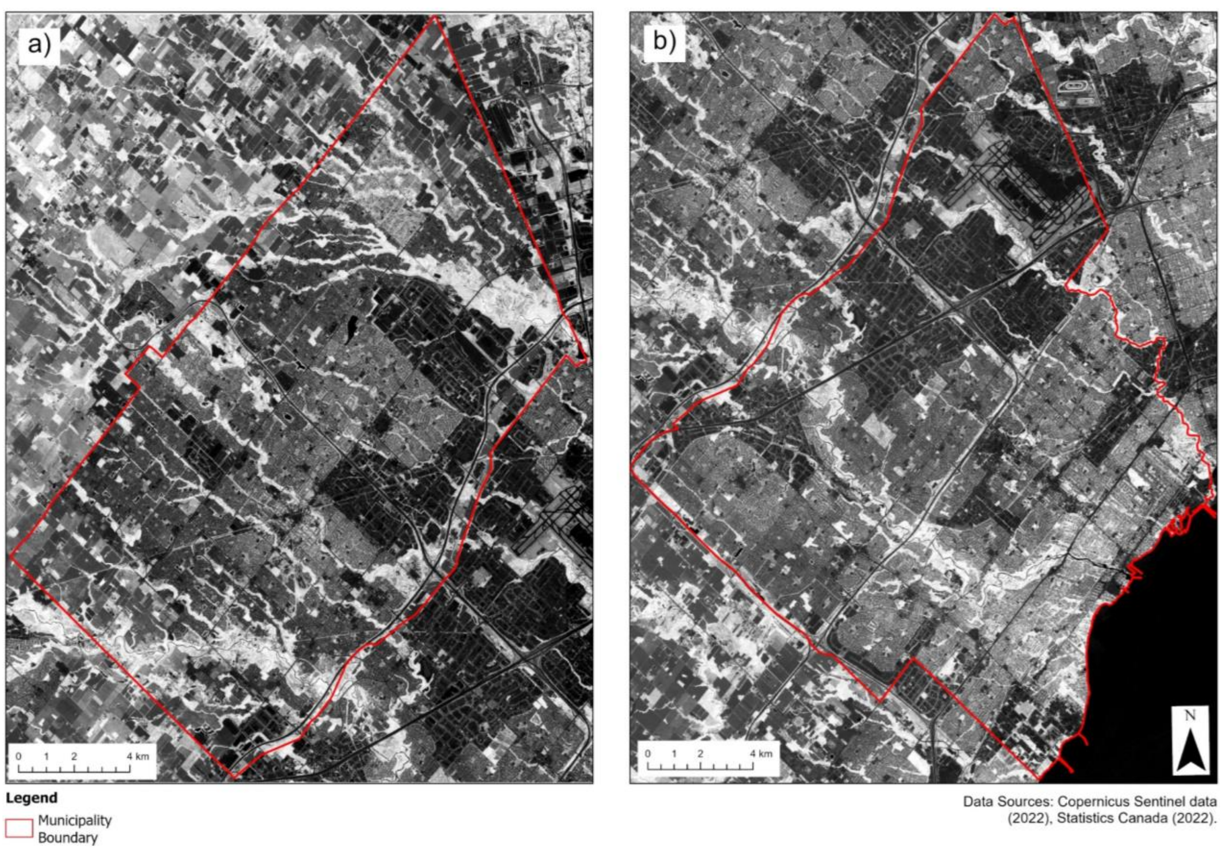


**Figure 4.1:** NDVI analysis results for Brampton (a) and Mississauga (b) from June 25, 2022.

### 4.2 Supervised Classification Results

Figure 4.2 shows the results of the supervised classification for Brampton and Mississauga. The images are divided into three classes: non-vegetation, vegetation cover and water. The figure also displays the CT boundaries to show the distribution of VC. The classification images show similar patterns seen in the NDVI results. For example, the bright white areas within the NDVI images correspond to the areas classified as VC within the classification images. Additionally, the dark gray and black areas in the NDVI images correspond to areas classified as non-vegetated surfaces, such as urban surfaces and agricultural land.

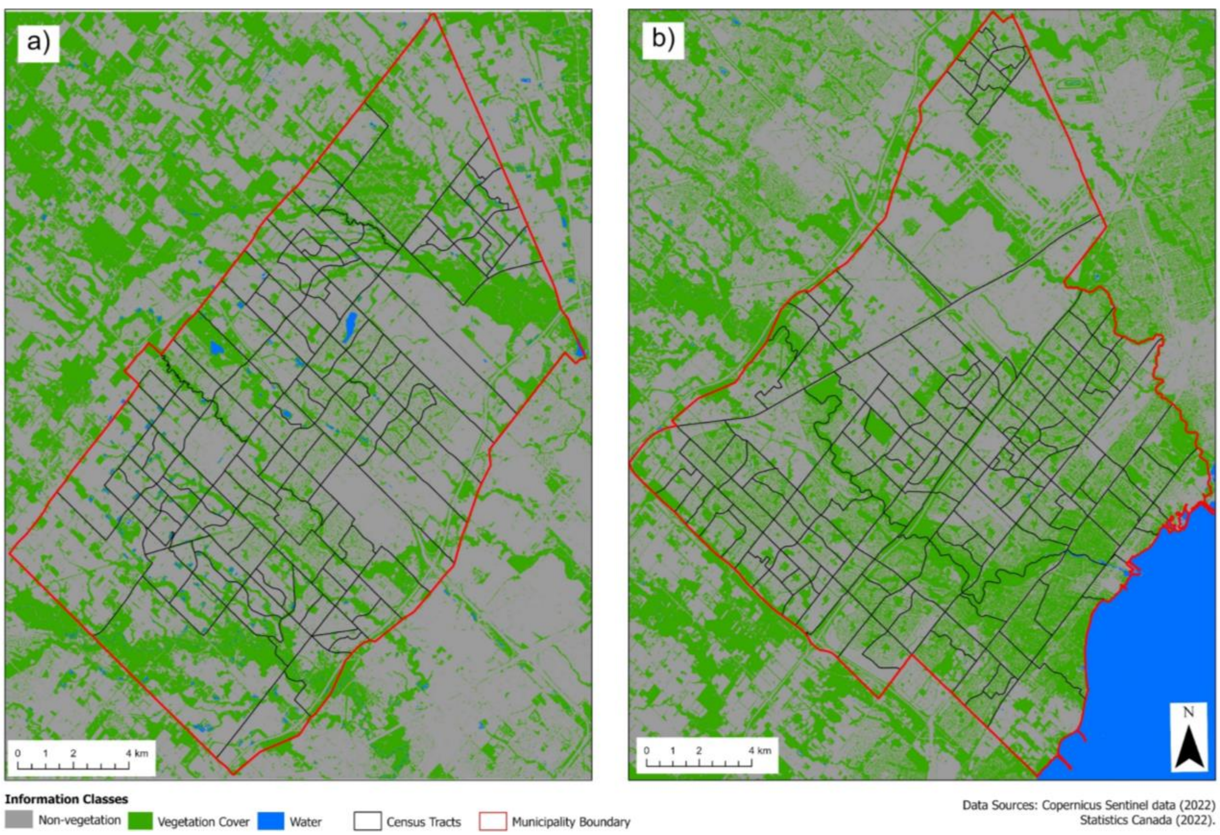


**Figure 4.2:** Supervised classification results for Brampton (a) and Mississauga (b) from June 25, 2022.

Tables 4.1 to 4.4 show the results of the accuracy assessment after conducting the supervised classification. Tables 4.1 and 4.3 display the error (confusion) matrix for each municipality. The tables show how many of the sample pixels were placed in the correct information class. Tables 4.2 and 4.4 show the results of the accuracy statistics. They display the producer's accuracy, the user's accuracy, and the overall accuracy of the assessment. The producer's accuracy represents the probability that the ground cover type will be correctly classified. It is calculated by dividing the number of correctly classified pixels for a category by the number of ground truth pixels for that category (column total) (Story and Congalton, 1986). The user's accuracy represents the probability that a pixel labeled as a certain class is in that class. It is calculated by dividing the correctly classified pixels of each category by the total number of samples that were classified in the category (row total) (Story and Congalton, 1986). The overall accuracy represents the total classification accuracy and is important for this study (Story and Congalton, 1986).

As seen in table 4.2, the user's accuracy for all three classes in Brampton is above 90%. Non-vegetation has a user's accuracy of 91.837%, vegetation cover has a user's accuracy of 92.523% and water has a user's accuracy of 100%. However, the producer's accuracy is not as high for the three classes. Although non-vegetation and vegetation cover have a producer's accuracy of 97.122% and 81.148%, water has a producer's accuracy of 50%. As seen in table 4.1, the reason the producer's accuracy for water is 50% is because during the accuracy assessment process it was determined that the actual ground cover for a pixel classified as non-vegetation was water. As seen in table 4.4, the user's accuracy for non-vegetation, vegetation cover, and water in Mississauga is 92.963%, 91.071%, and 100%. The producer's accuracy for non-vegetation, vegetation cover and water in Mississauga is 96.169%, 84.298%, and 100%. As seen in the tables 4.2 and 4.4 the overall accuracy shows that Brampton is 92.040% correctly classified and Mississauga is 92.786% correctly classified. It seems that the Mississauga image has slightly better accuracy statistics than Brampton. However, the overall accuracies of both Brampton and Mississauga show that majority of the pixels for each information class were correctly classified.

**Table 4.1:** Brampton Error (Confusion) Matrix.

| | **Non-vegetation** | **Vegetation Cover** | **Water** | **Row Total** |
|---|---|---|---|---|
| **Non-Vegetation** | **270** | 23 | 1 | 294 |
| **Vegetation Cover** | 8 | **99** | 0 | 107 |
| **Water** | 0 | 0 | **1** | 1 |
| **Column Total** | 278 | 122 | 2 | 402 |

**Table 4.2:** Brampton Accuracy Statistics.

| **Class Name** | **Producer's Accuracy** | **95% Confidence Interval** | **User's Accuracy** | **95% Confidence Interval** | **Kappa Statistics** |
|---|---|---|---|---|---|
| **Non-Vegetation** | 97.122% | (94.977% 99.267%) | 91.837% | (88.537% 95.137%) | 0.7354 |
| **Vegetation Cover** | 81.148% | (73.797% 88.498%) | 92.523% | (87.072% 97.974%) | 0.8927 |
| **Water** | 50.000% | (-44.296% 144.296%) | 100.000% | (50.000% 150.000%) | 1.0000 |
| **Overall Accuracy: 92.040%**<br>Overall Kappa Statistics: 0.807 | | | 95% Confidence Interval: (89.269% 94.810%)<br>Overall Kappa Variance: 0.008 | | |

**Table 4.3:** Mississauga Error (Confusion) Matrix.

| | **Non-vegetation** | **Vegetation Cover** | **Water** | **Row Total** |
|---|---|---|---|---|
| **Non-Vegetation** | **251** | 19 | 0 | 270 |
| **Vegetation Cover** | 10 | **102** | 0 | 112 |
| **Water** | 0 | 0 | **20** | 20 |
| **Column Total** | 261 | 121 | 20 | 402 |

**Table 4.4:** Mississauga Accuracy Statistics.

| Class Name | Producer's Accuracy | 95% Confidence Interval | User's Accuracy | 95% Confidence Interval | Kappa Statistics |
|---|---|---|---|---|---|
| **Non-Vegetation** | 96.169% | (93.648% 98.689%) | 92.963% | (89.727% 96.199%) | 0.7994 |
| **Vegetation Cover** | 84.298% | (77.402% 91.193%) | 91.071% | (85.344% 96.799%) | 0.8723 |
| **Water** | 100.000% | (97.500% 102.500%) | 100.000% | (97.500% 102.500%) | 1.0000 |
| **Overall Accuracy: 92.786%** | | 95% Confidence Interval: (90.133% 95.440%) | | | |
| Overall Kappa Statistics: 0.849 | | Overall Kappa Variance: -0.208 | | | |

### 4.3 Median Household Income and Average Vegetation Cover

The graphs in Figure 4.3 illustrate the correlation between MHI and VC in Mississauga and Brampton. It shows the average VC for each income range. As seen in the two graphs, the CT with lower MHI have less VC compared to the higher MHI ranges. In Brampton, CT lesser than or equal to $60,000 have an average of 17.94% VC, whereas the CT with incomes greater than $100,000 have a 22.70% VC. At the highest income level, there is a slight drop as there are some wealthy households that are near large industrial areas with little vegetation cover. In Mississauga, there is a steady increase in VC as the MHI increases. Like Brampton, CT with incomes lesser than or equal to $60,000 have an average of 22.70% VC, whereas the CT with incomes greater than $100,000 have an average VC of 38.24%. It should be noted that there were only two CT that were below or equal to a median household income of $60,000.

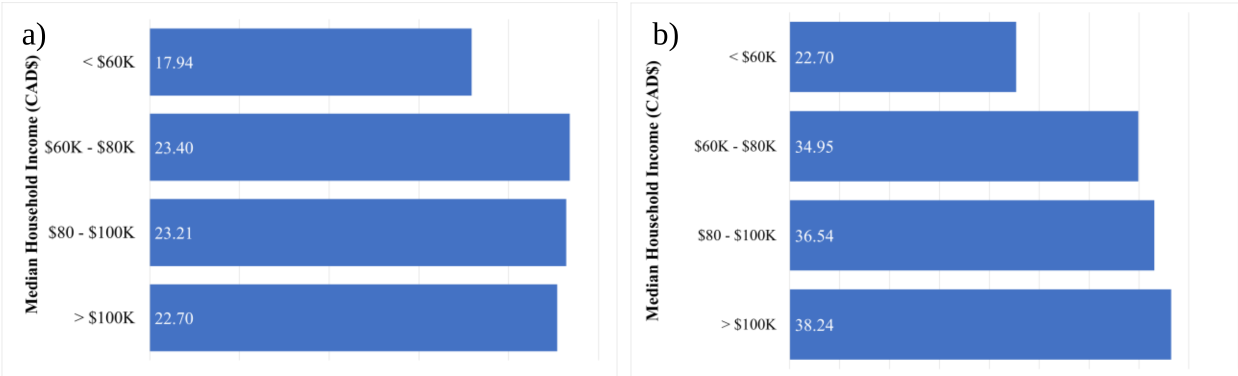


**Figure 4.3:** Median household income range and average vegetation cover (%) for CTs in Brampton (a) and Mississauga (b).

The images in Figures 4.4 and 4.5 show two choropleth maps for each municipality, one displaying the distribution of MHI and the other showing the distribution of VC. The two maps side-by-side illustrate how MHI corresponds to VC. As seen in Figure 4.4, CT with a higher MHI have higher VC. CT in the highest income range in the east and west of Brampton have greater VC compared to the CT in the lowest income range. CT within the highest MHI range typically have a greater abundance of conservation areas, parks, and golf clubs. For example, the CT in the south-east corner of Brampton, contains the Claireville Conservation Area. Figure 4.4 also shows the lowest income ranges having minimal VC compared to the higher income ranges. Two out of the three CTs in the lowest income range contain industrial and commercial spaces with little VC.

Figure 4.5 shows similar trends in Mississauga as seen in Brampton. Like Brampton, the CT in the highest income range have a greater VC compared to the CT in the lowest income range. The most significant division is seen in the south of Mississauga in the Port Credit area. The CT in the ≤$60K range is surrounded by CT from the >$100K range. In the vegetation cover choropleth map, it shows the CT in the ≤$60K range in the 11.85% - 20.41% class, whereas the surrounding >$100K CT have the highest percentage of VC. Like Brampton, higher income CT are typically adjacent to parks, conservation areas, and natural spaces. The CT along the Credit

River are in the two highest income ranges and have a higher percentage of VC. However, like Brampton, some high-income CT have minimal VC because they are adjacent to industrial areas, as seen in the north of Mississauga. Overall, there is a pattern in both municipalities where higher income CT have higher VC compared to their lower income counterparts.

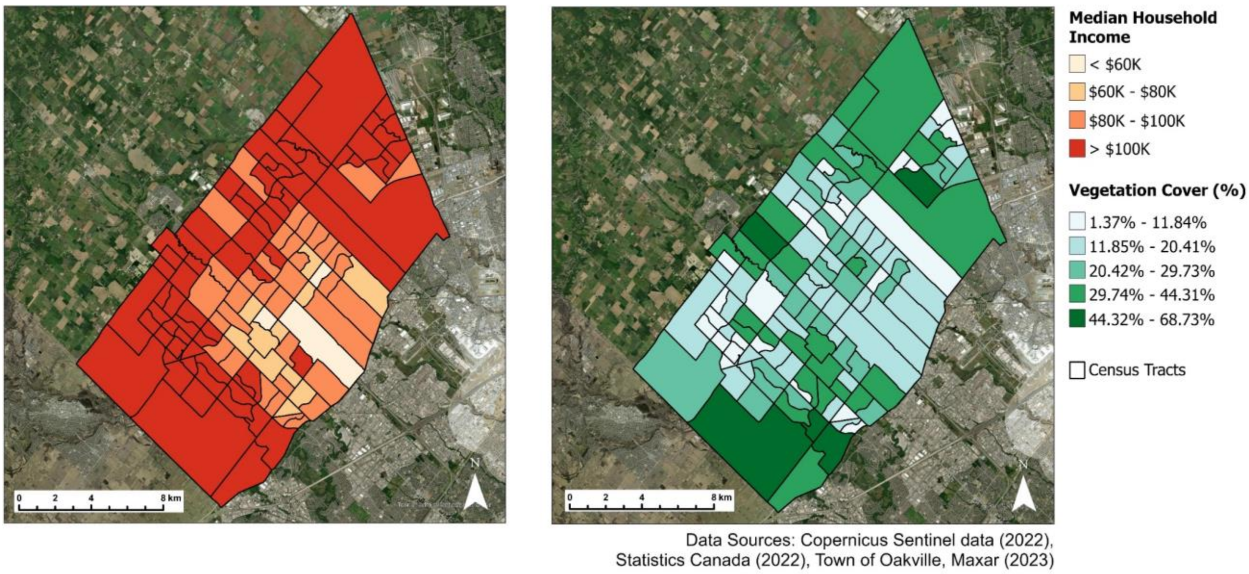


**Figure 4.4:** Median household income and vegetation cover choropleth maps for CTs in Brampton.

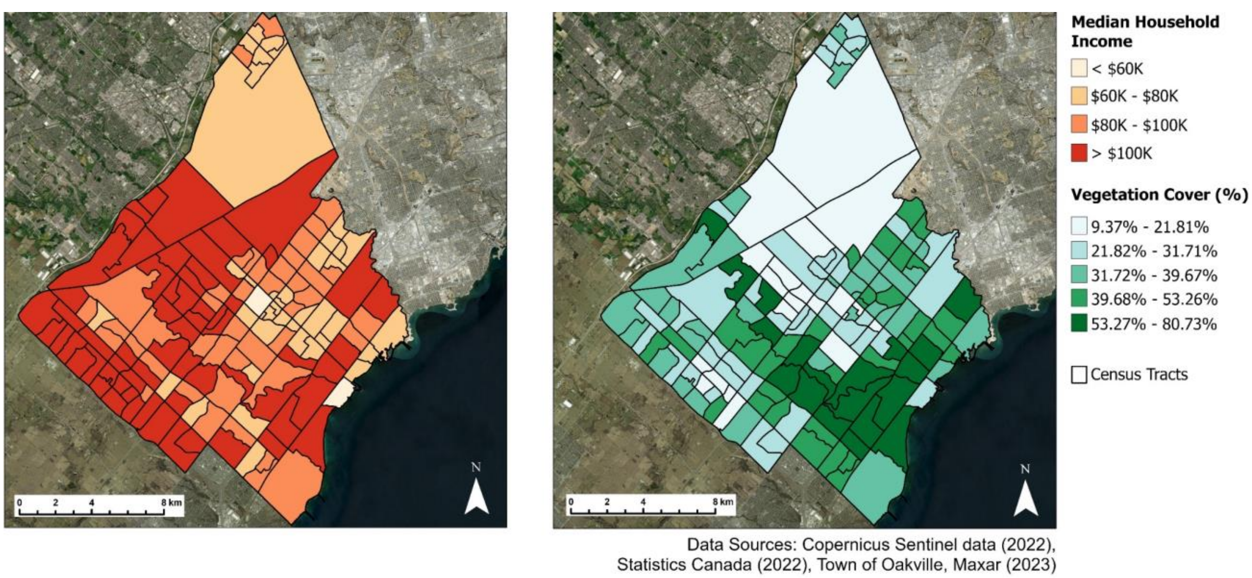


**Figure 4.5:** Median household income and vegetation cover choropleth maps for CTs in Mississauga.

### 4.4 Analysis of the three lowest income CTs and three highest income CTs

Figure 4.6 displays the six CT that were analysed to show their location within each municipality. Figures 4.7, 4.8, and 4.9 show the comparison in VC between three CT with the lowest MHI in Brampton and three CT with the highest MHI in Brampton. As seen in Figure 4.7, the MHI for CT0570.01 is $55,600 and has a VC of 14.9%, whereas CT0576.73 has a MHI of $139,000 and a VC of 38.5%. There is a clear distinction in VC between the two CT. As seen in Figure 4.8, CT0563.01 has a MHI of $58,800 and a VC of 9.2%, whereas CT0576.47 has a MHI of $142,000 and a VC of 38.5%. Both CT0570.01 and CT0563.01 are situated in industrial and commercial areas (Figure 4.7 and 4.8) and are lacking in VC. CT0563.01 contains a shopping centre, Bramalea City Centre, in the middle of the CT, and has high-rise apartment buildings all around its peripheries. Conversely, CT0576.73 and CT0576.47 both contain farmland and natural spaces with an abundance of VC. As seen in Figure 4.9, CT0575.02 has a MHI of $59,200 and a VC of 29.7% and CT577.04 has a MHI of $145,000 and a VC of 28.4%. Unlike the other images, the CT with the lower MHI has a higher VC compared to the higher income CT. This is because CT0575.02 contains several spaces, such as parks, and parkettes, which provide greenspace and vegetation. Additionally, a portion of the Etobicoke Creek runs through the CT, providing surrounding areas with vegetation and greenspace. However, it is also located across from industrial and commercial areas, possibly resulting in lower housing prices. Although CT0577.04

has less VC, it contains several greenspaces and forested areas, and is surrounded by other similar CT.

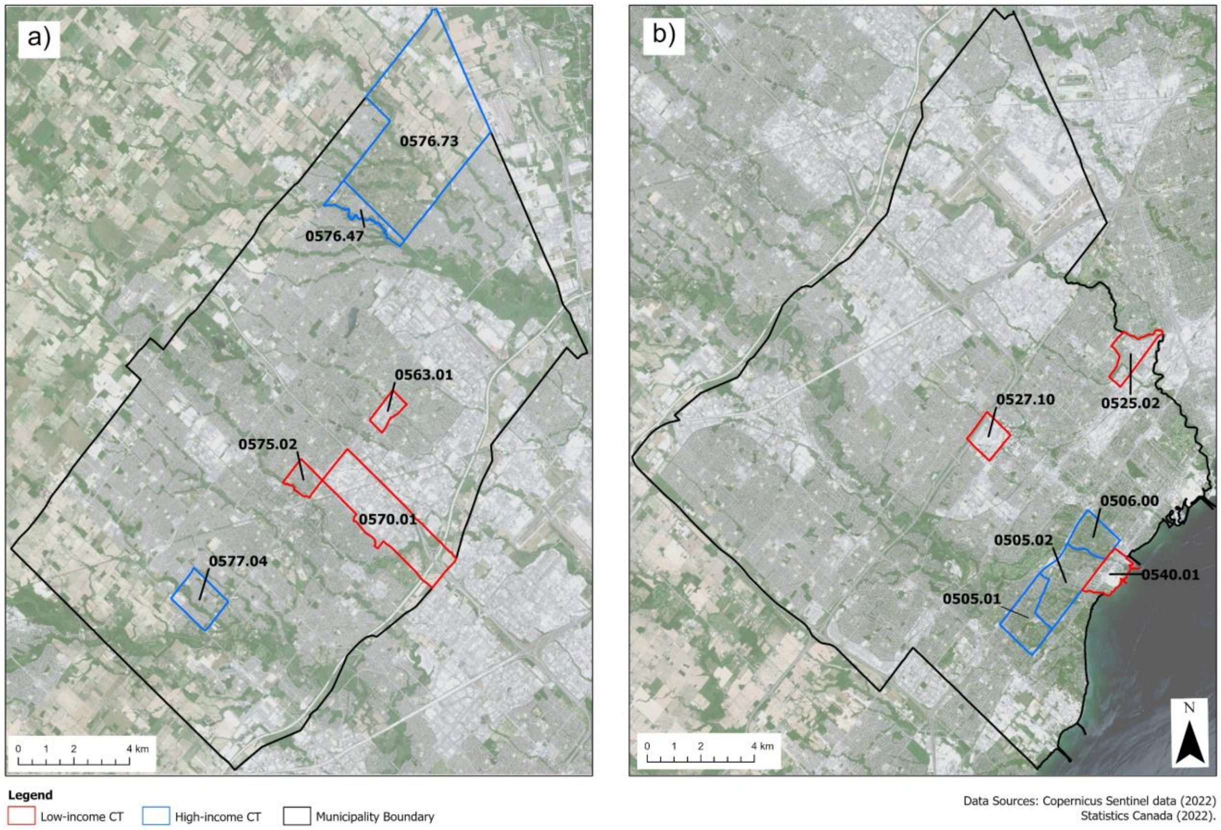


**Figure 4.6:** The three low-income and three high-income CT in Brampton (a) and Mississauga (b) and their locations.


**Figure 4.7:** Vegetation cover comparison in Brampton between CT0570.01 (lower MHI) and CT0576.73 (higher MHI). The red dot on the inset map represents the low-income CT and the blue dot represents the high-income CT.


**Figure 4.8:** Vegetation cover comparison in Brampton between CT0563.01 (lower MHI) and CT0576.47 (higher MHI). The red dot on the inset map represents the low-income CT and the blue dot represents the high-income CT.

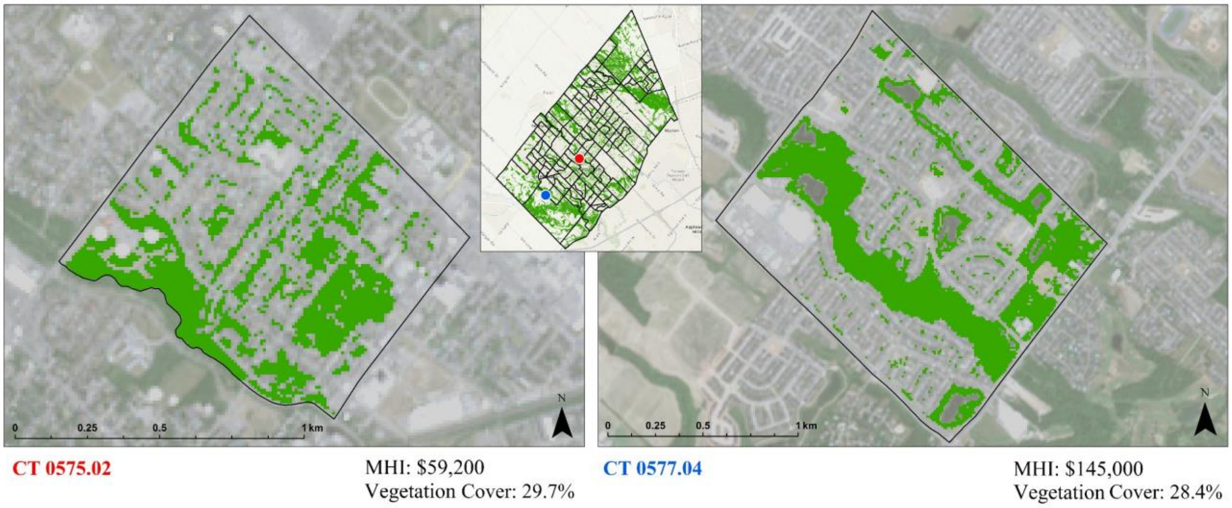


**Figure 4.9:** Vegetation cover comparison in Brampton between CT0575.02 (lower MHI) and CT0577.04 (higher MHI). The red dot on the inset map represents the low-income CT and the blue dot represents the high-income CT.

Figures 4.10, 4.11, and 4.12 show the comparison in VC between three CT with the lowest MHI and three CT with the highest MHI in Mississauga. As seen in Figure 4.10, CT0540.01 has a MHI of $59,200 and a VC of 30.5%, whereas CT0505.01 has a MHI of $160,000 and a VC of 69.3%. Both CT are within the Port Credit neighbourhood but show the significant division in VC between low-income CT and high-income CT. In fact, all three CT with the higher MHI (CT0505.01, CT0505.02, and 0506.00) and CT0540.01 are adjacent to each other. As seen in Figure 4.10, CT0527.10 has a MHI of $60,000 and a VC of 15%, whereas CT0505.02 has a MHI of $170,000 and a VC of 65.3%. CT0527.10 contains the Square One shopping mall, large parking lots, and apartment buildings. It has very limited vegetation compared to CT0505.02, which alternatively, contains a lot of parks and large single-detached homes with an abundance of vegetation. As seen in Figure 4.12, CT0525.02 has a MHI of $62,400 and a VC of 28.8%, whereas CT0506.00 has a MHI of $180,000 and a VC of 76.2%. CT0525.02 contains a residential area with a mix of housing types, including single-detached, high-rise, and mid-rise apartments, in between large commercial areas on both ends of the CT. As seen in the image, majority of the vegetation is concentrated in the middle (i.e., where the residential area is situated), and along the eastern edge of the CT. In comparison, CT0506.00 does not have any large commercial or industrial areas, only consists of residential neighbourhoods, where the primary housing types are large single-detached homes. Trees and other vegetation are densely packed, and houses back into forested areas. In both municipalities, the low-income CT always contained commercial or industrial areas, whereas the high-income CT only consisted of residential areas and both large and small parks.

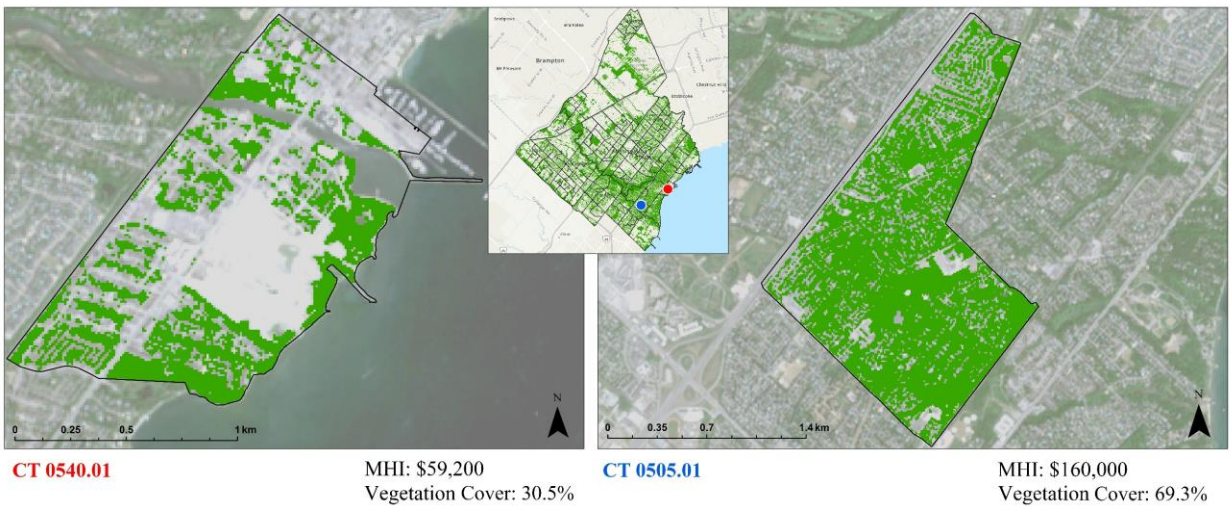


**Figure 4.10:** Vegetation cover comparison in Mississauga between CT0540.01 (lower MHI) and CT0505.01 (higher MHI). The red dot on the inset map represents the low-income CT and the blue dot represents the high-income CT.


**Figure 4.11:** Vegetation cover comparison in Mississauga between CT0527.10 (lower MHI) and CT0505.02 (higher MHI). The red dot on the inset map represents the low-income CT and the blue dot represents the high-income CT.


**Figure 4.12:** Vegetation cover comparison in Mississauga between CT0525.02 (lower MHI) and CT0506.00 (higher MHI). The red dot on the inset map represents the low-income CT and the blue dot represents the high-income CT.

## CHAPTER 5: DISCUSSION AND CONCLUSION

### 5.1 Discussion

The aim of this study was to investigate the correlation between socioeconomic factors, particularly wealth, and urban forests in Mississauga and Brampton. Existing literature shows that there is an association between household income and vegetation cover. These previous studies show that neighbourhoods with higher incomes typically have an increase in canopy and vegetation cover, whereas neighbourhoods with lower incomes typically see a decrease in canopy and vegetation cover. The findings in this study show similar results within CT in Brampton and Mississauga. Overall, CT with a lower MHI had less VC compared to CT with higher MHI. This was further proven by evaluating three CT with the lowest MHI and three CT with the highest MHI income from each municipality and comparing them side-by-side. The results showed that on average the three CT with the highest MHI had a greater VC compared to the CT with the lowest MHI.

There were a few characteristics that were observed between low-income CT compared to high-income CT. Low-income CT typically contained large industrial and commercial areas with little VC that covered majority of the CT. For example, CT0570.01 and CT0563.01 in Brampton, and CT0527.10 and CT0525.02 in Mississauga, all contained industrial and commercial areas that took up significant space in the CT. Additionally, low-income CT typically had a higher percentage of apartment buildings compared to high-income CT. This was particularly noticeable in CT0563.02 in Brampton and CT0527.10 in Mississauga, where there were no single detached, townhomes, or semi-detached homes in the CT. This is further proven in Tables 5.1 and 5.2 (Statistics Canada, 2023a). Inversely, the high-income CT analysed, were not situated near large industrial or commercial areas, in fact the three high-income CT in Mississauga and CT0576.73

in Brampton, did not contain any small or large commercial areas. The high-income CT did not have any mid-rise or high-rise residential buildings and only consisted of low-rise homes, such as single detached, semi-detached, and townhomes. In fact, some CT, such as CT0576.73 and CT0576.47 in Brampton and all three CT in Mississauga had large single detached properties. Furthermore, high-income CT were surrounded by natural spaces, green spaces, and parks. All three CT in Mississauga, were adjacent to the Mississauga Golf and Country Club. Homes in CT0506.00 and CT0505.01 in Mississauga had backyards facing forested areas.

**Table 5.1:** Comparison of percentage of apartments and single detached homes between low-income and high-income CTs in Brampton.

| | Lower Income | | | Higher Income | | |
|---|---|---|---|---|---|---|
| | **CT0570.01** | **CT0563.01** | **CT0575.02** | **CT0576.73** | **CT0576.47** | **CT0577.04** |
| **Percentage of Apartments** | 74.1% | 100% | 67.8% | 3.9% | 4.3% | 1.6% |
| **Percentage of single detached** | 4% | 0% | 19.7% | 94.5% | 95.7% | 93.2% |

**Table 5.2:** Comparison of percentage of apartments and single detached homes between low-income and high-income CTs in Mississauga.

| | Lower Income | | | Higher Income | | |
|---|---|---|---|---|---|---|
| | **CT0540.01** | **CT0527.10** | **CT0525.02** | **CT0505.01** | **CT0505.02** | **CT0506.00** |
| **Percentage of Apartments** | 70.6% | 97.3% | 62.3% | 1% | 1.1% | 2.4% |
| **Percentage of single detached** | 16.6% | 0% | 17.2% | 99% | 97.7% | 97% |

There were a few anomalies that did not match with the overall results. Firstly, CT0575.02 (low-income) in Brampton had a higher VC than CT0577.04 (high-income). VC in CT0575.02 was 1.3% higher than CT0577.04. Unlike the other two low-income CTs in Brampton, CT0575.02 contains an abundance of green space and natural spaces, such as the Etobicoke Creek and Duggan Park. However, CT0575.02 is still situated near industrial areas, whereas CT0577.04 is adjacent to natural spaces and a large golf club with an abundance of greenspace and vegetation.

Based on Google Maps and development applications, low-income CT seemed to have newer residential neighbourhoods compared to high-income CT. This pattern was more apparent in Mississauga than Brampton. For example, CT0505.01, CT0505.02, and CT0506.00 in Mississauga are in Lorne Park, a historic neighbourhood established in 1879, however, residential buildings started being built in 1930s (Heritage Mississauga, 2018). However, it was difficult to determine which homes were built in the mid-1900s and which ones were built recently, as there are still homes being built as of this year. Conversely, low-income CT have newer residential development. For example, CT0527.10 contains Square One Shopping Centre, which was built in 1973 (Insauga, 2022). Based on City of Mississauga development applications, the residential developments within the CT were not built until the early 2000s. Unlike Mississauga, Brampton does not show such a pattern. For example, although CT0577.04 is a high-income CT, residential development did not start until 2011 based on Google Maps. Whereas CT0575.02 was already established before CT0577.04. Overall, despite there being a pattern, it is difficult to verify, as even well-established neighbourhoods are undergoing continuous changes and development.

There are a few possible reasons for the patterns seen between MHI and VC. One possible reason is that trees increase the overall aesthetic appeal and therefore, property values. Escobedo et al. (2015) found that property values increased on average by $1586 per tree in Florida, U.S. They also found that the tree crown density of a tree also played a role in increasing property values (Escobedo et al., 2015). Wealthier individuals have the resources to afford houses in more expensive and aesthetically pleasing neighbourhoods (Landry et al., 2020). Furthermore, Chuang et al. (2017), suggests wealthier individuals have more spatial mobility than lower income individuals, and can live in neighbourhoods that provide attractive amenities such as green space and trees. The relationship between VC and MHI could possibly be a result of a feedback loop where a higher number of trees increase property value, and attracts wealthier households (Schwarz et al., 2015).

Additionally, the size of the residential property could also result in an increase in VC, and larger properties are mainly observed in high-income neighbourhoods (Landry et al., 2020). A pattern that was observed in this study was the prevalence of VC in high-income CT due to larger residential properties. For example, CT0576.73 in Brampton, which has a MHI of $142,000 and a VC of 38.5%, has large homes, with large front and backyards, allowing for more green infrastructure. This pattern was also observed in the high-income CT in Mississauga. Larger properties allow for more space for green infrastructure, and high-income CT typically have more large residential properties (Landry et al., 2020)

Another possible reason high-income CT displayed higher percentages of VC could be the cost of maintaining greenspaces and trees for governments and individuals. Neighbourhoods with more valuable homes that have a greater property tax, and public investment in green infrastructure are more likely to have greater VC compared to low-income CT (Chuang et al., 2017). Furthermore, wealthier individuals typically have more disposable income to spend on maintaining trees and vegetation, whereas maintenance such as watering, pruning, and leaf clean-up can dissuade low-income individuals (Schwarz et al., 2015). Individuals in low-income CT may have fewer resources or motivation to increase property values because they are renters or on fixed incomes. There may be a fear of potential gentrification and rising rent due to an increase in VC (Schwarz et al., 2015).

### 5.2 Conclusion

With the use of remote sensing, results of this study show that low-income CT have less vegetation cover compared to high-income CT in both Brampton and Mississauga. This research further supports previous research that household income affects canopy and vegetation cover, and low-income CT experience environmental inequality. There are multiple reasons why this pattern is so prevalent such as trees increasing property values, high-income CT having larger properties allowing for greater investment into green infrastructure and high maintenance costs for trees.

The NDVI method allowed for the evaluation of vegetation cover across Brampton and Mississauga. Furthermore, the use of the supervised classification method allowed for the accurate classification of the three information classes (non-vegetation, vegetation, and water). The accuracy assessments completed after conducting a supervised classification determined the quality of the information derived through remote sensing. As seen in table 4.2 the producer's accuracy for the vegetation cover class in Brampton was 81.148%, the user's accuracy was 92.523% and the overall accuracy was 92.040%. As seen in table 4.4 the producer's accuracy for vegetation cover in Mississauga was 84.298%, the user's accuracy was 91.071%, and the overall accuracy was 92.786%. This indicates that most of the pixels in the vegetation cover class were accurately classified. Studies such as this one could assist planners and policy makers in Brampton and Mississauga in addressing environmental inequality across their neighbourhoods using remote sensing technology.

### 5.2.1 Limitations

This study examined six CT, all of different physical sizes, from each municipality. In an ideal situation, the CT being compared would be similar in size to improve comparability. However, some CT were larger than others. For example, CT0576.73 was significantly larger than the other five CT in Brampton.

Sentinel-2 images were divided into three information classes in this study: non-vegetation, vegetation cover, and water. Certain information classes had to be overlooked when creating training areas. For example, since some agricultural lands had similar spectral characteristics as urban spaces, instead of creating a separate information class, agricultural lands and urban spaces were grouped into one class: non-vegetation.

In addition to the previous point, this study examines trees, smaller vegetation, and greenspaces together. Ideally, trees and greenspaces would be examined separately to see the percentage of trees. However, since these two categories had similar spectral characteristics, information was perhaps not accurately being portrayed. It was easier to distinguish trees and greenspace in larger areas where trees were more densely packed, such as conservation areas. However, tree data would often get misinterpreted as greenspace in neighbourhoods where buildings were closer together. By grouping trees and greenspace together as one class, there was no misinterpretation of either land cover.

### 5.2.2 Future Research

Future studies should examine other socioeconomic factors and their correlation with trees and greenspaces in Brampton and Mississauga. Landry et al. (2020) and Schwarz et al. (2015), researched the correlation between canopy cover and socioeconomic factors which assess social vulnerability, such as proportion of renters, average dwelling price, poverty rate, and prevalence of low-income. MacDonald et al. (2021) also examined how population density affected canopy cover. They found that neighbourhoods with higher population density were typically lower-income and had less canopy cover. Researching the relationship between these factors and urban forests in Brampton and Mississauga could identify certain patterns between socioeconomic factors other than wealth.

Future studies for Brampton and Mississauga should also focus on how species diversity differs between low-income and high-income neighbourhoods. Previous studies on this topic have found that wealthier neighbourhoods tend to have more diversity in tree species (Landry et al., 2020; Lin et al., 2021). The quantity of canopy cover is not the only factor to consider when examining socioeconomic factors and environmental inequality (Berland et al., 2015). Urban forests with a high diversity of species are often more resilient to the effects of climate change, extreme weather patterns, pests, and diseases (Steenberg et al., 2013). Researching the relationship between other socioeconomic factors and canopy cover and the effects of wealth on species diversity in Brampton and Mississauga could help policy makers and planners improve urban forest management in low-income neighbourhoods.

Furthermore, future studies should incorporate the use of other analysis methods along with NDVI to distinguish between trees and greenspaces. One of the limitations of this study was the difficulty in differentiating between trees and greenspaces. Texture analysis has been shown to improve the classification accuracy between trees, grass, and shrubs (Feng et al., 2015). NDVI can be used in combination with texture analysis to distinguish between trees, pastures, baseball fields and golf courses (McDonald et al., 2021). Distinguishing between tree canopy and greenspace could further improve studies as it allows the analyst to examine how the two land covers are distributed separately.

### 5.2.3 Recommendations

To improve tree distribution and reduce the gap in vegetation cover between low-income and high-income neighbourhoods in Brampton and Mississauga, policy makers can improve current initiatives to be more inclusive. Both Brampton and Mississauga have the “One Million Trees” program, which aims to plant one million trees by 2032 in Mississauga and 2040 in Brampton (City of Brampton, 2019; City of Mississauga, 2023). As of 2023, approximately, 16,229 trees have been planted in Brampton and 500,000 in Mississauga (City of Brampton, ; City of Mississauga, 2023). However, to improve these existing initiatives should focus on addressing inequalities that persist in the distribution of tree canopy in low-income neighbourhoods. Currently, the initiatives do not highlight environmental inequality and the ways these initiatives can improve distribution of trees in low-income neighbourhoods. However, simply planting trees in low-income neighbourhoods is not enough. The initiatives also need to engage the community in these neighbourhoods, and begin discussions about tree planting, maintenance, organizational support, and funding (Sousa-Silva et al., 2023).

It should be noted however, that trees and greenspaces do not always provide benefits in low-income neighbourhoods. The maintenance of trees and greenspaces is expensive. Residents in low-income neighbourhoods may incur the cost of maintenance, which they may not be able to afford (Schwarz et al., 2015). There may also be a fear of potential gentrification and rising rent and housing costs due to an increase in VC, as trees do increase property value (Escobedo et al., 2015; Schwarz et al., 2015). Therefore, tree cover must be assessed in a spatially explicit way. In some circumstances, trees and greenspaces will have positive outcomes, but in other situations, there may be a lack of benefits (Schwarz et al., 2015). On a wider scale, there needs to be policies and actions taken by all three levels of government to control cost of housing or provide more accessible housing that is not affected by the distribution of trees and greenspaces.

## REFERENCES


Atkinson, R. W., Butland, B. K., Anderson, H.R., and Maynard, R. L. (2018). Long-tern concentrations of nitrogen dioxide and mortality: A meta-analysis of cohort studies. *Epidemiology, 29*(4), 460-472. 10.1097/EDE.0000000000000847.

Berland, A., Schwarz, K., Herrmann, D. L., and Hopton, M. E. (2015). How environmental justice patterns are shaped by place: terrain and tree canopy in Cincinnati, Ohio, USA. *Cities and the Environment (CATE), 8*(1), 1-15. https://digitalcommons.lmu.edu/cate/vol8/iss1/1.

Bowler, D. E., Buyung-Ali, L., Knight, T. M., Pullin, A. S. (2010). Urban greening to cool towns and cities: A systematic review of the empirical evidence. *Landscape and Urban Planning, 97*(3), 147-155.https://doi.org/10.1016/j.landurbplan.2010.05.006

Canadian Institute for Climate Choices (CICC). (2021). *Growing Forests in a City.* https://climatechoices.ca/wp-content/uploads/2021/04/Urban-Trees-study_April26_EN_Final.pdf.

Carrus, G., Scopelliti, M., Lafortezza, R., Colangelo, G., Ferrini, F., Salbitano, F., Agrimi, M., Portoghesi, L., Semenzato, P., and Sanesi, G. (2015). Go greener, feel better? The positive effects of biodiversity on the well-being of individuals visiting urban and peri-urban green areas. *Landscape and Urban Planning, 134,* 221-228. https://doi.org/10.1016/j.landurbplan.2014.10.022.

Chuang, WC, Boone, C. G., Locke, D. H., Grove, J. M., Whitmer, A., Buckley, G., Zhang, S. (2017). Tree canopy change and neighborhood stability: A comparative analysis of Washington, B.C. and Baltimore, MD. *Urban Forestry & Urban Greening, 27,* 363-372. http://dx.doi.org/10.1016/j.ufug.2017.03.030.

City of Brampton. (2019). *Brampton one million trees program.* https://www.brampton.ca/EN/residents/Trees/Documents/Brampton_One_Million_Trees_Program_Strategy.pdf.

City of Mississauga. (2021). *2021 City of Mississauga - Parks* [Data set]. https://data.mississauga.ca/datasets/mississauga::2021-city-of-mississauga-parks-/explore.

City of Mississauga. (2023). *Mississauga celebrates the 10th anniversary of One Million Trees campaign.* https://www.mississauga.ca/city-of-mississauga-news/news/mississauga-celebrates-the-10th-anniversary-of-one-million-trees-campaign/.

Enderle, D.I.M., and Weih, R.C. (2005). Integrating Supervised and Unsupervised Classification Methods to Develop a More Accurate Land Cover Classification. *Journal of the Arkansas Academy of Science*, *59*(10), 65-73.

ESRI. (2023). *Data classification methods.* https://pro.arcgis.com/en/pro-app/latest/help/mapping/layer-properties/data-classification-methods.htm.

Escobedo, F. J., Adams, D. C., and Timilsina, N. (2015). Urban forest structure effects on property value. *Ecosystem Services*, *12,* 209-217. http://dx.doi.org/10.1016/j.ecoser.2014.05.002.

Feng, Q., Liu, J. and Gong, J. (2015). UAV Remote Sensing for urban vegetation mapping using random forest and texture analysis. *Remote Sensing*, *7*(1), 1074 – 1094

Government of Canada. (2013). *Image Classification and Analysis.* https://natural-resources.canada.ca/maps-tools-and-publications/satellite-imagery-and-air-photos/tutorial-fundamentals-remote-sensing/image-interpretation-analysis/image-classification-and-analysis/9361.

Greene, C., Robinson, P.J., Millward, A. A. (2018). Canopy of advantage: Who benefits most from city trees? *Journal of Environmental Management*, *208*, 24-35. https://doi.org/10.1016/j.jenvman.2017.12.015.

Grilli, G. and Sacchelli, S. (2020). Health Benefits Derived from Forest: A Review. *International Journal of Environmental Research and Public Health*, *17*(17), 6125. https://doi.org/10.3390/ijerph17176125.

Heritage Mississauga. (2018). *Lorne Park Estates.* https://heritagemississauga.com/lorne-park-estates/.

Huang, S., Tang, L., Hupy, J. P., Wang, Y., and Shao, G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *Journal of Forestry Research*, *32* (1), 1-6. https://doi.org/10.1007/s11676-020-01155-1.

Insauga. (2022). *A look back at Square One in 1973 in Mississauga*. https://www.insauga.com/a-look-back-at-square-one-in-1973-in-mississauga.

Kingsley, M. and EcoHealth Ontario. (2019). Commentary – Climate change, health and green space co-benefits. *Health Promotion and Chronic Disease Prevention in Canada*, *39*(4), 131-135. https://doi.org/10.24095/hpcdp.39.4.04.

Landry, F., Dupras, J., and Messier, C. (2020). Convergence of urban forest and socio-economic indicators of resilience: A study of environmental inequality in four major cities in eastern Canada. *Landscape and Urban Planning*, *202* (1), 1-10. https://doi.org/10.1016/j.landurbplan.2020.103856.

Lin, J., Wang, Q., Li, X. (2021). Socioeconomic and spatial inequalities of street tree abundance, species diversity, and size structure in New York City. *Landscape and urban Planning*, *202*(1), 1-11. https://doi.org/10.1016/j.landurbplan.2020.103992.

Marshman, K.A. (2018). Do trees in Halifax grow on money?: A comparison of urban tree canopy cover and median household income in north end and south end Halifax. *Dalhousie Journal of Interdisciplinary Management, 14.* https://ojs.library.dal.ca/djim/article/view/7875.

McDonald RI, Biswas T, Sachar C, Housman I, Boucher TM, Balk D, et al. (2021). The tree cover and temperature disparity in US urbanized areas: Quantifying the association with income across 5,723 communities. *PLOS ONE 16*(4). https://doi.org/10.1371/journal.pone.0249715.

NASA. (2000). *Measuring Vegetation (NDVI & EVI).* https://earthobservatory.nasa.gov/features/MeasuringVegetation/measuring_vegetation_2.php.

Pinault, L., Christidis, T., Olaniyan, T., and Crouse, D. L. (2021). Ethnocultural and socioeconomic disparities in exposure to residential greenness within urban Canada. *Statistics Canada Health Reports, 32*(5), 1-14. https://www.doi.org/10.25318/82-003-x202100500001-eng.

Plan-It Geo LLC. (2014). *An Assessment of urban forest canopy Mississauga, Ontario.* http://www7.mississauga.ca/departments/rec/parks/forestry/pdf/Mississauga%20Urban%20Forest%20Canopy%20Assessment%20Report.pdf.

Schwarz, K., Fragkias, M., Goone, C. G., Zhou, W., McHale, M., Grove, J. M., O'Neil-Dunne, J., McFadden, J. P., Buckley, G. L., Childers, D., Ogden, L., Pincetl, S., Pataki, D., Whitmer, A., Cadenasso, M. L. (2015). Trees grow on money: Urban tree canopy cover and environmental justice. *PLOS ONE 10*(4), 1-17. http://dx.doi.org/10.6084/m9.figshare.1213775.

Sousa-Silva, R., Duflos, M., Ordonez Barona, C. and Paquette, A. (2023). Keys to better planning and integrating urban tree planting initiatives. *Landscape and Urban Planning, 231*, 1-8. https://doi.org/10.1016/j.landurbplan.2022.104649.

Statistics Canada. (2022a). *Canada's large urban centres continue to grow and spread.* https://www150.statcan.gc.ca/n1/daily-quotidien/220209/dq220209b-eng.htm.

Statistics Canada. (2022b). *Census Profile: 2021 Census of Population* [Data set]. https://www12.statcan.gc.ca/census-recensement/2021/dp-pd/prof/details/download-telecharger.cfm?Lang=E.

Statistics Canada. (2022c). *Census Tract (CT).* https://www150.statcan.gc.ca/n1/pub/92-195-x/2021001/geo/ct-sr/ct-sr-eng.htm.

Statistics Canada. (2023a). *Census Program Data Viewer.* https://www12.statcan.gc.ca/census-recensement/2021/dp-pd/dv-vd/cpdv-vdpr/index-eng.cfm.

Statistics Canada. (2023b). *Distribution of employment income of individuals by sex and work activity, Canada, provinces, and selected census metropolitan areas. https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1110024001*.

Steenberg, J. W.N., Duinker, P. N., Charles, J. D. (2013). The neighbourhood approach to urban forest management: The case of Halifax, Canada. *Landscape and Urban Planning, 117*, 135-144. http://dx.doi.org/10.1016/j.landurbplan.2013.04.003.

Story, M., and Congalton, R. G. (1986). Accuarcy Assessment: A User's Perspective. *American Society for Photogrammetry and Remote Sensing*, *52*(3), 397-399. https://www.asprs.org/wp-content/uploads/pers/1986journal/mar/1986_mar_397-399.pdf.

Szantoi, Z., Wagner, J. E., Smith, S. E. (2012). Socioeconomic factors and urban tree cover policies in a subtropical urban forest. *GIScience & Remote Sensing*, *49*(3), 428-449. http://dx.doi.org/10.2747/1548-1603.49.3.428.

Toronto and Region Conservation Authority (TRCA). (2011). *City of Mississauga Urban Forest Study*. https://www.mississauga.ca/file/COM/2012eacagendapart3_june5.pdf.

Turner-Skoff, J. B. and Cavender, N. (2019). The benefits of trees for livable and sustainable communities. *Plants, People, Planet*, *1*(4), 323-335. 10.1002/ppp3.39.

United States Geological Survey (USGS). (2022a). *Landsat Normalized Difference Vegetation Index.* https://www.usgs.gov/landsat-missions/landsat-normalized-difference-vegetation-index#:~:text=NDVI%20is%20used%20to%20quantify,)%20%2F%20(NIR%20%2B%20R.

United States Geological Survey (USGS). (2022b). *What is remote sensing and what is it used for?* https://www.usgs.gov/faqs/what-remote-sensing-and-what-it-used#faq.

Xue, J. and Su, B. (2017). Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *Journal of Sensors*, (2017), 1-17. https://doi.org/10.1155/2017/1353691.