The equity of Toronto's urban forest: Examining the relationship between urban forest change between 2008 and 2018, resulting tree frequency, and marginalization

by

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Abstract

Urban forests provide a myriad of social, environmental, and economic benefits that help make cities desirable and safe places to live. However, despite the widely acknowledged importance of urban forests, they are often inequitably distributed across cities and leave marginalized populations with disproportionately low access to them and their associated benefits. For this reason, understanding the distribution and change of urban forests is key to ultimately achieving their equitable presence and management. Though urban forest equity is becoming a well-researched phenomenon, there are relatively few studies that address the equity of urban forest change and the associated implications. This study addresses these gaps by examining the relationship between changes in Toronto's urban forest over a ten-year period and its resulting frequency with four indicators of population marginalization. Diameter growth rate, mortality rate, and establishment rate were used to quantify urban forest change, while basal area per hectare and stems per hectare were used to quantify urban forest frequency. The four indicators of marginalization used in this study were residential instability, economic dependency, ethnocultural composition and situational vulnerability, from the Canadian Index of Multiple Deprivation. Bivariate correlation, multiple linear regression, and geographically weighted regression were used to determine if there was a relationship between each urban forest variable and each indicator of marginalization. Bivariate cluster analysis was also used to identify areas in Toronto with the highest occurrences of urban forest inequity. Significant correlations are found between several indicators of marginalization with diameter growth rates, establishment rates, and both frequency measures. Subsequent exploratory data analysis also confirmed that areas in Toronto with the highest establishment rates were also the areas with the highest tree frequency before this change analysis. Ultimately, this suggests that urban forest change in Toronto is not on a path to resolving its inequity, and if the City of Toronto is going to achieve the equitable distribution of its urban forest it needs to adjust its approaches to its development.

Keywords: Urban forest change; Tree frequency; Urban equity; Environmental justice; Toronto, Ontario

1. Introduction

1.1 Motivation

Over the past fifty years, there has been a global shift in population distribution to urban areas, a pattern that is expected to continue well into the future (United Nations Department of Economic and Social Affairs 2019). This same trend occurs in Canada, where as of 2021 over 80% of the population lived in urban environments (Statistics Canada 2022). There are several benefits associated with living in an urban area, including accessibility to active transportation and increased cultural diversity, but there are also downfalls, such as higher pollution concentrations (Hulin et al. 2010) or disproportionally warmer summers (Wang et al. 2016). Many of these negative associations are also being exacerbated by drivers like climate change and increasing urbanization (Imhoff et al. 2010; Patella et al. 2018), meaning that as the populations of cities increase, so too does the risk associated with living in them. For this reason, it is important that cities consistently work to keep themselves socially, economically and environmentally sustainable by maintaining conditions in which their populations can continue to thrive into the future.

One approach to sustainable development in cities is the development and growth of urban forests. Urban forests are extremely valuable components of cities that provide a myriad of environmental, social and economic benefits to their surrounding areas. For this reason, many cities have developed management plans for the growth and distribution of their urban forests (Ordóñez and Duinker 2013). However, even with such plans in place, certain marginalized populations in cities often have disproportionately low access to urban forests and their associated ecosystem services (Locke and Grove 2014). It is important to understand this inequity and where it stems from to best create strategies that are designed to decrease the gap in urban forest accessibility. This study contributes to this understanding in Toronto, Ontario, where it examines if recent developments in the city’s urban forest have been equitable and or resulted in its equitable distribution by determining the relationship between metrics of change for and distribution of the urban forest and marginalization.

1.2 Background

Urban forests are defined differently across multiple sources, but for this study will be primarily considered to be all trees within an urban area (City of Toronto 2012). Urban forests are important for many reasons, including that they provide several ecosystem services to the areas around them and the people that live there. Ecosystem services are benefits that humans derive from the functions of an ecosystem (Escobedo et al. 2019), in this case, functions that occur within urban forests. Such services they provide range from carbon sequestration and air, water and soil pollution removal (Livesley et al. 2016) to reducing building energy use (Soares et al. 2011; Livesley et al. 2016) and benefitting human health (Tan 2022).

As time goes on and cities continue to develop, many of the ecosystem services provided by urban forests will become increasingly important. This is because factors like increasing impermeable surface cover, which is associated with population growth and urbanization in cities, exacerbate issues like the urban heat island effect (Imhoff et al. 2010). Furthermore, climate change is expected to worsen several health hazards in cities that trees help mitigate, for example, respiratory diseases resulting from exposure to particulate matter (Tallis et al. 2011; Patella et al. 2018). Because urban trees presently benefit people in cities in several ways and will continue to mitigate hazards associated with urban environments in the future, it is important that populations across cities have access to them.

Ecosystem services provided by urban forests have long been a subject of urban forest research. More recently, a growing body of literature is being produced that focuses on equality and equity of access to urban forests and their benefits. With few exceptions, these studies find that more marginalized or vulnerable populations, often with respect to income or race, have disproportionately low access to urban forests (Watkins and Gerrish 2018; Nyelele and Kroll 2020). This is important because disproportionate access to urban forests also means disproportionate access to the benefits they provide, many of which can only be reaped at local levels.

While there are many studies that examine urban forest equity, there are few studies that look at this relationship using measures of urban forest density to quantify urban forests and fewer that look at the equity of urban forest change over time. Across this study, urban forest density is defined as the quantity of an urban forest variable per unit of area. Due to the variables used in this study, it is more specifically considered to be comprised of both stand density, which is the number of trees per areal unit, and the density of basal area in a given stand, as described by (Bettinger et al. 2017). Because of the multitude of ways that the term density can be interpreted, especially when discussing urban environments (Churchman 1999), the term "frequency" will be used in this study to address two key measures of urban forest density: stems per hectare and basal area per hectare. Understanding how equitable the distribution of urban forest frequency is, especially with respect to the number of trees across a city, provides important insight into characteristics of the urban forest that people can more readily control (Conway and Bourne 2013), which has important implications for urban forest management. Similarly, understanding how urban forests are changing over time and who is benefiting most from these changes is crucial to understanding the urban forest and its benefits in the future, and is necessary for developing any plan to address potential inequity.

The City of Toronto, which is the largest municipality in Canada by population (Statistics Canada 2022), currently has an unequally distributed urban forest. In 2018 there existed a difference of 60.9 percentage points (4.3% vs. 65.2%) between the neighbourhood with the highest and lowest total canopy cover in Toronto (City of Toronto 2019). Furthermore, research has found that canopy cover across Toronto is negatively correlated with the population's median income, meaning that areas in the city with higher median incomes often also have higher percent canopy cover (Greene et al. 2018). Identifying and resolving inequalities like those in Toronto's urban forest is important so that cities can develop strategies to decrease said inequities and provide populations with urban forest access. However, this cannot be done without first understanding the distribution of one's urban forest and how it is changing.

1.3 Introduction to Study

The objective of this study was to determine if the change that took place in Toronto's urban forest between 2008 and 2018 was equitable with respect to marginalization, and subsequently, if that change resulted in the equitable distribution of its frequency in 2018. To assess urban forest change, diameter growth rates, mortality rates and establishment rates of the urban forest were calculated. To quantify frequency, basal area per hectare and stems per hectare were determined. To represent marginalization, the four dimensions of multiple deprivation defined in the Canadian Index of Multiple Deprivation (Statistics Canada 2019) were used. These four dimensions are residential instability, economic dependency, ethnocultural composition and situational vulnerability, which each examine a different aspect of population marginalization, and can all be derived from census data (Statistics Canada 2019). Ultimately, this study aimed to answer the following research questions:

1) How are diameter growth rates, mortality rates, and establishment rates of the urban forest between 2008 and 2018 related to the four dimensions of multiple deprivation in Toronto?
2) How are basal area per hectare and stems per hectare of the urban forest in 2018 related to the four dimensions of multiple deprivation in Toronto?

The spatial extent of this study was the regional municipal boundary of Toronto, as defined by the City of Toronto (2019). The unit of analysis for all urban forest variables was study plots located across Toronto that were assessed in two urban forestry studies done by the City of Toronto in 2008 and 2018. The data used to quantify marginalization was derived by Statistics Canada from 2016 census data at the dissemination area level (Statistics Canada 2019), which is also the level that it was analyzed at in this study. The data to assess urban forest change will be from i-Tree Eco outputs from 2008 and 2018 studies of Toronto's urban forest, and data used to assess urban forest frequency will be from i-Tree Eco outputs from the 2018 study. Both urban forest datasets were provided by the City of Toronto.

1.4 Summary of Approach

To address the above research questions, a combination of spatial and aspatial statistical analyses were performed. First, bivariate correlation coefficients for each pair of dependent and independent variables were assessed to gain a preliminary understanding of their relationships. For this study, urban forest data were used as the dependent variables and the indicators of marginalization were considered the independent variables. Multiple linear regression models were then developed for each urban forest variable using all indicators of marginalization. This was done to determine if any indicators of marginalization affect urban forest change or frequency. Due to an increasing body of literature that finds that the spatial structure of urban forest and sociodemographic data needs to be accounted for in these types of analyses (e.g., Landry and Chakraborty 2009; Schwarz et al. 2015; Nesbitt et al. 2019), each regression model was assessed for spatial dependence and spatial non-stationarity. If spatial structure was found in the data, depending on the type, spatial lag or spatial error terms were added to regression models, or geographically weighted regression (GWR) was done. Finally, bivariate Moran's I tests were done on each variable pair to determine if and where clustering of inequality occurred across Toronto.

2. Literature Review

This literature review focuses on urban forestry and sociodemographic research over the past two decades, specifically to provide context on the impact urban forests can have on different populations within a city. It addresses the benefits of urban forests, the varying degrees to which different populations have access to them, and the associated implications and drivers of this inequality. This review references journals including Urban Forestry and Urban Greening, Landscape and Urban Planning, and the Journal of Environmental Management. The literature addressed spans multiple decades, which is crucial for understanding how patterns of urban forestry and environmental justice have emerged throughout time. Knowledge gaps surrounding variables used to assess the relationships between urban forests and sociodemographic factors, primarily with respect to urban forest change, were addressed.

2.1 Urban Forests

2.1.1 The importance of urban forests

Urban forests provide a myriad of social, environmental and economic benefits to cities and their populations. From an environmental standpoint, urban forests improve water quality (Livesley et al. 2016), filter air pollutants (Nowak et al. 2006; Tallis et al. 2011; Livesley et al. 2016), provide local scale cooling (Jenerette et al. 2007; Livesley et al. 2016; Wang et al. 2016) and sequester carbon dioxide (Escobedo et al. 2010; Davies et al. 2011). Economically, the benefits of urban forests include reducing energy use and associated costs in buildings (Pandit and Laband 2012), increasing property values (Pandit and Laband 2012; Escobedo et al. 2015), as well as absorbing costs associated with many of the environmental ecosystem services (Soares et al. 2011). Furthermore, socially-based benefits of urban forests include mitigating illnesses, including those that can be exacerbated by living in urban environments (Tallis et al. 2011) and increasing perceived safety in areas with higher urban forest presence (Mouratidis 2019). Similarly, cultural benefits derived from urban forests include appreciation for their aesthetic value, association with a connection to place, and association with positive memories (Peckham et al. 2013; Ostoic et al. 2020), and they have even been found to positively impact peoples' moods (Martens et al. 2011). As can be discerned from this non-exhaustive review of ecosystem services, urban forests play a very important role in urban sustainability, both physically and psychologically, making them integral parts of urban environments.

Understanding not just the state of an urban forest at a given point in time but also how it is changing is crucial because of intensifying risks associated with living in urban environments. Climate change, population growth, and urbanization are exacerbating many human health risks in cities that urban forests help mitigate. For example, the intensification of climate change has already been found to increase the risks of respiratory disease and heat stroke (Michelozzi et al. 2009; D'Amato et al. 2014). Since trees help mitigate some of these factors through processes like local cooling (Wang et al. 2016) and atmospheric pollution removal (Tallis et al. 2011), having access to urban forests is going to grow in importance. Urbanization by way of increasing impermeable surface cover is also intensifying the urban heat island effect (Imhoff et al. 2010) which trees can help offset through shade and other cooling effects (Jenerette et al. 2007). Ultimately, because of the continuously changing conditions cities and their residents will likely face, it is important that cities start taking actions like prioritizing the growth of their urban forests, now to mitigate against these future conditions. However, this cannot be done until a city understands their urban forests and the processes that are shaping them.

2.1.2 Urban forest structure

While it has been widely acknowledged that urban forests produce several ecosystem services, it is also important to note that not all trees or stands of the urban forest produce the same amounts and sometimes even types of these benefits. Rather, characteristics such as the species or biomass of a given tree dictate the quantity of certain ecosystem services, for example atmospheric pollution removal, derived from it (Parsa et al. 2020). More specifically, as trees age, increase in size and increase in leaf area, many ecosystem services derived from the tree also increase in both quality and quantity (Díaz-Porras et al. 2014; Mullaney et al. 2015; Felipe-Lucia et al. 2018; Lai et al. 2020). The implications of this are two-fold for urban forest management and research. First, strategically selecting trees to plant when developing an urban forest can be done to maximize some of the benefits that will be derived from it (Locke et al. 2010; Bodnaruk et al. 2017). Second, when it comes to quantifying or exploring more broadly the benefits that are derived from urban forests, several factors of their structure need to be considered. As such, this means that when studying urban forests and their equity, it is important to include different urban forest measures to best understand in what ways people are or are not benefiting from them.

Urban forests are inherently complex in several ways due to the combination of processes and factors that affect them. Due to the management practices that guide them, urban forests are diverse, both in structure and composition, and spatially heterogeneous (Zhang et al. 2015). Trees across cities are also subject to a wide range of environmental conditions due to the many different land use types across cities. As a result of this variation and complexity, the way urban forests change and develop and how they interact with components of the built and natural environments are also variable (Ren et al. 2014; Konijnendijk et al. 2021). This means that while many processes that shape urban forests across different cities are typically similar, they will not all respond the same to different drivers or stressors and as such need to be understood on individual city scales to be the most effectively managed.

2.1.3 Drivers of urban forest change

Municipal policies, specifically those related to urban forests themselves, have direct impacts on the development of a city's urban forest. Therefore, understanding municipal policies is also key to understanding urban forests. Planning and policy decisions, specifically those that affect land use change, drive changes to urban forests at municipal scales (Johnson et al. 2020). Unequal distribution of trees on private and public lands, which is observed frequently across large cities (e.g., Landry and Chakraborty 2009), can suggest that policy regarding resource distribution in a city is inadequate (Gerrish and Watkins 2018). Though the priorities of urban forest management have been found to vary across municipalities, building density and thus space available to plant new trees is one of the most common barriers that policy makers face when it comes to expanding urban forests (Ordonez et al. 2020). However, having financial resources, setting attainable goals and having a strong vision for their urban forests are all things that can be done to help cities address some of these potential inadequacies and barriers (Wirtz et al. 2021). Understanding a municipality's policies regarding urban forest management is instrumental to accurately analyzing the change in a city's urban forest because such policies directly affect the structure and therefore function of the forests.

Within urban environments, individuals, community organizations and non-profits all also affect the development of urban forests. The people that choose to or not to plant trees in their yards largely drive urban forest change on private lands. The hesitancy of people to plant trees due to their associated ecosystem disservices and maintenance requirements, lack of knowledge about the benefits provided by trees, and even mistrust of the municipal government can be barriers people face when it comes to planting trees (Carmichael and McDonough 2019). Community or organization-based tree planting groups often help to facilitate this change for property owners and across different aspects of the city as well. However, even though such groups exist, they also face many barriers when it comes to the implementation of these projects. For example, some people feel that tree planting programs do not reflect their values and the existence of a perceived power dynamic between residents and facilitators often also deters people from participating in such programs (Carmichael and McDonough 2018). Certain more marginalized areas that experience higher crime levels also experience increased tree and greenspace presence as a disservice, for example this presence has been found to lower property values, while the opposite is true for less marginalized areas (Troy and Grove 2008), likely providing an additional disincentive for certain populations to plant trees (Donovan and Mills 2014). All of these factors ultimately shape the patterns and development of a city's urban forest, and understanding these aspects is an important step in addressing equitable urban forest development.

In addition to planning and management decisions, the harsh physical environment to which urban forests are exposed can contribute to their decline. In addition to large-scale environmental factors such as climate, air quality and geology, which are drivers of change in urban forests (Johnson et al. 2020), so too are more localized stressors. Urban environments, specifically factors like shade, confined space for growth, impermeable surfaces, land use change, infrastructure presence, and pollution make it difficult for trees to survive to their natural lifespan (Jim 2004; Mullaney et al. 2015; Steenberg et al. 2016). Furthermore, the densification of cities and urban expansion are causing declines in urban forests, even in older and more vulnerable trees (Le Roux et al. 2014). Trees that make up urban forests face several threats related to their location in urban environments. To ensure trees have a higher chance of surviving to maturity, planners and policy makers must be conscious of these threats and account for them in their urban forest management plans.

2.2 Urban environmental justice

2.2.1 Access to ecosystem services

While there is a substantial body of literature that addresses the equity of ecosystem services across cities, there does not appear to be a consensus on the true meaning of the term and, across studies, it seems to be used interchangeably with the word equality. Because equity is discussed frequently in this section and this study aimed to draw conclusions regarding it, throughout this paper equity includes both the distribution of events while also taking into account people's circumstances, as described by McDermott et al. (2013).

Internationally and across multiple scales, marginalized populations, with respect to factors such as income or race, have disproportionately low access to ecosystem services. For example, populations with higher levels of income and education have higher access to vegetation in cities (Nesbitt et al. 2019). Consequently, historically marginalized populations, specifically people of colour and lower income households, therefore are at a higher risk for phenomena like extreme heat exposure (Uejio et al. 2011). Similar trends have been observed in studies that assess the inequity in the supply and demand of ecosystem services in urban environments. In general, those who would benefit most from ecosystem services have the least access to them (Herreros-Cantis and McPhearson 2021). As was described with respect to urban forest ecosystem services, this is an issue because some of the hazards associated with living in cities are increasing, and this gap in ecosystem service access will mean that more vulnerable populations will be impacted more severely than others. Despite these long-standing inequities, there is no comprehensive framework for addressing environmental justice issues in cities (Calderon-Argelich et al. 2021). This is something that municipal policy makers should be mindful of, and hopefully, researchers that observe these inequities, or lack of, can help facilitate that change.

2.2.2 Access to urban forests

Access to urban forests and their associated ecosystem services has been widely shown to be inequitable. Numerous studies have identified inequities in urban tree canopy cover, specifically related to income and race (Gerrish and Watkins 2018; Watkins and Gerrish 2018; Nyelele and Kroll 2020). In addition to tree frequency and canopy cover, populations with lower income are also associated with lower species richness and tree health (Lin and Wang 2021). The growing body of literature on the equity of urban forests shows that it is often the same populations that are suffering from this disproportionate access, an important finding. However, relatively little is known about how direct changes in urban forest structure are perpetuating or slowing this inequity.

Due to the complexity of urban forests, there are several perpetrators of this frequently observed inequity. For one, when looking at the change in urban forest structure over time, poorer conditions such as lower tree health, less abundance, and damage to sidewalks from trees are associated more with marginalized populations, specifically populations that are racialized, young, poor and or have lower levels of education (Lin and Wang 2021), which can lead to higher rates of tree mortality (Nowak et al. 2004). If this continues to be the case across cities, then tree mortality rates may be higher than in other areas and further drive this inequity. To date, however, there seems to be a literature gap regarding the direct relationship between tree mortality and race, which this study aimed to address.

In addition to mortality-based perpetrators of urban forest inequity, tree planting initiatives done by both non-profits and municipal governments have been seen to benefit certain populations over others. Trees planted from government funding incentives are more likely to be planted in areas with higher median income, often because cities have found their outreach strategies to be most effective in these areas (Locke and Grove 2014). Unfortunately, these do not account for the fact that these areas often have the lowest need for new trees (Locke and Grove 2014). On the contrary, tree planting programs run by non-profit organizations are more likely to be targeted at neighbourhoods with lower median income, but experience varying levels of success (Watkins et al. 2016). It has also been observed that efforts by non-profit tree planting groups also sometimes perpetuate existing urban forest race-based inequities (Watkins et al. 2016). The barriers mentioned previously regarding tree planting are seen to perpetuate inequity as well, for example through language barriers between organizers and residents (Riedman et al. 2022). Understanding these general perpetrators of urban forest inequity is vital to making progress towards equitable urban forest development.

2.3 The City of Toronto

2.3.1 Sociodemographic characteristics and background

Toronto is Canada's largest municipality by population (Statistics Canada 2022), meaning that the choices it makes with respect to urban development have very far-reaching implications. Both for the well-being of its population and to set an example of development for other growing cities, it is important that Toronto take actions toward urban planning that are adaptable, long-term, and equitably benefit its population.

Several factors influence municipal policy direction in Toronto and understanding these factors helps contextualize the results of this study. Urban forest management decisions are frequently made at the municipal level (City of Toronto 2012; Cheng et al. 2021), meaning that many policies and programs implemented by the City of Toronto will directly influence the city's urban forest structure and distribution. Urban forest governance has been somewhat intertwined with other municipal policies in Toronto, for example, its climate change framework (Cheng et al. 2021). However, the way in which it proposes urban forest development is different than the urban forest guidance itself (Cheng et al. 2021). This has the potential to lead to ineffective urban forest management because such inconsistencies are often indicative of a lack of awareness of future threats that an urban forest may face as a result of climate change and a misaligned vision for an urban forest that could cause conflict in future management decisions (Cheng et al. 2021). If not accounted for, this could result in urban forest development that is unstructured and inefficient for meeting urban forestry goals.

2.3.2 Toronto's urban forest

Broadly speaking, urban forest development in Toronto, like other cities, is affected by individuals, organizations, and the city itself. Toronto has an urban forest management plan that outlines goals and pathways to achieve these goals for the city between 2012 and 2022 (City of Toronto 2012). Goals that Toronto's Strategic Forest Management Plan hopes to achieve include increasing canopy cover, increasing biodiversity, reaching equitable distribution, increasing public knowledge and awareness of the forest, promoting stewardship, and improving monitoring of the urban forest (City of Toronto 2012). To monitor the progress towards these goals, studies of Toronto's urban forest were conducted in 2008 and 2018 by the city (City of Toronto 2019). These studies collected and examined data from 407 plots across the city, including variables such as diameter at breast height, percent dieback, and tree species (City of Toronto 2019). An i-Tree Eco assessment of the data was conducted for both datasets, which provided a summary of the urban forest structure as well as an estimation of ecosystem services provided by the forest (City of Toronto 2019). The studies done on Toronto's urban forest were comprehensive and replicated using methods that allow them to be effectively compared, providing many opportunities for further research.

The state of Toronto's urban forest between 2008 and 2018 observed in each of these studies was compared to each other to develop an understanding of how the forest changed during this time. Key findings of the studies on a city-wide scale that were in line with the goals of the city's forest management plan include an overall increase in canopy cover, an increase in the number of trees in the city by over one million, and an increase in street tree condition (City of Toronto 2019). Findings that the city considers negative, or not in line with their goals, included a decrease in permeable surface across the city, spread of invasive tree species, a reduction in total leaf area, a decline in the overall tree condition, and a decrease in overall ecosystem services provided by the urban forest (City of Toronto 2019). These results also revealed that the distribution in canopy cover in Toronto was unequal, with certain neighbourhoods with higher values than others (City of Toronto 2019). It has subsequently been found that the areas with highest canopy cover are also the areas with higher household income (Greene et al. 2018). This can indicate the need for an improved approach to urban forest management in Toronto, however, that cannot be said for certain as it is unknown how changes in Toronto's urban forest, resulting from the city's forest management plan or otherwise, are affecting this inequity.

2.4 Knowledge gaps

The study of urban forest equity is rather new to the past twenty years, and as such still has remaining literature gaps and areas that can be further explored. One such gap is the variables commonly used to quantify the urban forest and its benefits in environmental justice studies. As mentioned earlier in this chapter, several urban forest characteristics determine the amount of ecosystem services derived from urban forests. Many existing studies investigate the correlation between urban forest presence and different sociodemographic factors, however, almost all of these studies only use canopy cover as the urban forest metric to assess this correlation (e.g., Greene et al. 2018; Nyelele and Kroll 2020; Volin et al. 2020). This is likely due to the high availability of canopy cover data across cities. However, canopy cover is a somewhat limiting variable to use in urban forest equity studies because of its low association with many of the ecosystem services urban forests provide (Felipe-Lucia et al. 2018). The three most significant urban forest characteristics that are correlated with ecosystem services are instead tree diameter, vertical heterogeneity, and shrub richness (Felipe-Lucia et al. 2018). Furthermore, between 2008 and 2018 in Toronto's urban forest there was an increase in canopy cover across the city but a decrease in the ecosystem services provided by the urban forest (City of Toronto 2019), indicating as well that in Toronto specifically canopy cover is not likely a strong indicator of ecosystem services derived by the urban forest. Though most of these studies, this one included, are not meant to predict ecosystem services different populations are exposed to, urban forest equity studies are ultimately driven by and important because of these ecosystem services, so it is important that they use the urban forest metrics that are best representative of them when possible. Studies that account for other variables do exist, for example, Lin and Wang (2021), which examines measurements such as tree abundance, species richness and average DBH, but only includes street trees, which make up relatively small portions of urban forests. This is an important literature gap to consider and address because using a variation of urban forest metrics for this assessment could provide new information on the equity of urban forests.

Another literature gap identified in this review is the lack of research on the equity of urban forest change, specifically with respect to tree establishment. Several studies allow for indirect conclusions to be drawn, for example, studies that link tree condition to mortality and race separately but not together, however, very few look at direct relationships with respect to urban forest change. These gaps across different measures of urban forest change are important to address because they provide context to the existing studies that identify urban forest inequity in a given year. Understanding urban forest change is also crucial for understanding how to best approach addressing this inequity by providing insight into the processes that may be driving it.

2.5 Conclusion

This literature review has established background of and need for future research on Toronto's urban forest and overall urban forest change. Urban forests are integral parts of cities because of the benefits they provide in the form of ecosystem services. However, due to their variability and complexity, there are many factors that affect urban forests and their distributions. Environmental justice has been and continues to be an issue in urban areas where marginalized populations lack access to important ecosystem services, including those provided by urban forests. Understanding how urban forests are changing and if these changes are perpetuating this inequity is an important step to resolving it. As Canada's largest city, Toronto, though currently faced with the unequal distribution of its urban forest, also has a unique opportunity to address this issue and set an example for other large cities with respect to urban forest development. This literature review has provided context for further urban forest research and has identified a need for not only more research on but also a new approach to studying Toronto's urban forest and its connection to environmental justice.

3. Methods

3.1 Methods Overview

This study investigates the relationship between indicators of marginalization and Toronto's urban forest between 2008 and 2018. Using a combination of spatial and aspatial statistical analyses, R, ArcGIS Pro, and GeoDa were used to assess the equity of Toronto's urban forest at the dissemination area and forest survey plot levels. Bivariate correlation and linear regression were used to determine if there was a significant relationship between the studied variables. A series of spatially-weighted regression models provided insight into if there was any significant spatial structure to the data that could not be explained solely with linear regression. Finally, bivariate Moran's I assessments were used to determine areas across Toronto with significant clustering of inequity.

3.2 Study Area

This study looked at the City of Toronto, specifically within the municipality boundaries (Figure 1). Toronto is the capital of Ontario and has the largest population of any municipality in Canada (Statistics Canada 2022) with a population density of approximately 4,000 people per square kilometre (Statistics Canada 2020). The Greater Toronto Area is Ontario's fastest-growing region (Government of Ontario 2021), which when coupled with the city's large population makes it important to understand how changes in urban planning, including changes in the urban forest, affect populations in the city. Toronto is comprised of 140 social neighbourhoods of varying land-use types, which to an extent define boundaries of different approaches to planning, including the development of the urban forest (City of Toronto 2019). These neighbourhoods vary significantly in sociodemographic characteristics such as population growth (City of Toronto 2022a), as well as the extent of the urban forest, such as the percentage of canopy cover by neighbourhood (City of Toronto 2019). The predominate tree species in Toronto's urban forest include northern white cedar (*Thuja occidentalis*), sugar maple (*Acer saccharum*), and Norway maple (*Acer platanoides*) (City of Toronto 2019). Toronto is located in the Mixedwood Plains ecozone, meaning its natural environment is characterized by warm summers, cool winters and between 720 and 1,000 mm of annual precipitation (Crins et al.

2009). Toronto was also selected as the study area for this research because of its recent and detailed tree inventories that allow for the urban forest change over time to be examined.

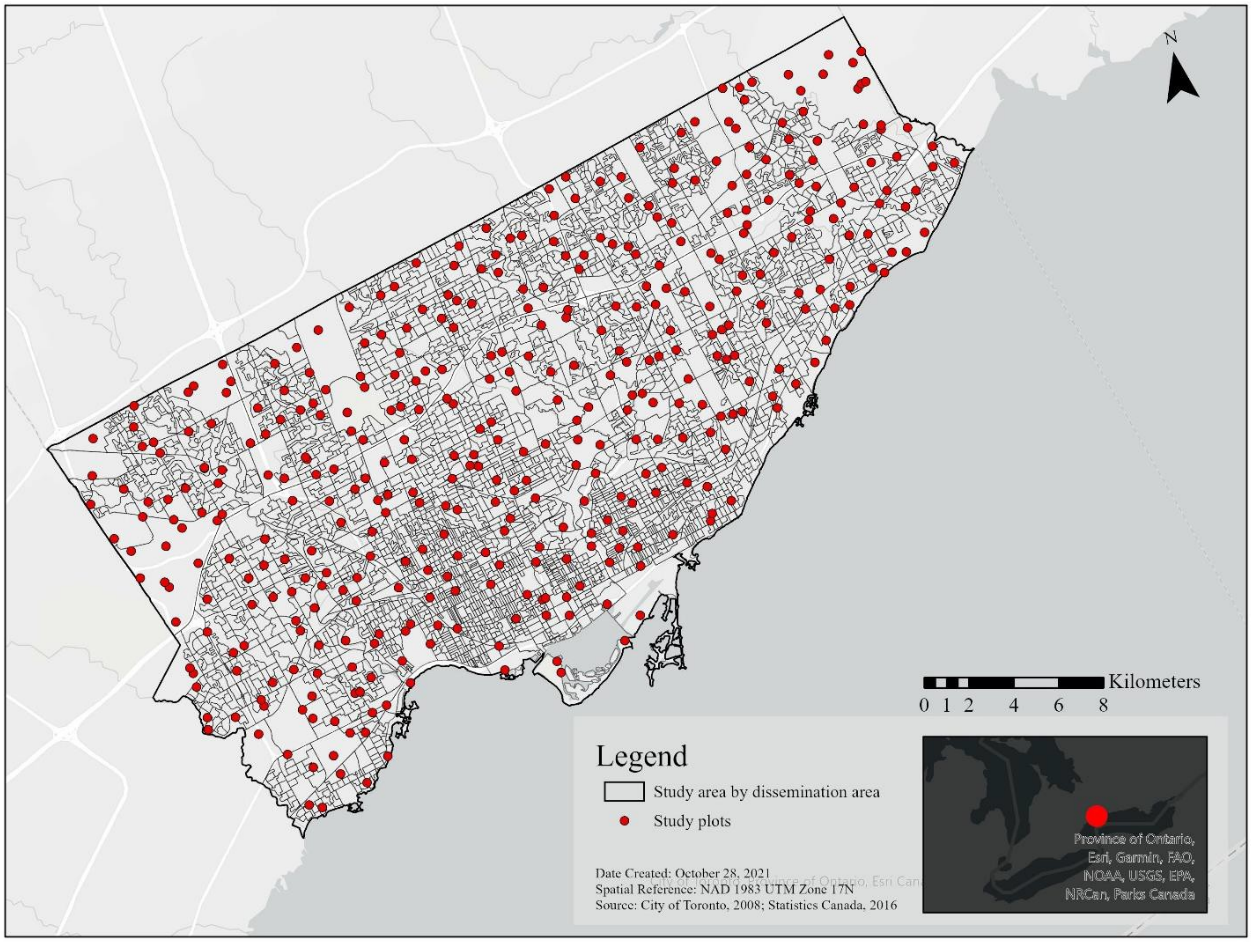


Figure 1 The geographic extent of the Municipality of Metropolitan Toronto, represented by dissemination areas, with the locations of the plots used in this study overlayed.

3.3 Data Processing

3.3.1 Urban forest change data

The data that was used to assess urban forest change for this study was provided by the City of Toronto in the form of two i-Tree Eco datasets derived from data they collected in the field at each plot location in 2008 and 2018. These studies systematically sampled 407 plots across Toronto, in each one collecting information related to the structure and composition of the urban forest (City of Toronto 2019). Each plot was 0.04 hectares in area (City of Toronto 2013). The plots measured in each study were identical between study years, aside from 15 plots from the 2008 study that were inaccessible in 2018 and therefore were substituted for. These substituted plots were not used to assess change in this study because of the specific comparison of trees required to calculate rates of change in the urban forest. The forest variables provided in the i-Tree assessments that were used for this analysis were the DBH of surveyed trees and the presence and absence of matched trees in each study. To assess change in the urban forest across each of the plots, and subsequently, its correlation with marginalization in Toronto, three metrics of change were used: diameter growth rate, mortality rate, and establishment rate.

Diameter Growth Rate

The diameter at breast height (DBH) of a tree is defined as its diameter at 1.37 meters above the ground (City of Toronto 2019). It was measured in the field for every tree within the surveyed plots in both the 2008 and 2018 Toronto tree studies. A unique identification number for each tree sampled was derived from the plot and tree numbers provided in the city's i-Tree Eco dataset, which allowed for the direct comparison of trees, and their diameters, between studies. Diameter growth rates for each tree were calculated (Equation 1) in centimetres per year using a simple rate of change equation applied to urban forestry by Steenberg et al. (2019):

[1] $$\textit{growth rate} = (D_1 - D_0)/t$$

where *growth rate* is the diameter growth rate (cm/year) of a tree, D_1 is the DBH of the tree in the 2018 study, D_0 is the DBH of the same tree in the 2008 study, both in centimetres, and t is the number of years in between the two studies. The mean diameter growth rate for all trees within each plot was then taken and used as the diameter growth rate for that plot (Table 1). This was done entirely in Excel. Plots that did not have any trees in both study years, or plots that did not have any of the same trees present across both of the study years were not given a diameter growth rate. Growth rate is looked at as a metric of change in this study because it can provide insight into urban forest health and the future of urban forest structure in a given area.

Mortality Rate

Annual mortality rate refers to the proportion of trees in an original population that die each year between study years (Table 1). Mortality rates are looked at in this study because they provide insight specifically into tree loss across an urban forest and can be indicative of future urban forest structure from both tree health and planning contexts. It is important to know where and why trees are being lost to determine how to slow those rates if needed across a city. They were calculated for each plot between 2008 and 2018 by determining which trees present in the 2008 study were absent in the 2018 study. Excel was used to make this determination. From here, for each plot, the annual mortality rate was calculated (Equation 2) using the equation that was developed by Nowak et al. (2004) and altered in 2012 by Lawrence et al.:

[2] $$mortality\ rate = 1 - (N_1/N_0)^{1/t}$$

where *mortality rate* is the annual mortality rate per plot per year, N_0 / N_1 is the proportion of the original trees remaining in the 2018 study, and t is the number of years between the surveys. Plots that had no trees present in either study year, or plots with no trees present in just 2008 were not given a mortality rate.

Establishment Rate

Urban forest establishment rates refer to the number of new trees in one study compared to another (Table 1). Excel was used to determine which trees present in the 2018 study were not present in the 2008 study, which constituted new trees. Annual rates of tree establishment were measured for each plot (stems/hectare/year) (Equation 3) using the equation derived by Nowak (2012):

[3] $$establishment\ rate = (N/A)/t$$

where *establishment rate* is the number of new trees established per hectare per plot per year between studies, N is the number of new trees in the 2018 study not in the 2008 study in each plot, A is the area, in hectares, of each plot, and t is the number of years between studies. Unlike the other two metrics of change, any plots that had no trees present in one or both studies were given an establishment rate of 0. Establishment rates in this study are assessed because they provide key insight into urban forest growth and therefore structure across regions, which is key to predicting future urban forest benefit from a planning context and determining where future forest development initiatives are needed.

3.3.2 2018 urban forest data

After the change in Toronto’s urban forest was assessed, its basal area per hectare and stems per hectare in 2018 were analyzed. These two variables quantified the frequency of Toronto’s urban forest in 2018, the most recent year for which plot-level data was available, using the previously mentioned i-Tree eco outputs provided by the City of Toronto. Both frequency measures are used in urban forest literature to supplement different types of urban forest analyses (e.g., Steenberg 2018). All 407 plots sampled in 2018 were included in this analysis.

Basal area per hectare

Basal area per hectare is a measure of frequency that accounts for the size of trees present in an area (Table 1). Tree size is a forest measure that is a good predictor of ecosystem service quantity derived by a tree (Lai et al. 2020), an important factor to consider when studying urban forest equity. Basal area per hectare was calculated in Excel using the tree diameter in the i-Tree assessments and the formula in Equation 4:

$$[4] \qquad \textit{basal area per hectare} = (\Sigma\ (\ \pi\ (DBH/2)^2\ )\ )\ /\ A$$

where *basal area per hectare* is the sum of the basal area in meters squared for each tree, divided by the area of the plot, *DBH* is the diameter of each tree within the plot, and *A* is the area of the plot, in hectares.

Stems per hectare

Stems per hectare quantifies the number of trees present in each plot across the city (Table 1). It is a valuable metric to use because tree frequency is another strong indicator of the quantity and quality of ecosystem services that will be provided to surrounding areas by that portion of the urban forest (Salmond et al. 2016). The stems per hectare variable was calculated using the number of trees present in each plot in 2018 and the area of the corresponding plot (Equation 5):

$$[5] \qquad \textit{stems per hectare} = N/A$$

where *N* is the number of trees present in 2018 in a plot and *A* is the area of the plot in hectares. This calculation was done in Excel.

3.3.3 Sociodemographic data

The Canadian Index of Multiple Deprivation (CIMD) was used to assess marginalization in this study. This index was developed by Statistics Canada using 2016 census data to identify sociodemographic characteristics that are most associated with and representative of marginalization faced by people in Canada (Statistics Canada 2019). By amalgamating several census variables that can be used to represent marginalization into four, this index was designed to allow for a broad-scope understanding of marginalization in research, policy and planning (Statistics Canada 2019). Each factor used to develop each dimension was tested to ensure it only influenced one of the four highlighted themes to ensure multicollinearity would not be a problem faced by researchers using this dataset (Statistics Canada 2019).

The four indicators of marginalization ultimately derived in this analysis were residential instability, economic dependency, ethnocultural composition and situational vulnerability (Figure 2) (Table 1). These were therefore the four variables that were used to quantify equity in this study. Residential instability addresses sociodemographic characteristics that pertain to fluctuations in neighbourhoods over time, both directly by including the number of people in each dissemination area that recently moved, and indirectly by accounting for factors found to lead to or prevent this fluctuation, for example, percent homeownership (Statistics Canada 2019). Economic dependency addresses each dissemination area's dependence on the workforce, by both accounting for populations not expected to be working (e.g., people aged 0 to 14 or over 65) and those currently without work and therefore relying on a source of income unrelated to employment (Statistics Canada 2019). Ethnocultural composition addresses the sociodemographic characteristics of a dissemination area that are based on immigrant populations (e.g., the proportion of the population that recently immigrated into Canada), as well as the proportion of the population that is a visible minority (Statistics Canada 2019). Situational vulnerability is the fourth indicator of marginalization and addresses a final set of sociodemographic data comprised of education level, housing conditions and Indigenous population in each dissemination area (Statistics Canada 2019).

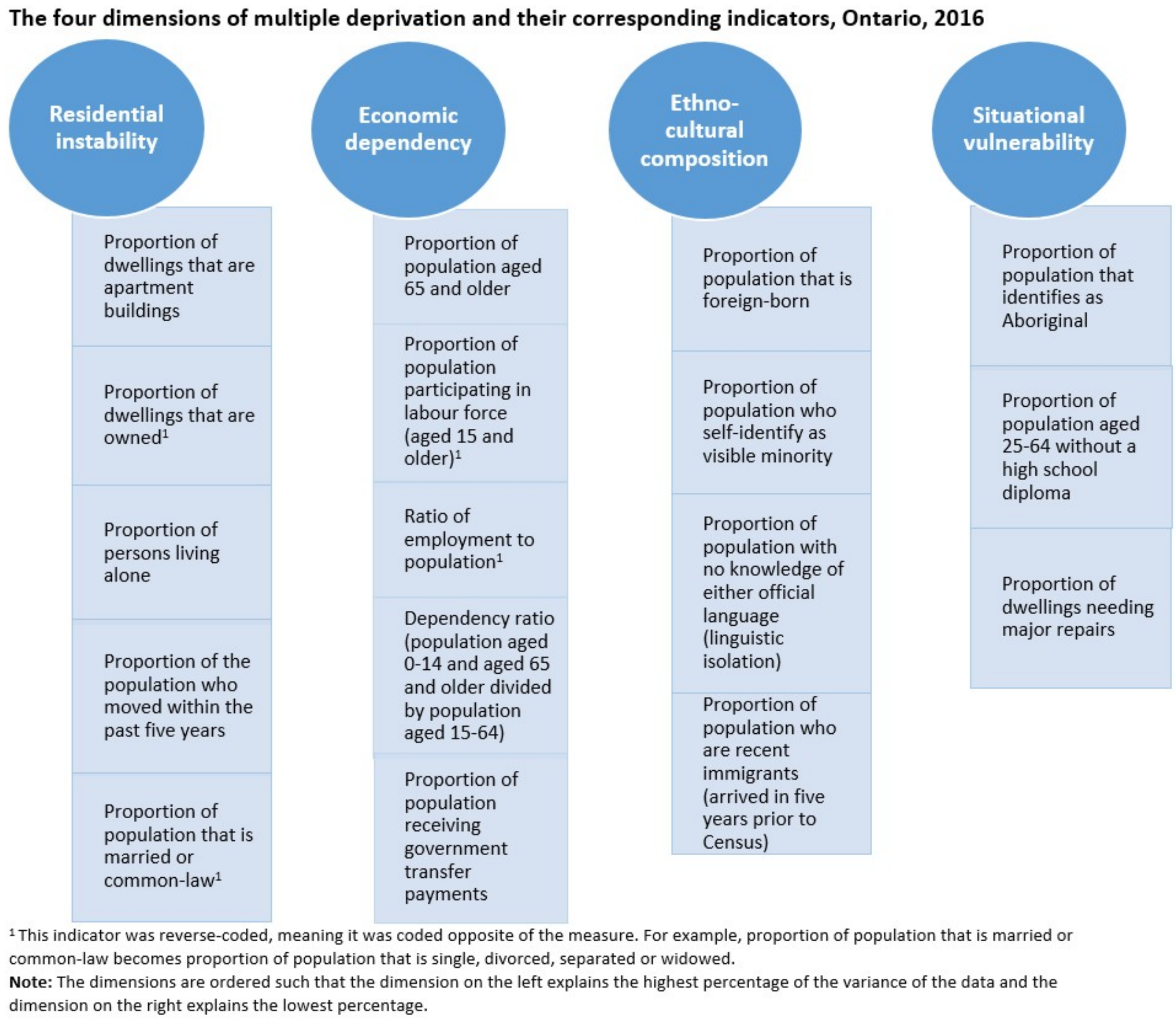


Figure 2 The four dimensions of the Canadian Index of Multiple Deprivation for Ontario in 2016 and the factors that influence the value of each dimension (Statistics Canada, 2019).

This index was chosen to represent marginalization in this study because the range of themes addressed by the CIMD allows the findings of this study to be compared to a range of existing literature on urban forest equity. Furthermore, exploring a range of different ways populations face deprivation and marginalization allows for a better understanding of the types of inequity occurring in Toronto's urban forest.

This data is available at the dissemination area level and is provided by factor scores and quantiles for each factor. Factor scores were used in this study because they provide more detailed information on the level of deprivation across dissemination areas than the quantile scores. These scores were derived using factor analysis as described by O'Rorke and Hatcher (2014). When analyzing factor scores, lower factor scores equate to lower levels of marginalization (Statistics Canada 2019), and factor scores have been used in regressive and predictive capacities across a variety of disciplines (e.g., DiStefano et al. 2009; Testi and Ivaldi 2009; Tahtali 2019).

Table 1 Summary of the variables used in this study, including their units and description.

Variable	**Description**	**Units**
Basal area per hectare	Measure of urban forest density by basal area of the urban forest	m^2/ha
Stems per hectare	Measure of urban forest density by number of trees of the urban forest	Number of stems per hectare
Diameter growth rate	Rate of growth of trees in the urban forest	cm/yr
Mortality rate	Rate at which trees die in the urban forest	Percent of original population per year
Establishment rate	Rate at which new trees are established in the urban forest	Number of trees per year
Residential instability	Measure of vulnerability facing populations based on residential fluctuation	Factor scores
Economic dependency	Measure of vulnerability facing populations based on the proportion of the population dependent on the workforce	Factor scores
Ethnocultural composition	Measure of vulnerability facing populations based primarily on immigrant and visible minority populations	Factor scores
Situational vulnerability	Measure of vulnerability facing populations based on education levels, condition of dwellings, and proportion of the population that identifies as Aboriginal	Factor scores

3.4 Data Analysis

To assess the relationship between the change in and state of Toronto's urban forest and marginalization in the city, bivariate correlation and regression models were developed. The spatial unit used to examine these relationships was the urban forest plots. The forest data was available at the plot level, and the CIMD data was available at the dissemination area level. A spatial join in ArcGIS Pro was done to join the CIMD data to the plots that they encompassed.

3.4.1 Normality Test

Before data was assessed to any capacity, all variables were subjected to a normality test to determine their distribution. This was done in R using the Shapiro test method on all variables. Variables were considered normally distributed if the resulting p-value from the Shapiro test was greater than 0.05. Testing for normality was needed because the results of the normality tests determined whether parametric or non-parametric methods were used in later analyses.

3.4.2 Bivariate Correlation

Bivariate correlation was done on all dependent and independent variable pairs across all plots, making for a total of 20 tests. This was done to determine the preliminary nature of the relationships between the urban forest metrics and indicators of marginalization.

The bivariate correlation tests were done in R using the "cor.test" function. If both variables being tested were normally distributed, the Pearson correlation method was used to assess their correlation. If one or both variables were not normally distributed, the Spearman correlation method was used. Correlations were considered significant if the resulting p-value from the correlation test was less than or equal to 0.05.

3.4.3 Multiple Regression

A multiple linear regression model was developed for each dependent variable in the study (diameter growth rate, mortality rate, establishment rate, basal area per hectare and stems per hectare) using all independent variables (residential instability, economic dependency, ethnocultural composition and situational vulnerability). This was done in R using the "lm" function, and the resulting beta (ß) and p-values for each term were assessed to determine whether each variable was significantly associated with the dependent variable. Terms were found to significantly affect the dependent variable if the corresponding p-value was less than or equal to 0.05. The R^2 and p-values of the overall models were also assessed to determine how much variation in each urban forest variable could be explained by the combination of marginalization indicators, and to what significance. Models were deemed significant if their resulting p-value was less than or equal to 0.05.

The assumptions of linear regression were also assessed to understand the nature of the data and determine the potential implications of model interpretation. Scatter plots for each variable pair were assessed prior to regression to determine if the relationship between variables appeared linear. Assumptions of residual normality, homoskedasticity and independence of residual error were assessed in R by examining diagnostic plots for each model using the "autoplot" function. The five multiple regression models were also assessed for multicollinearity in R using the variance inflation factor diagnostic ("vif" function) to determine if issues of multicollinearity would affect the interpretability of these linear or future GWR models. Multicollinearity was determined to affect the model if the VIF value for any independent variable was greater than 6.

3.4.4 Spatial structure assessment

Multiple linear regression models are commonly used in research to assess the relationships between urban forests and sociodemographic data. However, these models do not account for any spatial structure associated with the data which can sometimes come with consequences for regression model interpretation (Chi and Zhu 2007). Existing studies with similar premises to this one have found that spatial models are needed to best explain relationships related to urban forest equity (Landry and Chakraborty 2009; Schwarz et al. 2015; Gerrish and Watkins 2018). To address this issue and attempt to understand these relationships as comprehensively as possible, this study explored the potential of three additional regression models to account for two common themes in data like this that limit the interpretability of linear regression models: spatial dependence and spatial non-stationarity.

The first step taken to assess spatial dependence in this study was to examine the nature and location of spatial autocorrelation of each variable using a local indicator of spatial autocorrelation (LISA). Identifying spatial autocorrelation in dependent and or independent variables can indicate that the assumption of independent error terms in linear regression may be violated (Chi and Zhu 2007). Therefore, it is important to determine the extent of spatial autocorrelation present to determine if there may be limitations interpreting the results of a given multiple regression model. This was done in Arc GIS pro using the Local Moran's I geoprocessing tool and evaluating the resulting map of significant high and low clusters across Toronto. The spatial weight matrices used for urban forest variables were inverse distance squared with a Euclidian distance method and row standardization, and for the CIMD variables was queen contiguity (edges and corners).

Spatial dependence in data occurs when similar values of a variable are located nearer to each other in space, and observations further away from each other are less similar (Chi and Zhu 2007). The determination of the presence of spatial dependence in each multiple regression model was done in GeoDa by assessing the Moran's I, Lagrange Multiplier (lag) and Lagrange Multiplier (error) values. A significant (p-value < 0.05) Moran's I indicates spatial autocorrelation in the residuals of the regression model and means that the assumption of independent error terms for linear regression was violated (Chi and Zhu 2007). The detection of a significant (p-value < 0.05) spatial lag term indicates that not only do the independent variables affect their associated dependent variable, but also the dependent variables at nearby observations (Chi and Zhu 2007). Significant presence of spatial error (p-value < 0.05) indicates spatial autocorrelation in the regression model's error terms (Chi and Zhu 2007). If the p-value of the Lagrange Multiplier for lag or error was found to be less than 0.05, this was accounted for with the addition of lag or error terms into the regression models.

When data used for a study may be nonstationary, this is another indication that non-spatial linear regression analysis is not going to sufficiently explain the relationship between variables being explored. Spatial non-stationarity describes a phenomenon in which the relationship between variables differs across space, meaning, for example, that the increase in an independent variable will not have the same influence on the dependent variable at different locations (Brunsdon et al. 2010). Seeing as linear regression provides a global regression equation, meaning the same equation across a study area, it inherently cannot account for spatial non-stationarity. Because of the inherent nature of both sociodemographic and urban forest data to be non-stationary, GWR should be done after linear regression to better understand the spatial structure, or lack of, of a dataset.

Geographically weighted regression (GWR) was run for each dependent variable with a significant multiple regression model. GWR provides a step beyond linear regression by accounting for location and spatial non-stationarity in the model that the latter does not. It is especially insightful if any of the variables are found to be spatially autocorrelated. However, due to the nature of GWR, it does not produce the same robust diagnostics as linear regression models (e.g., it does not provide a p-value), and therefore it should only be run on models that were found to be significant using linear regression (Rosenshein et al. 2011).

GWR was done in ArcGIS Pro using the Geographically Weighted Regression (GWR) geoprocessing tool. For the parameters used, the model type was Continuous (Gaussian), the neighbourhood type was Distance band, and the neighbourhood selection method was Golden search. These parameters were selected to optimize the regression results based on the point data representing the study plots. The rest of the parameters were left as the default. The R^2 value was assessed from the outcome of the regression model.

Bivariate Local Moran’s I

As a final step in this study intended to best understand the relationship between the urban forest and marginalization in Toronto, a bivariate local Moran’s I test was used to identify areas of most significant urban forest inequity across the city. Bivariate Moran’s I tests for clustering of high and low values between two variables in datasets (Anselin et al. 2002), making it a useful addition to other tests such as a Getis Or or Local Moran’s I that only test for spatial autocorrelation in one variable (Greene et al. 2018). It can be used to display at the plot level where extremes of one variable are seen with extremes of the other, and therefore is a compliment to bivariate correlation as well. For most variable pairs, inequity was suggested by a low-high result (low urban forest metric values and high levels of marginalization), but for mortality rate assessments, high-high results are indicative of inequity. This assessment was done in GeoDa using the Bivariate Local Moran’s I test. The spatial weights used for all assessments were inverse distance-based, used Euclidian distance, and used a kernel method. A different spatial weights matrix was developed for each dataset because of the difference in plots used in each, but the parameters were the same.

3.4.5 Comparison of Regression Models

After regression models had been developed for each dependent variable, the model that best fit the data was determined by comparing the R^2 values for all statistically significant models. The model that had the highest R^2 value was deemed to be the best fitting model as it could explain the most variation in the dependent variable. This comparison was done because determining the model that best fit the datasets also allowed for a better understanding of the spatial structure of the data. For example, if a spatial regression model was able to explain more variation than linear regression, it can be concluded that there was spatial structure in the data influencing the relationship between variables.

3.4.6 Exploratory data analysis

Beyond the methodologies outlined above, exploratory data analysis was done to provide the results with additional insight and context. The methods explored here were largely the result of the originally obtained results and questions that resulted.

One component of this analysis included looking at the correlations between and regression models for the urban forest change variables and indicators of marginalization for plots located in residential land-use types only. Because of variety of land use types are covered by plots in this study, and because subsections of the urban forest develop differently depending on their surroundings (e.g., naturally forested areas in urban forests see higher establishment rates than those in areas with higher urbanization (Nowak 2012)), residential plots were looked at separately in hopes of eliminating some of this noise and gaining an additional understanding of what is happening in plots likely to be driven more by social processes. The same methodology for this analysis was done as outlined above, except no bivariate cluster analysis was done. This includes correlation analysis, linear regression, and spatial regression. These results were then compared to the relationships observed regarding equity and the urban forest across the entire study area to determine if there was any difference in the strength or significance of the resulting relationships.

The second avenue of exploratory data analysis included assessing the relationship between the frequency of Toronto's urban forest at each plot in 2008 with their corresponding establishment rates. This was done to determine if the new trees in the urban forest had been established in areas that had fewer trees to begin with. To assess this relationship, first, a bivariate Spearman correlation was done between establishment rate and stems per hectare in 2008. Then, a new multivariate regression model was developed using the stems per hectare in 2008 as well as all of the indicators of marginalization as independent variables of establishment rate. The significance of the relationship between stems per hectare in 2008 and tree establishment between 2008 and 2018 was then used to draw conclusions about the equity of urban forest change not tied directly to marginalization. In this case, a significant positive relationship between stems per hectare and establishment rate would be indicative of inequity.

3.5 Limitations

3.5.1 i-Tree Data

One limitation associated with the i-Tree data for this study was the change of fifteen of the plots between 2008 and 2018. This eliminated those fifteen plots from use in this study, which in turn will have increased uncertainty around the regression models developed. There is also a degree of human error that needs to be considered when evaluating this data (for example different people taking DBH measurements across studies), which leads to some error in both physical measurements and somewhat subjective qualitative assessments. This error was seen, for example, in the diameter growth rate calculations, where some rates were found to be negative, which is not something that would occur. Therefore, results relating to tree DBH must be interpreted with a degree of caution.

3.5.2 CIMD

As with most census datasets, there are limitations associated with the CIMD data used in this study, most of which result from dissemination area suppression. One such limitation is the global non-response rate. Since the CIMD is derived from census data, it is also subject to census response rates. If the non-response rate for a dissemination area for any factors contributing to a particular indicator of marginalization was greater than 50% or if a population in a dissemination area was less than 40 individuals that dissemination area was not included in the factor analysis (Statistics Canada 2019).

3.5.3 Present study

In addition to limitations associated with data used to conduct this study, the study design and the use of this data also have associated limitations. One key limitation is the modifiable areal unit problem (MAUP). The MAUP describes uncertainty and errors that can arise from the aggregation of data used in a study (Lloyd 2010). In this case, when looking at dissemination areas, since they are defined by a population range they are also subject to displaying or representing data in ways that are not actually representative of the underlying data as a whole (Lloyd 2010).

Furthermore, it should be noted that the regression models produced by this study are not meant to be inferred as models of prediction or causation of change in Toronto's urban forest. For this study, they were meant only to provide insight into the relationship between metrics that describe the urban forest and the sociodemographic characteristics with which they were compared.

4. Results

This results chapter presents the quantitative and qualitative results of this study. First, it outlines the summary statistics for each variable used to provide background specific to this study area. It then presents the results used to answer this study's first research question regarding the equity of urban forest change in Toronto and presents the results of the supplementary exploratory data analysis. It will then do the same for the second research question regarding the equity of the state of Toronto's urban forest in 2018, including the results identifying areas of inequitable clustering of the urban forest variables.

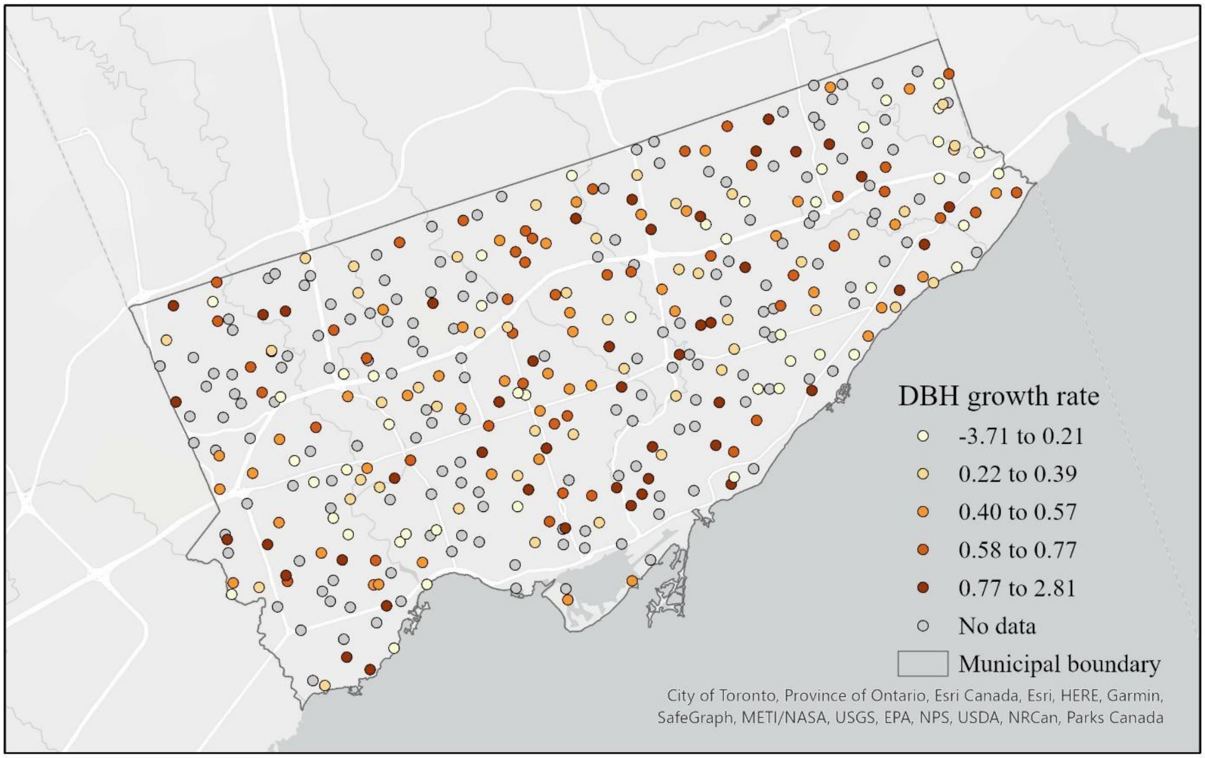
4.1 Toronto's urban forest

Table 2 presents the summary statistics for variables quantifying Toronto's urban forest in 2018 and its change between 2008 and 2018. The distribution of observed values for each measure was variable across plots, as can be observed by the large interquantile ranges (IQR) and overall data ranges. None of these variables were normally distributed.

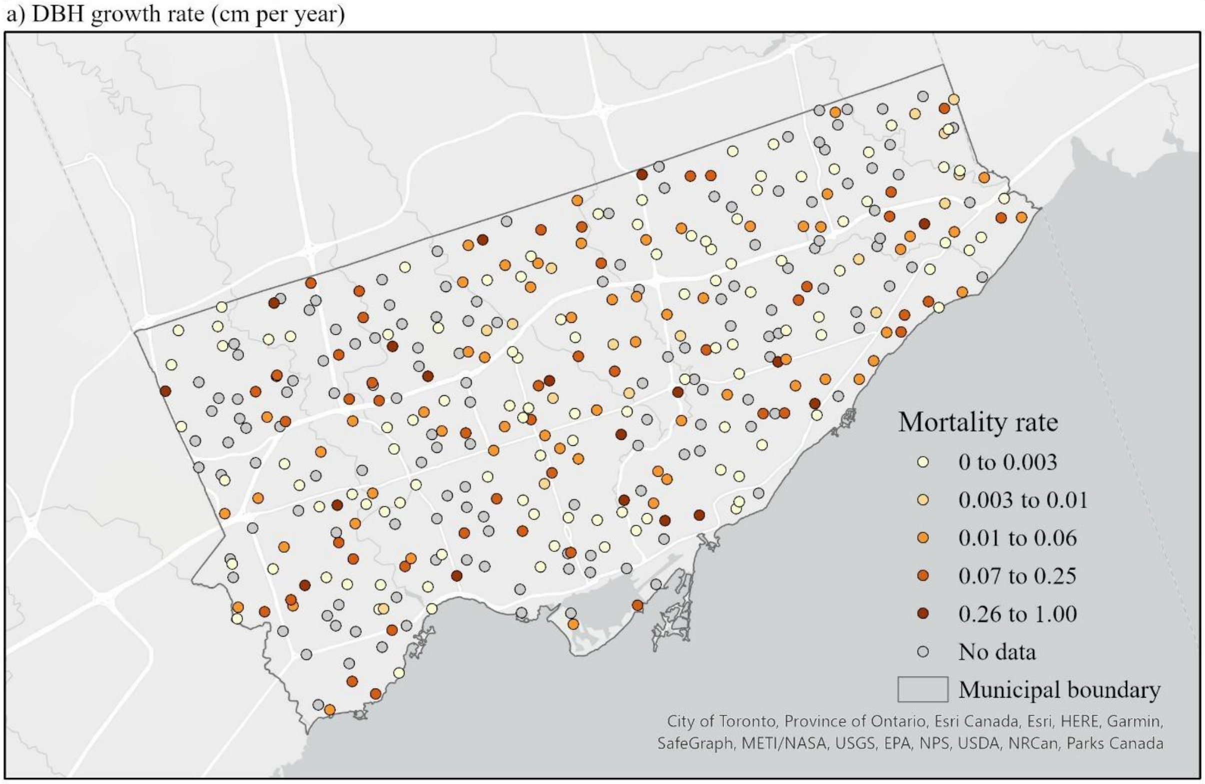
Table 2 Summary statistics for measures of the change between 2008 and 2018 of Toronto's urban forest and its 2018 state.

Forest variable	N	Median	IQR	Range
Diameter at breast height growth rate	230	0.47	0.48	-3.71 - 2.81
Mortality rate	248	0.015	0.07	0 - 1
Establishment rate	392	2.50	10.00	0 - 202.5
Basal area (m^2) per hectare	415	1.10	6.57	0 - 74.23
Stems per hectare	415	50.00	200.00	0 - 2,250

Figure 3 depicts the distribution of each urban forest change metric across study plots in Toronto. All diameter growth rates, mortality rates and establishment rates were found to have a low presence of significant spatial clustering using Local Moran's I, but to different extents.



a) DBH growth rate (cm per year)



b) Mortality rate (proportion of original population per year)

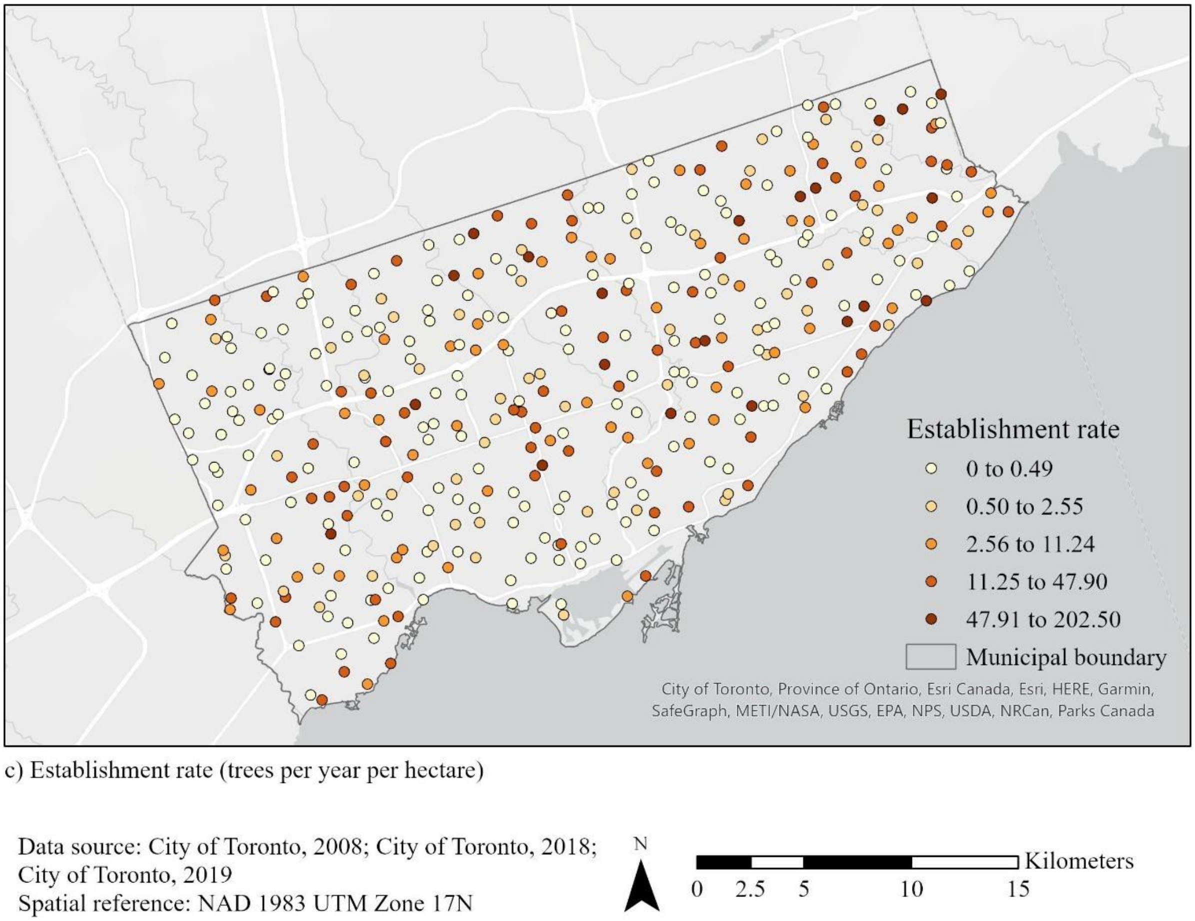
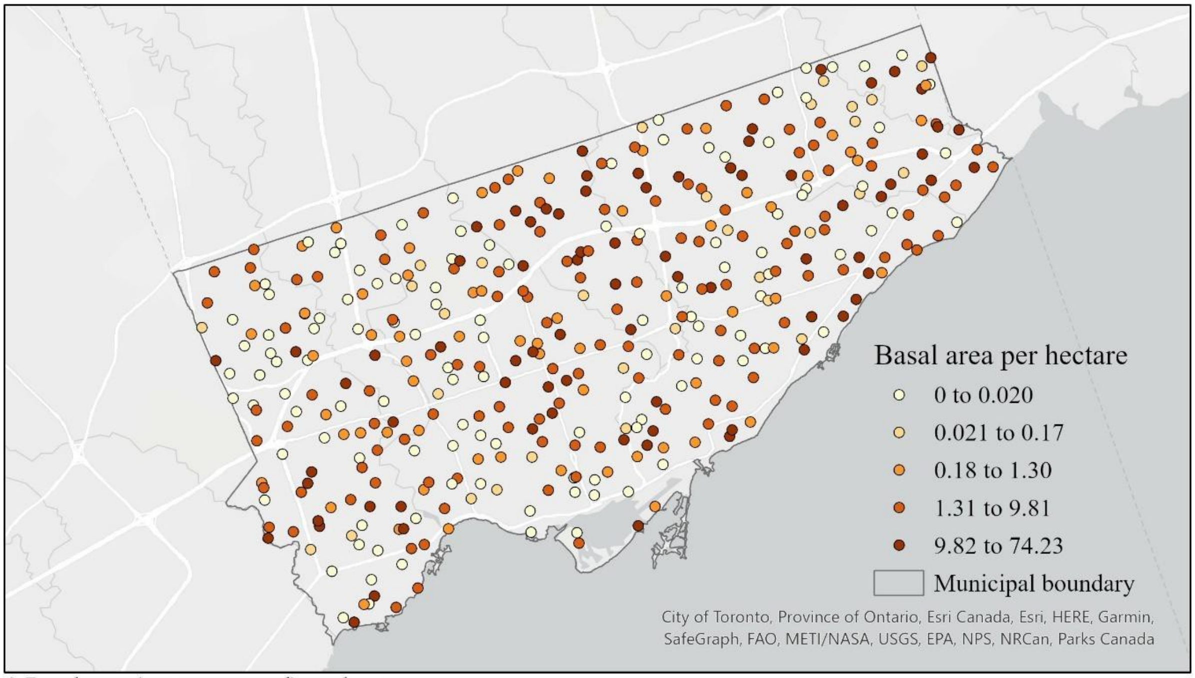
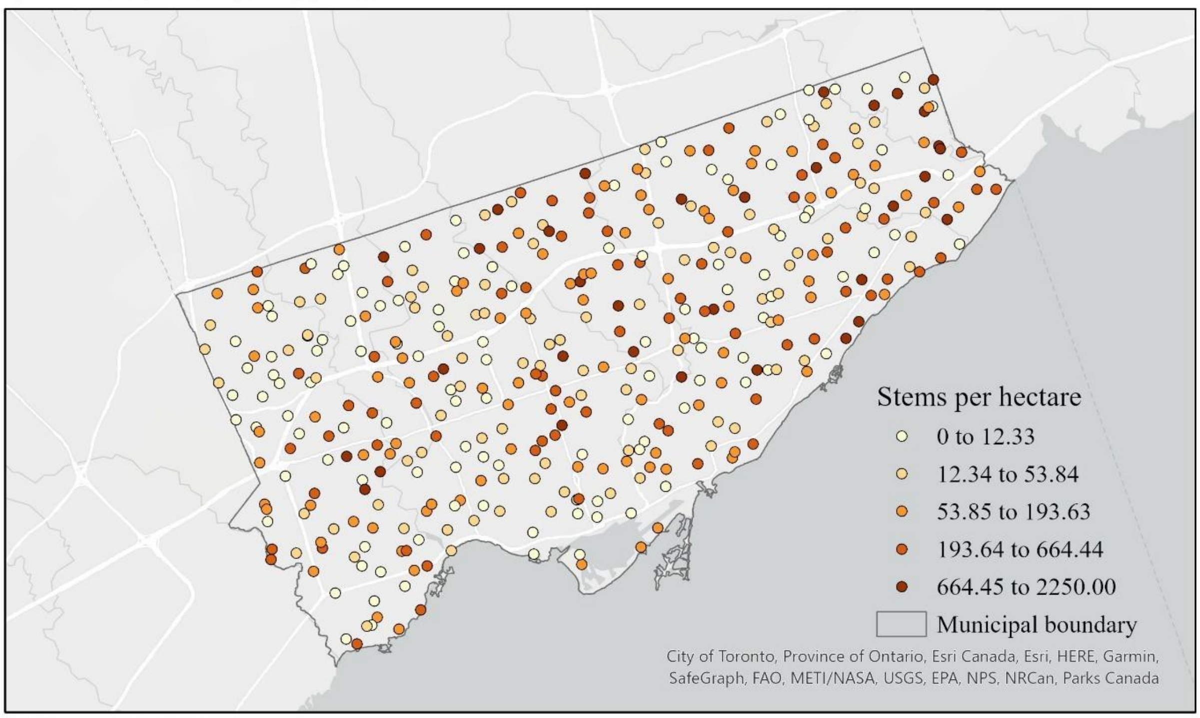


Figure 3 Urban forest change by a) diameter at breast height growth rates, b) mortality rates, and c) establishment rates between 2008 and 2018 for 392 sample plots of the urban forest in Toronto, Ontario.

Figure 4 depicts the distribution of stems per hectare and basal area per hectare across study plots in Toronto. The results of the Local Moran's I test for both basal area per hectare and stems per hectare showed few significant areas of clustering across the city.



a) Basal area (meters squared) per hectare



b) Stems per hectare

Data source: City of Toronto, 2018; City of Toronto, 2019.
Spatial reference: NAD 1983 UTM Zone 17N.

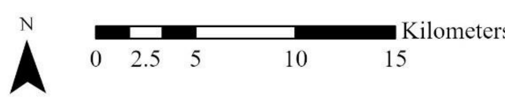


Figure 4 Urban forest frequency by a) basal area per hectare and b) stems per hectare in 2018 for 407 sample plots of the urban forest in Toronto, Ontario.

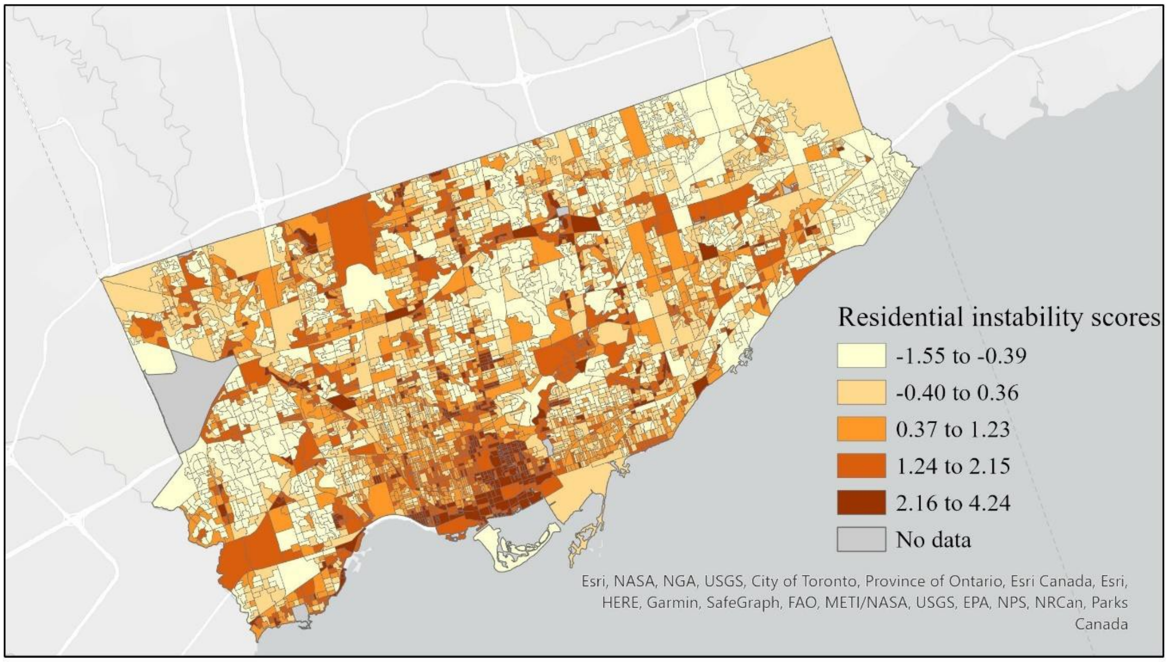
4.2 Marginalization in Toronto

Table 3 presents the summary statistics for variables quantifying marginalization in Toronto, based on the Canadian Index of Multiple Deprivation factor scores. The differences in the median and interquantile ranges for each indicator between plots corresponding with the state and with the change do not vary greatly, and the ranges are identical across datasets except for residential instability. None of these variables were found to be normally distributed.

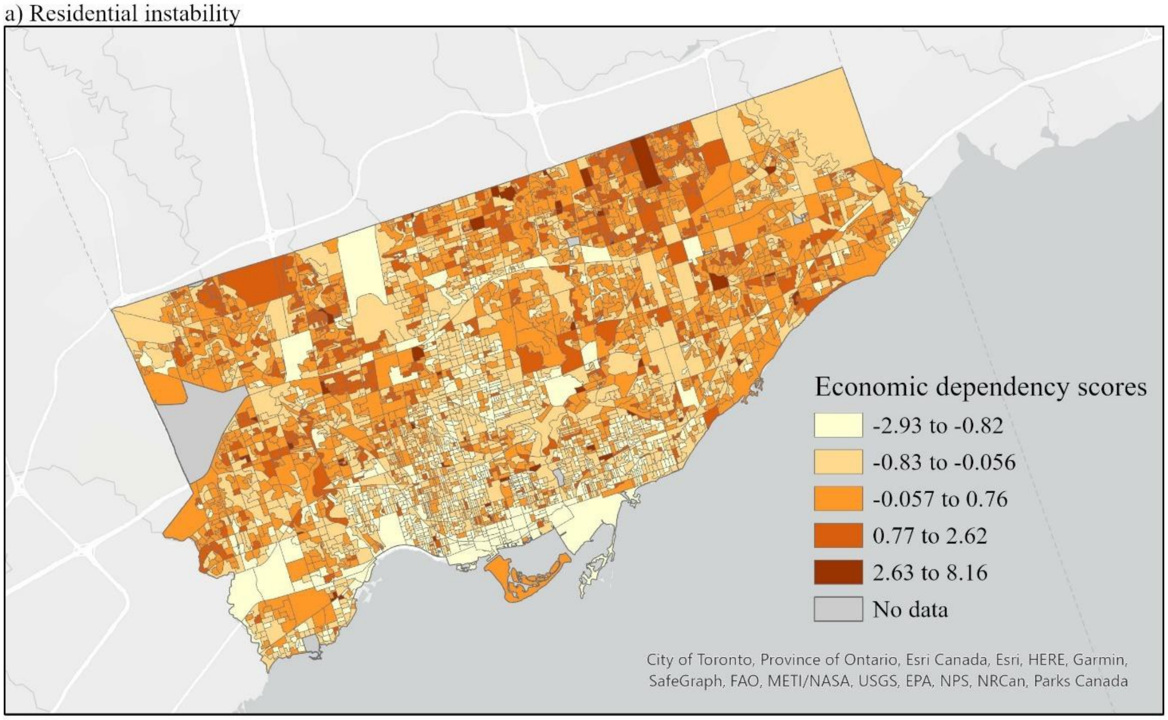
Table 3 Summary statistics for indicators of marginalization for the dissemination areas in Toronto that correspond to the plots assessed for the state of Toronto's urban forest and its change.

Marginalization variable	**N**	**Median**	**IQR**	**Range**
For dissemination areas corresponding to plots used to assess urban forest change				
Residential instability	379	-0.074	1.463	-1.55 – 3.348
Economic dependency	379	-0.047	1.017	-2.927 – 8.160
Ethnocultural composition	379	0.955	1.490	-0.765 – 5.654
Situational vulnerability	379	0.304	0.907	-2.037 – 3.293
For dissemination areas corresponding to plots used to assess the 2018 urban forest state				
Residential instability	394	-0.074	1.469	-1.550 – 3.428
Economic dependency	394	-0.068	0.997	-2.927 – 8.160
Ethnocultural composition	394	0.942	1.49	-0.765 – 5.654
Situational vulnerability	394	-0.315	0.908	-2.037 – 3.293

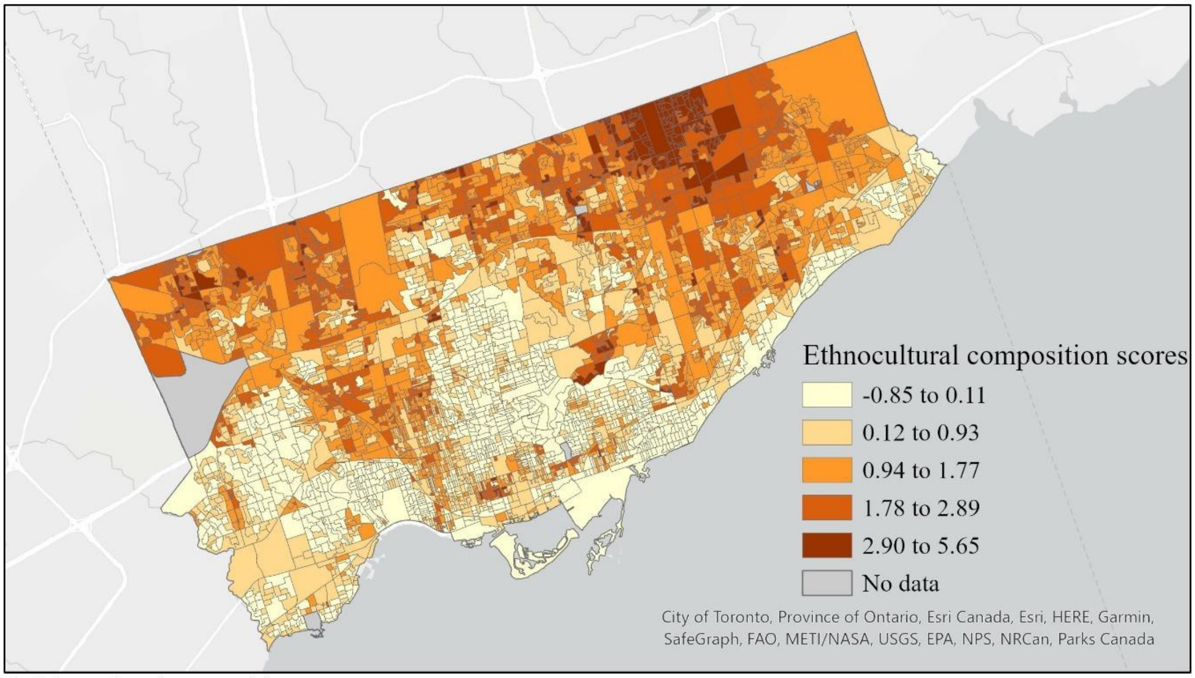
Figure 5 illustrates the distribution of each indicator of marginalization across the municipality of Toronto. The Local Moran's I assessment of all four variables revealed many areas of significant clustering across Toronto that varied somewhat across indicators.



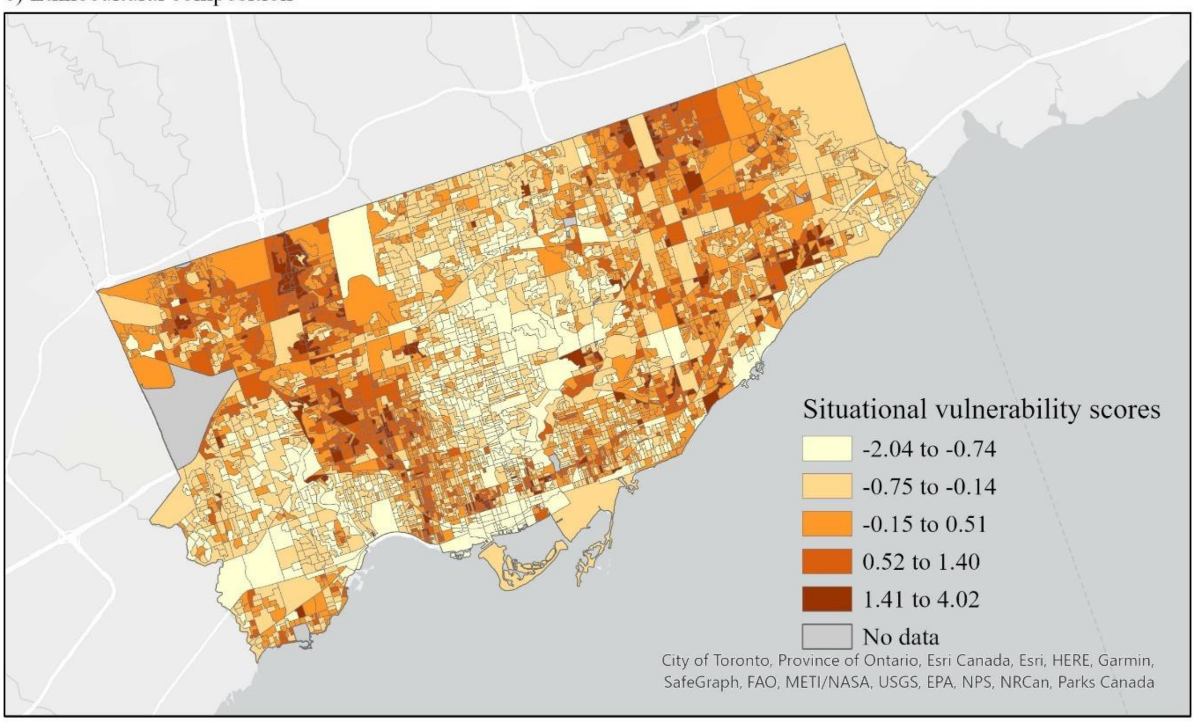
a) Residential instability



b) Economic dependency



c) Ethnocultural composition



d) Situational vulnerability

Data source: Statistics Canada, 2019.
Spatial reference: NAD 1983 UTM Zone 17N.

N

Kilometers
0 2.5 5 10 15

Figure 5 Factor scores for the four variables represented in the Canadian Index of Multiple Deprivation, a) residential instability, b) economic dependency, c) ethnocultural composition and

d) situational vulnerability across Toronto, Ontario in 2016, where higher scores equate to higher levels of marginalization.

4.3 The relationship between urban forest change and marginalization

Table 4 shows the correlation between each metric of urban forest change and the four indicators of marginalization. Of the twelve correlations, four were significant. One, residential instability, was weakly positively correlated with diameter growth rate, and the other three, residential instability, ethnocultural composition and situational vulnerability, were weakly negatively correlated with establishment rate. This indicates that there is more rapid tree growth in areas with higher residential instability and higher establishment rates in areas with lower residential instability, ethnocultural composition and situational vulnerability. No marginalization variables were significantly correlated with mortality rates, indicating there is no relationship between the two datasets in this study area.

Table 4 Spearman's rho and p-values for rates of urban forest change and indicators of marginalization in Toronto.

	Diameter growth rate		**Mortality rate**		**Establishment rate**	
	Spearman's rho	p-value	Spearman's rho	p-value	Spearman's rho	p-value
Residential instability	**0.14**	0.040	-0.04	0.578	**-0.11**	0.026
Economic dependency	-0.01	0.853	0.10	0.104	0.06	0.239
Ethnocultural composition	0.08	0.242	-0.07	0.305	**-0.10**	0.043
Situational vulnerability	0.01	0.850	-0.01	0.850	**-0.10**	0.045

The results of the multivariate linear regression models developed for the three measures of urban forest change are shown in Table 5. These relationships, with p-values ranging from 0.14 to 0.946 across all models, show that no indicators of marginalization significantly affect diameter growth rates, mortality rates or establishment rates of Toronto's urban forest. None of the regression models performed well at explaining variability in the dependent variables, only being able to explain 1% of the variability for diameter growth rate and establishment rate, and 0% of the variability for mortality rate. They also were not found to be significant for any urban forest change variables. Overall, this indicates that these indicators of marginalization are not predictors of these rates of change across Toronto's urban forest.

Table 5 Multiple linear regression analysis of diameter at breast height growth rate, mortality rate, and establishment rate of the urban forest by the four indicators of marginalization, in Toronto.

Independent variable	**Diameter growth rate**		**Mortality rate**		**Establishment rate**	
	ß	p-value	ß	p-value	ß	p-value
Residential instability	0.05	0.225	0.02	0.301	-1.72	0.140
Economic dependency	-0.01	0.848	0.01	0.612	0.52	0.677
Ethnocultural composition	0.04	0.427	0.00	0.888	0.35	0.794
Situational vulnerability	-0.04	0.624	0.00	0.946	-1.90	0.313
R^2	0.010	0.703	0.00	0.864	0.01	0.490

4.4 The relationship between the 2018 state of the urban forest and marginalization

Table 6 presents the correlation between each measure of urban forest frequency and the four indicators of marginalization. Of the eight correlations, six were significant, with the insignificant relationships being between both frequency measures and economic dependency. Each of the significant correlations was negative and weak, with the correlation coefficients ranging between -0.15 and -0.18. The significant results all seem to indicate that the more marginalized a population is, the lower the frequency of the urban forest in the corresponding area.

Table 6 Spearman’s rho and p-values for measures of urban forest frequency and indicators of marginalization.

	Basal area per hectare		**Stems per hectare**	
	Spearman’s rho	p-value	Spearman’s rho	p-value
Residential instability	**-0.16**	0.001	**-0.18**	<0.001
Economic dependency	0.063	0.214	0.075	0.135
Ethnocultural composition	**-0.17**	<0.001	**-0.15**	0.003
Situational vulnerability	**-0.16**	0.001	**-0.15**	0.004

The results of multivariate regression analysis done for basal area per hectare and stems per hectare are presented in Table 7. Residential instability and ethnocultural composition are the only variables that were found to have a significant effect on basal area per hectare (ß: -1.27, p-value: 0.013; ß: -1.27, p-value: 0.028, respectively). Residential instability was the only variable found to have a significant impact on stems per hectare (ß: -40.73, p-value: 0.033). Overall, though both regression models were found to be significant, neither performed well. The models for basal area per hectare and stems per hectare were only able to explain 4.2% and 2.6% of the associated variability, respectively.

Table 7 Multiple regression analysis of basal area per hectare and stems per hectare of the urban forest by the four indicators of marginalization.

Independent variable	**Basal area per hectare**		**Stems per hectare**	
	ß	p-value	ß	p-value
Residential instability	**-1.27**	0.013	**-40.73**	0.033
Economic dependency	0.51	0.356	31.13	0.132
Ethnocultural composition	**-1.27**	0.028	-8.09	0.709
Situational vulnerability	-0.81	0.326	-55.65	0.071
R^2	0.042	0.002	0.028	0.026

4.5 Spatial structure of the regression models

The multiple linear regression models for basal area per hectare and stems per hectare were the only two found to be significant and they were also therefore the only two models assessed for spatial structure. No spatial lag or error was significantly detected for either model and therefore neither lag nor error terms were added. Similarly, the Moran's I values of both models were found to be insignificant, indicating the residuals of the models were not spatially autocorrelated. The Lagrange Multiplier values for lag and error as well as the Moran's I values for these two models can be found in Table 9 in Appendix A.

4.6 Geographically Weighted Regression

GWR models were developed for only basal area per hectare and stems per hectare of the urban forest, again because they were found to be the only two significant multiple regression models. The associated R^2 values were found to be 0.05 for basal area per hectare and 0.10 for stems per hectare.

4.7 Regression model comparison

Both measures of urban forest frequency were significantly modelled by linear regression resulting in also the development of GWR models. Comparing the R^2 values across models developed for each dependent variable shows that GWR was able to account for slightly more of the variability of both stems per hectare and basal area per hectare than multiple linear regression (Table 7). This indicates that there is a degree of spatial structure present in the data that linear regression cannot account for. The difference in R^2 values across models was greater for stems per hectare than basal area per hectare, also indicating that the degree of spatial non-stationarity is larger for the former. None of the variables representing urban forest change had linear regression models that significantly modelled them. Therefore, GWR models were not developed and thus there were no models to compare.

Table 8 Summary of the regression models developed for each dependent variable used in this study using all four indicators of marginalization as independent variables.

Dependent Variable	**R^2 value**	**p-value**
Multiple Linear Regression		
Diameter growth rate	0.01	0.70
Mortality rate	0.00	0.86
Establishment rate	0.01	0.49
Stems per hectare	**0.03**	0.027
Basal area per hectare	**0.04**	0.0022
Geographically Weighted Regression		
Stems per hectare	**0.10**	–
Basal area per hectare	**0.05**	–

4.8 Bivariate Moran's I

When bivariate Moran's I tests were run between each metric of change and each indicator of marginalization, similar patterns of inequitable clustering were seen across dependent variables. Inequity in these associations is denoted by low-high values (areas with relatively low values of rates of change, with high values of marginalization scores) for diameter growth rate and establishment rate, and high-low values (areas with high values of rates of change and high values of marginalization scores) for mortality rates. The maps associated with this bivariate analysis that illustrate this clustering can be found in Appendix B.

Across variables for urban forest rates of change, many of the inequitable clusters of plots associated with residential instability were seen in downtown Toronto. When their association with economic dependency was assessed, inequitable clusters were seen in the northern end of Scarborough, which encompasses approximately the eastern third of the Toronto municipality, and along the northern boundary of the city. When their association with ethnocultural composition was assessed, inequitable clustering was seen commonly throughout Scarborough with diameter growth rates and establishment rates, and along the northern edge of Toronto with mortality rates. When their association with situational vulnerability was assessed, the observed patterns were very similar to those with ethnocultural composition, with inequitable clustering throughout Scarborough and towards the northwest corner of the city.

When bivariate Moran's I tests were run between each measure of forest frequency and each indicator of marginalization, very similar spatial patterns were seen between the two frequency measures at each indicator. In the case of all variable pairs, the areas of highest inequity are characterized as low-high areas, which represent low urban forest frequency and high levels of marginalization. When both stems per hectare and basal area per hectare were assessed with residential instability, these low-high clusters were observed primarily in the downtown core and down to the southwest corner of Toronto. When frequency measures were assessed with economic dependency, inequitable clustering was seen frequently along the northern edge of the municipality. Areas of highest inequity with respect to frequency and ethnocultural composition were widely observed along the northern edge of the city and in the Scarborough area. Clustering of low frequency and high situational vulnerability was seen throughout the western half of Toronto and along the northern edge of the city.

4.9 Exploratory data analysis

Based on the results displayed above concerning the equity of change in Toronto's urban forest, two questions resulted. The first was: are the same relationships observed between urban forest change and marginalization when only plots located in residential areas are assessed? The second was: since regression analysis did not indicate any inequity in the establishment of new trees across Toronto's urban forest, were these new trees also being established in areas with originally lower tree frequency?

When the change in the urban forest was assessed for only plots located in residential areas, different results were observed. There were no significant correlations between any rates of change and any indicators of marginalization across Toronto's residential plots (see Table 10 in Appendix C for the resulting correlation coefficients and p-values). Similarly, there were no significant relationships found in any of the three linear regression models (see Table 11 in Appendix C for beta and p-values for regression terms and R^2 and p-values for the overall models). Because these models were not significant, they were not assessed for spatial structure.

On the other hand, examining the numbers of trees per hectare in Toronto's urban forest in 2008 as an independent variable of urban forest development did produce statistically significant results. The bivariate correlation between establishment rate and stems per hectare in 2008 was moderately positive (correlation coefficient: 0.49, p-value: < 0.001), indicating that areas with a higher stem frequency in 2008 had higher rates of urban forest establishment. As such, a linear regression model that included the 2008 frequency as an independent variable along with the four indicators of marginalization was run. The stems per hectare in 2008 variable was found using this regression model to be significantly positively associated with establishment rate (ß: 0.03, p-value: < 0.001), with the overall regression model being significant as well (p-value: < 0.001) and able to account for 14% of the variability associated with establishment rates (R^2: 0.14). See Table 12 for the full summary of the linear regression model.

Because this new regression model was statistically significant, it was evaluated for spatial structure. This model was not found to have significant spatial lag (value: 0.07, p-value: 0.789) or error (value: 0.01, p-value: 0.911), and did not have significantly correlated residuals (Moran's I: 0.06, p-value: 0.954). A GWR model was run for this relationship and had a resulting R^2 value of 0.15, which was slightly higher than that of the linear regression model.

5. Discussion

5.1 Change in Toronto's urban forest

The results of this study show that the change that took place in Toronto's urban forest between 2008 and 2018 was not uniform across the city. This was not surprising, as the complexity of socio-ecological systems like urban forests and the processes that affect them lend themselves to variability (Liu et al. 2007; Mincey et al. 2013). More specifically, this is because of the countless different types of processes that drive these systems, for example, the natural and political factors that affect urban forests, which can lead them to vary across space (Liu et al. 2007).

The results of urban forest change for this study were first compared to similar change-based results the City of Toronto (2019) presented in their 2018 Tree Canopy Study to determine what ways these rates of change aligned with conclusions made by the city. When this was done it was noted that the rates of change determined across studies for the entire urban forest were marginally different. Though it cannot be said for certain why these differences arose because Toronto's study did not include a description of how they derived the values, it is not of concern because of the number of ways the data could have been manipulated to present those values (e.g., taking averages of values across land use types). Because these three rates, derived in some form from the same dataset as this study, and their drivers have already been explored (City of Toronto 2019), they will not comprise a large portion of this discussion.

This study finds that the diameter growth rate from 2008 to 2018 varies across plots in Toronto's urban forest. Variation in growth rate can be attributed to several factors including tree species composition, tree size, tree condition and growing conditions such as soil compaction and land use type (Lawrence et al. 2012; Steenberg et al. 2019). Stand density (urban forest frequency) is also known to be a primary driver of tree growth (Lawrence et al. 2012), but it is important to note that tree frequency affects tree growth in different ways. More specifically, trees grown in denser conditions exhibit lower levels of diameter growth, but tend to grow taller (Uhl et al. 2015). This is to say that natural processes in urban forests, specifically tree frequency, seem to have thus far been found to affect tree growth more than any social or anthropogenic influences, and that sometimes, when smaller or varying diameter growth rates are observed, it may not be indicative of factors relating to tree conditions that are related to urban and anthropogenic stressors. All of these points are important to keep in mind when considering the diameter growth rates and their variations in this study. The median diameter growth rate observed in Toronto's urban forest was marginally lower than globally observed rates which ranged from 0.5 to 1.1 cm per year (Dervishi et al. 2022). A potential reason for this difference is that Dervishi's (2022) study addressed diameter growth of urban trees across a range of climatic conditions globally, as well as the variation in tree species used in their study differed compared to those found in Toronto's urban forest.

Though the range in mortality rates across Toronto study plots was large, the median value aligns well with existing data on urban forest mortality, where it has been found to range between 0 and 20.2% depending on land use type and species (Nowak et al. 2004; Lawrence et al. 2012). Tree mortality rates in Toronto's urban forest are affected by both natural and anthropogenic factors including pests such as the emerald ash borer, diseases like beach bark disease, competition with invasive species (City of Toronto 2019) and land use (Lawrence et al. 2012). Tree frequency, due to resulting higher levels of competition, is also a large driver of tree mortality, especially in more naturalized areas of urban forests that are less subjected to anthropogenic stressors (Lawrence et al. 2012).

Tree establishment between 2008 and 2018 was the result of trees being planted or growing into plots naturally – no distinction was made between the two in this study. As such, the establishment rates are a combination of policy and planning, individual action, and natural processes. A range of groups are responsible for the planting of trees in Toronto's urban forest, including property owners, non-profit groups, and the city's Urban Forestry Branch (City of Toronto 2012). Across urban forests as a whole, though, natural tree ingrowth is a greater driver of tree establishment than tree planting (Nowak 2012). Compared to a study done on the establishment of new trees in two U.S. cities (Nowak 2012), Toronto's establishment rate of 2.5 trees per year was comparable to their observed ranges. Nowak's (2012) study calculated separate establishment rates for trees which were planted and those that were naturally ingrown, resulting in a range of 0.2 to 7.9 trees per hectare per year depending on the city and establishment type. Considering that this study included both types of establishment in these rates, it makes sense for the median value to fall within this range.

5.2 The relationship between urban forest change and equity

The lack of significant correlation between most metrics of urban forest change and indicators of marginalization indicates that some changes that took place in Toronto's urban forest between 2008 and 2018 were not inequitable. Though there were significant correlations between some rates of change and some indicators of marginalization, there were no significant regression terms found for those same relationships. This may have occurred because the relationship between the two variables, both in terms of correlation and dependence, is low enough that though there is a correlation it cannot be significantly determined that one variable directly impacts the other.

Diameter growth rate

Residential instability was the only indicator of marginalization significantly correlated with diameter growth rates. The relationship between the two variables was weak but positive, meaning that typically areas with higher residential instability were seen to have higher diameter growth rates. Residential instability, however, was not determined to have any significant impact on diameter growth rate. The correlation between these variables supports the research by Steenberg et al. (2019) which found faster rates of diameter growth in areas of multi-family residential and apartment building land use types. Though this finding may seem somewhat counterintuitive, as lower tree conditions and growing environments have been associated with marginalization (Steenberg et al. 2019) there are a few reasons that this could be occurring. First, this relationship in part could be the result of establishment rates prior to 2008. When trees are transplanted from a nursery or establishment environment to a new location, especially in a city, they undergo a type of shock which results in a lack of initial growth for several years following the transplant (Sherman et al. 2016). This is what is known as the establishment period for a tree and its length is dependent on the conditions it is exposed to and the species it is (Sherman et al. 2016). Since this study has shown an inequitable pattern in tree establishment rate across Toronto with respect to residential instability, an abundance of tree planting in areas with lower residential instability could have resulted in lower average plot diameter growth rates in these areas in subsequent years. The positive relationship could also be the result of less competition in the plots with higher diameter growth rates and residential instability but lower tree frequency. Finally, more residentially unstable areas may also be seeing this faster growth if people living on these properties are less likely to care for their yards, as discussed by Perkins et al. (2004), which could allow for more introduction of invasive and rapidly-growing yet short-lived species that could be a driver of this trend.

The insignificant correlation and regression relationship observed between diameter growth rate and economic dependency was not surprising. No existing studies were found that looked directly at the relationship between tree growth and any factors that affect economic dependency. Thus, these results were not compared to or found to support existing data. As noted in the methods chapter, economic dependency expresses a population's reliance on the workforce, which could be connected to factors like family size in addition to its connection to people that could be employed but are not (Statistics Canada 2019). Though having higher economic dependency would make a household more vulnerable to situations like employment loss, it cannot be directly assumed for the reasons above and due to lack of literature on this topic, that populations in dissemination areas with higher economic dependency will always be the same populations who are historically marginalized. There is likely a combination of both instances across the study area, which may also be responsible for the lack of a significant relationship.

Ethnocultural composition encompasses a range of characteristics associated with race-based and other visible minority populations. Inequities of urban forests based on race have been identified in many existing studies (e.g., Watkins and Gerrish 2018), but a literature gap appears to exist concerning race and cultural-based equity of tree growth. The lack of significant correlation between diameter growth rates and situational vulnerability did support existing literature that has explored the relationship between similar variables. In one Toronto neighbourhood, diameter growth rate was not found to be significantly correlated with education level or housing value (Steenberg et al. 2019) which are both characteristics tied to situational vulnerability. One potential reason for this lack of significance is the same across both indicators, being that tree planting programs are often participated in more frequently by less marginalized populations (Locke and Grove 2014). As a result, more trees may be planted in areas with lower diversity and result in low diameter growth in those areas from shock, while subsequently there may also be lower rates in these historically marginalized areas due to lower tree conditions.

Mortality rate

Mortality rate was the only metric of change not correlated with any indicators of marginalization. Though it may seem that many of the causes of tree mortality are independent of social structures, this is not necessarily the case. Lower tree conditions or tree quality, which can make trees more vulnerable to mortality, for example, are correlated with lower education levels and dwelling values (Steenberg et al. 2019). Housing values as an indicator of socioeconomic status have also been found to negatively affect urban forest mortality (Ko et al. 2015). Similarly, in Indianapolis measures of residential fluctuation similar to those used to determine residential instability were found to be inequitably related to tree mortality (Vogt et al. 2015). The difference in significance between this study and the one based in Indianapolis is likely due to the difference in the selection of trees assessed. Vogt et al. (2015) looked at the mortality rate of planted trees only, whereas this study looks at both planted and naturally established trees. It has also been found that trees planted by individuals in residential settings can sometimes have higher mortality rates than those planted by experienced groups (Jack-Scott et al. 2013), which could also explain the lack of correlation detected between marginalization and mortality if, like in other cities, less marginalized populations are taking advantage of Toronto's tree pickup initiatives more frequently than others. For example, if there is higher tree planting taking place in less marginalized neighbourhoods then those places would also see corresponding mortality rates, while subsequently, more marginalized areas may be seeing similar mortality rates from lower tree conditions. These insignificant results could also in part be influenced by the MAUP, earlier identified as a limitation of this study. For example, if a dissemination area contains a higher proportion of a land use type more prone to tree mortality, independent of its associated sociodemographic characteristics, because of the ways its boundaries were drawn, a relationship between marginalization and tree mortality could be missed.

Establishment rate

Establishment rate was the only of the three metrics of change that was significantly correlated with multiple indicators of marginalization. Because the establishment of new trees, more specifically trees that are planted in the city rather than those that grow naturally, are often dictated by several different social factors with the opportunity to be biased by sociodemographic characteristics relating to equity, it is not surprising that these correlations were seen. Weak negative correlations were found between establishment rates and residential instability, ethnocultural composition and situational vulnerability. No existing studies were found that directly address equity of urban forest establishment rates, putting these results in a unique position in the literature. However, many studies do examine who benefits most from programs and policies that would affect establishment rates, for example, tree planting initiatives.

The negative correlation between residential instability and establishment rates indicates that there is likely higher establishment of trees in areas with lower levels of neighbourhood fluctuation. One reason for this may be that when cities or other organizations create tree planting programs, homeowners are significantly more likely to participate in these programs than renters (Perkins et al. 2004). It was hypothesized by Perkins et al. (2004) that renters participate infrequently in such programs because trees increase property values and that is something they would not be able to benefit from in the long run, while at the same time landlords were unlikely to participate due to associated maintenance. This is also likely perpetuated by the guidelines associated with the City of Toronto's own free tree planting program, where it seems that only property owners themselves can submit requests for city-owned trees to be planted in their yards (City of Toronto 2019; City of Toronto 2022b). It has also been noted that in areas with high residential fluctuation it is harder for individuals organizing tree planting efforts to connect with homeowners, thus resulting in a barrier to tree establishment (Riedman et al. 2022).

Like all other urban forest variables assessed in this study, establishment rates were not correlated with economic dependency, again likely because even though high levels of economic dependency do leave populations vulnerable to certain changes, they are not necessarily reflective of characteristics that perpetuate inequity on their own.

Though little research has investigated the correlation between urban forest change and ethnicity in this way, the negative correlation observed between establishment rates and ethnocultural composition was in line with literature that continues to find racial inequities in urban forest distribution. If studies that span decades, though often in different cities, come to the same conclusions regarding disproportionate access to urban forests, it is not surprising that this study found that fewer trees are established in areas with higher ethnocultural diversity. Furthermore, research has found that language barriers, which would be encompassed under ethnocultural composition in this study, between residents and those heading tree planting initiatives can deter people from participating in them (Riedman et al. 2022).

Negative correlations between establishment rates and situational vulnerability were also likely somewhat the result of bias in public policy with respect to visible minority populations, as a factor that affects situational vulnerability scores is the proportion of the population that is Indigenous. Additionally, there is likely to be a level of stigma associated with high scores of situational vulnerability separate from cultural and heritage-based differences. Situational vulnerability scores are also associated with the proportion of dwellings in need of major repairs, and it is reasonable to assume that planting programs could also be targeted toward neighbourhoods in better physical shape than others. Similarly, stigma can be associated with people with lower levels of education (Meisel et al. 2022), making areas with a high proportion of the population without high school diplomas (a factor in situational vulnerability) a lower priority for tree planting as well. Populations with higher proportions of the adult population without highschool diplomas have also been found to be less likely to participate in tree planting programs (Donovan and Mills 2014), meaning that it could be a combination and connection of societal and personal reasons that drive this observed relationship.

When the relationship between urban forest change and marginalization was assessed only for plots located in residential land use types, the results of all correlation and regression outputs were insignificant. This analysis was done to get a better understanding of urban forest change in areas less likely to have a level of noise associated with naturally forested plots, and also in part to determine how equitable the urban forest change was in closer proximity to peoples' homes. These insignificant findings were not expected and are somewhat contradictory to earlier-mentioned studies, specifically with respect to factors pertaining to residential instability. For example, based on studies that examine the difference between the populations more likely to be planting trees on their properties (Perkins et al. 2004; Greene et al. 2011), it would have been likely to see that inequality highlighted here. These results do support the notion that inequity is not a driver of urban forest change in Toronto, as previously represented by the lack of significant relationships observed in assessed regression models. One other factor that may contribute to this, though does not invalidate it, is that very few of the residential plots were located in areas with high marginalization, specifically the northwestern corner of Scarborough commonly identified to have inequitable clustering.

The last assessment done in this study concerning urban forest change, examining the relationship between original urban forest frequency and tree establishment rates, did highlight a pattern of inequity in Toronto's urban forest separate from marginalization. This analysis revealed that trees are being established significantly more frequently in areas that had more stems per hectare in 2008. This helps to fill an important knowledge gap specific to the management of Toronto's urban forest. In Toronto's Strategic Forest Management plan and their urban forestry studies the city states that one of its goals is to increase the equity of Toronto's urban forest by increasing tree cover in areas with the lowest existing cover (City of Toronto 2012; City of Toronto 2019). This specific analysis is important because it shows that that, overall, is not happening. Rather, trees are being established more frequently in areas with more existing trees. Based on existing research on both naturally and socially driven urban forest processes, there are two reasons this is likely occurring. The first is, by the nature of tree reproduction and the rate at which that takes place across environments, establishment rates of naturally growing trees could be significantly quicker in areas with more trees to produce seeds. The second is based in social policy which is likely to prioritize the planting of trees in more desirable areas resulting in higher tree frequency in some areas and low frequency in others. This has been observed in cities in the United States, where data from multiple tree planting initiatives showed that trees were being planted more frequently in areas with higher existing tree cover (Locke and Grove 2014), which this finding would support.

Though this was only an exploratory analysis and subsequent research would be needed to determine which of the two processes is likely to be driving this unequal establishment, it nonetheless has important implications for the management of Toronto's urban forest. Specifically, it highlights the need for targeted tree planting programs in the areas with the lowest tree frequency over the next decade.

5.3 The 2018 state of Toronto's urban forest

Both stems per hectare and basal area per hectare varied greatly across Toronto, showing that there is a larger urban forest presence in certain areas of the city than in others. This supports the conclusion by the City of Toronto (2019) that the urban forest distribution is unequal, but does so with new variables that provide additional insight into that distribution. When comparing urban forest data to sociodemographic data, especially when interested in understanding the social drivers of urban forests, tree count and frequency provide context on variables that people can more directly control (e.g., the number of individual trees), whereas canopy cover does not (Conway and Bourne 2013). These measures of frequency also provide an added layer of detail regarding the potential vulnerability and future of the urban forest at each plot by allowing for the determination of tree count.

The variability in the frequency of Toronto's urban forest is likely the result of multiple social and ecological factors. One such factor is likely to be differences in land use. Although this study did not compare urban forest frequency across land uses, existing studies have found that land use types similar to the classification associated with the plot data collected in Toronto are determinants of stem frequency (Fan et al. 2019). Other determinants include environmental conditions (e.g., precipitation and temperature) (Nowak and Greenfield 2012), housing density (Fan et al. 2019), urban forest governance practices (Wirtz et al. 2021), and historical development patterns of urban areas (Hoffman et al. 2020). It is reasonable to believe all of these factors could apply to Toronto and its urban forest given the general applicability of many of these findings to dense urban settings. However, the degree to which each factor affects forest distribution in a given city is going to be variable.

With respect to the median values of stems per hectare and basal area per hectare, existing studies show that urban forest frequency varies greatly across cities. Compared to the urban forest in the Peel Region, in the Greater Toronto Area, studied by Conway and Bourne (2013), Toronto's municipality has approximately 175 fewer trees per hectare than the surrounding areas of Mississauga, Brampton, Bolton, and Caledon. This is not surprising, as none of these areas are as dense or urbanized as the city of Toronto. More broadly, across major cities in the United States, this number has been found to vary between 12.1 and 190 stems per hectare (Nowak and Crane 2002; Fan et al. 2019), a range within which Toronto's median value of 50 falls. Fewer studies seem to exist on the basal area per hectare of urban forests, but it is expected that it too would be variable across cities.

5.4 A snapshot of equity in Toronto's urban forest

Assessing the relationship between tree frequency and marginalization in Toronto was done to determine if the distribution of Toronto's urban forest in 2018, the most recent year for which adequate data is available, was equitable. The results of this study show that in addition to the distribution of Toronto's urban forest being unequal, it is also inequitable. The root causes of this will include a combination of the historical distribution of Toronto's urban forest and its changes between 2008 and 2018, as displayed in this study, not accounting for existing inequities.

For both measures of frequency, weak negative correlations were found with all indicators of marginalization except for economic dependency, indicating that areas with higher marginalization often have a lower frequency of the urban forest, and vice versa, in multiple accounts across the city. This finding is consistent with a large body of existing literature. Many studies that address the idea of equality and or equity in urban forests have found significant relationships between a variety of measures of urban forest structure and marginalization (e.g., Landry and Chakraborty 2009; Schwarz et al. 2015; Gerrish and Watkins 2018; Nyelele and Kroll 2020).

Concerning the weak negative relationships found between both frequency measures and residential instability, similar studies have noted similar relationships between stem frequency and percent homeownership (Conway and Bourne 2013). Negative correlations between rentership rates and canopy cover have also been observed in cities (Perkins et al. 2004), again which this study supports. There could be several reasons for this recurring trend, including renters lacking the ability or motivation to plant trees on properties they do not own, or homeowners not prioritizing tree planting and related upkeep on properties they do not live on (Conway and Bourne 2013), which could both translate to a lower tree frequency in these areas.

The relationship between both frequency measures and economic dependency was not found to be significant, which may sound contradictory to the many studies that find negative relationships between urban forest presence and median income (e.g., Gerrish and Watkins 2018;

Nyelele and Kroll 2020). However, it should be noted again here that the economic dependency variable is not a product of median income in a dissemination area, but rather based on the population's age and overall dependency on the workforce (Statistics Canada 2019). Therefore, the fact that basal area and stems per hectare were not significantly related to economic dependency does not make this study contrary to others that examine the relationship between urban forest distribution and income.

Ethnocultural composition and situational vulnerability describe many indicators of marginalization that address ethnicity, citizenship, Indigenous identity, and recent immigrant populations, which are often characteristics that lead to racial bias in individuals and policies (Glaser et al. 2014; Drakulich 2015). Such factors have been found to be correlated with and in some instances determinants of urban forest structure (Conway and Bourne 2013; Fan et al. 2019; Nesbitt et al. 2019), which this study supports. Lower education levels have also been found to be associated with lower levels of urban forest cover (Nesbitt et al. 2019), which again the correlation between frequency and situational vulnerability supports. Among likely being related to many factors, the state of one's residence is also likely associated with the median value of their household and therefore the means to complete needed repairs. If this is the case, then this finding also supports and builds on studies that find inequities in urban forests and income. The third factor of situational vulnerability, the proportion of the adult population without a high school diploma, also somewhat indirectly aligns these findings as lower levels of education are typically associated with lower median incomes in Canada (Statistics Canada 2017).

Considering the modelling of each variable representing forest frequency, the fact that geographically weighted regression models were able to explain more of the variability associated with both stems per hectare and basal area per hectare than linear regression means that there is a level of spatial dependence in the data that the marginalization factor scores alone cannot account for. This supports existing studies that have found that ordinary least squares and other regression models are sometimes not enough to fully capture the relationships between urban forest characteristics and sociodemographic data (Landry and Chakraborty 2009; Schwarz et al. 2015; Nesbitt et al. 2019). Though the GWR model did not significantly impact the measure of variability accounted for over the linear regression models, it accounts for issues of spatial autocorrelation associated with those models, and should theoretically, therefore, result in a more accurate representation of the relationships.

Ultimately, the results of this analysis indicate there is inequity in the distribution of urban forest frequency in Toronto, which has implications for the city's population, as urban forests are associated with a myriad of ecosystem services, some of which can only be reaped at local levels. This means that in Toronto, populations with higher levels of residential instability, ethnocultural composition and situational vulnerability have disproportionately low access to many of the benefits derived from urban forests. This comes with increasing concern when it is also considered that increasingly marginalized populations, specifically with respect to race, not only disproportionately lack access to ecosystem services, but are the same populations with the largest need for them (Herreros-Cantis and McPhearson 2021).

5.5 Identifying areas of urban forest inequity

The bivariate Moran's I cluster assessments identified Scarborough, particularly the western half, to be a frequent location of inequity in urban forest change in the municipality of Toronto. This area is characteristic of high values of marginalization across economic dependency, ethnocultural composition and situational vulnerability, but has low levels of residential instability. This was also the area of Toronto most significantly impacted by the emerald ash borer between 2008 and 2018 (City of Toronto 2019). This exposure could have degraded the quality of surviving ash trees in the area and resulted in both stunted growth rates, in addition to the mortality of trees removed due to the ash borer, as it has been observed that trees in worse conditions have lower diameter growth (Steenberg et al. 2019). Some neighbourhoods within this Scarborough area also underwent significant development in this timeframe (City of Toronto 2019), which likely also increased tree mortality directly and negatively impacted the conditions of surviving trees.

The low establishment rates also seen in these areas could have resulted in hesitancy from homeowners to replant trees as a result of the associated urban forest degradation. Factors associated with economic dependency, for example having a lower proportion of people per household working, could mean that investing in new trees after such events or in general is not prioritized or even feared for financial or maintenance reasons (Carmichael and McDonough

2018; Riedman et al. 2022). It also could have been the result of low regeneration efforts by the city in these locations due to the high ethnocultural composition and associated diversity in this area relative to others throughout the city, a concept highlighted by Glaser et al. (2014) for general municipal policy and further highlighted by Riedman et al. (2022) for urban forests. For example, because of the damage and tree removals caused by the emerald ash borer and the 2013 ice storm, the City of Toronto adopted multiple tree planting programs (City of Toronto 2019). Even with these programs in place to take the burden of urban forest redevelopment off individuals, there not only remains inequity in the distribution of the urban forest but also in tree establishment, even in regions severely impacted by pests. One factor to note, with respect to this conclusion, though, is that young, smaller trees do have higher mortality rates than older trees (Steenberg et al. 2019), so there could have been more trees planted in these areas than were detected by the 2018 study if they died before the plots were surveyed. This would support earlier mentioned research regarding environmental conditions and marginalization, but it is more than likely a result of both processes to an extent.

Areas of inequitable clustering concerning residential instability were seen consistently but to varying extents in downtown Toronto across all change metrics. The low diameter growth rates and higher mortality rates were likely the results of both the harsh growing conditions associated with the denser urban core, as conflicts with buildings and infrastructure have been shown to impact tree growth (Steenberg et al. 2019) as well as development in the area between 2008 and 2018 (City of Toronto 2019). Due to the economic importance of this area paired with the low urban forest frequency, the low establishment rates in this area could be because there are very few areas remaining that are suitable for tree planting, especially considering many of the plots downtown did have an establishment rate of 0 trees per year.

The patterns of inequitable clustering of urban forest change and marginalization were also reflected in the clustering of inequitable urban forest frequency in 2018. Inequitable clusters with respect to residential instability were seen downtown, which is likely a result of both the low establishment rates and high impervious surface cover in that area (City of Toronto 2019). Inequitable clustering of urban forest frequency with all indicators of marginalization is also seen significantly in Scarborough which is likely heavily perpetuated by the lack of urban forest re-development in that area.

5.6 The future of Toronto's urban forest – future recommendations

Though this study neither predicts nor was meant to predict the future of Toronto's urban forest, it does provide insight on how it could continue to change into the future and associated implications for one of the city's urban forest goals. These results and subsequent discussion illustrate that the urban forest does not seem to be heading towards equitable or even distribution across Toronto, and that there are likely many reasons for this. If the City of Toronto wishes to meet its goal of equitable distribution it needs to devote the time and resources needed to develop an approach for urban forest development that accounts for and combats its perpetrators of inequity.

It is clear from the resulting correlation coefficients and R^2 values across regression models developed in this study that marginalization, at least with respect to the variables used in this study, is not the only, nor the major, driver of change in Toronto's urban forest. In using data from the CIMD, this study used factors to quantify marginalization that are each influenced by multiple census variables. Using individual census variables, be it the ones that feed into the CIMD factors or others that are also indicative of marginalization (e.g., median income), could be used in future studies to provide more specific insight into different aspects of populations that are being most inequitabley affected by urban forest change. It is more than likely that a variation in strength and significance of relationships between urban forest and marginalization would be observed if this was done, which could also help provide additional insight into what types of inequity are taking place, underlying drivers of this inequity, and also into some of the processes hypothesized in this discussion to be the reason for the results of this study.

In addition to the opportunity for a more detailed analysis, the low strength of observed relationships in this study mean that in addition to targeting future urban forest development towards marginalized neighbourhoods lacking trees, Toronto must also be conscious of other social and ecological drivers of change in these areas to ensure they sustain their progress towards equity. It is recommended that the City of Toronto use existing literature that highlights urban forest inequity to develop a tangible plan to reduce this inequity and incorporate it into the next version of the city's forest management plan. Though many factors should influence the development of such a plan, and this study was not designed to advise on how to do so, it should be noted that any change in the urban forest to increase equity should be done in a way that will not result in gentrification and should be done with community consultation. Similar studies to this can be used for decades to come as the urban forest plots continue to be measured to determine the success of any new planning or programs related to increasing the equity of the forest.

When looking to find areas most in need of increased urban forest frequency based on any indicators of marginalization used in this study, the bivariate cluster analyses shown in Appendix B can be used to identify areas of higher inequity. Particularly comparing those that look at tree frequency and establishment rates can be used to prioritize areas for tree planting as they develop their next urban forest management plan. As noted previously, based on only the relationship between the urban forest and the measures of vulnerability used, western Scarborough could be an ideal place to prioritize urban forest development.

This study leaves room for several new avenues of future research, specifically with respect to urban forest change over time and its equity and equality. In terms of applicability to Toronto urban forest management and obtaining equity in a way that most efficiently also increases benefits received by the urban forest, a study of the barriers facing urban forest development in Toronto, specifically in areas where it is identified to be the least equitable, would be quite beneficial. Those findings could then be used with the results of this study and others that identify areas of lowest urban forest equity in Toronto to not only prioritize uniform urban forest presence but also getting it to the areas that are in the most need of it.

6. Conclusions

This study was conducted to gain further insight into the equity of Toronto's urban forest change and distribution. This research has important implications for understanding where and how the City of Toronto should focus the future development of its urban forest to achieve the goal of its equitable distribution. Having this information and accounting for it in a planning context is important because of the many benefits urban forests provide that positively impact the well-being of urban populations.

The results of this study identified that the frequency of Toronto's urban forest remains unequal and inequitable in that populations with higher residential instability and ethnocultural composition are significantly associated with lower urban forest frequency across the city. The analysis of urban forest change also highlights that to increase equity in Toronto's urban forest going forward there need to be changes made to the way urban forest development takes place in Toronto. Locations of frequent inequitable clustering of the urban forest and its change were seen predominantly in Scarborough and along the northern boundary of Toronto, indicating that these areas are likely good candidates for some form of urban forest development prioritization.

With respect to some of the insignificant relationships observed between urban forest change and marginalization, it is important to remember that just because marginalization was not observed to be a driver of urban forest change or inequity in Toronto, does not mean that the urban forest is becoming more equitable. These findings come at an ideal time because Toronto's current urban forest management plan is coming to an end. This presents the City of Toronto with the opportunity to use existing research on the equity of its urban forest to implement measures that address these gaps in its municipal planning and increase access to the urban forest for those that would benefit from it the most. Studies like this can be used again in 2028 and subsequent decades as Toronto's urban forest continues to be studied and surveyed to monitor the progress that is being made towards a more equitable urban forest. So long as cities, Toronto and others, root their urban forest management in research and community engagement, it should be possible for them to begin to increase the equity of their urban forests.

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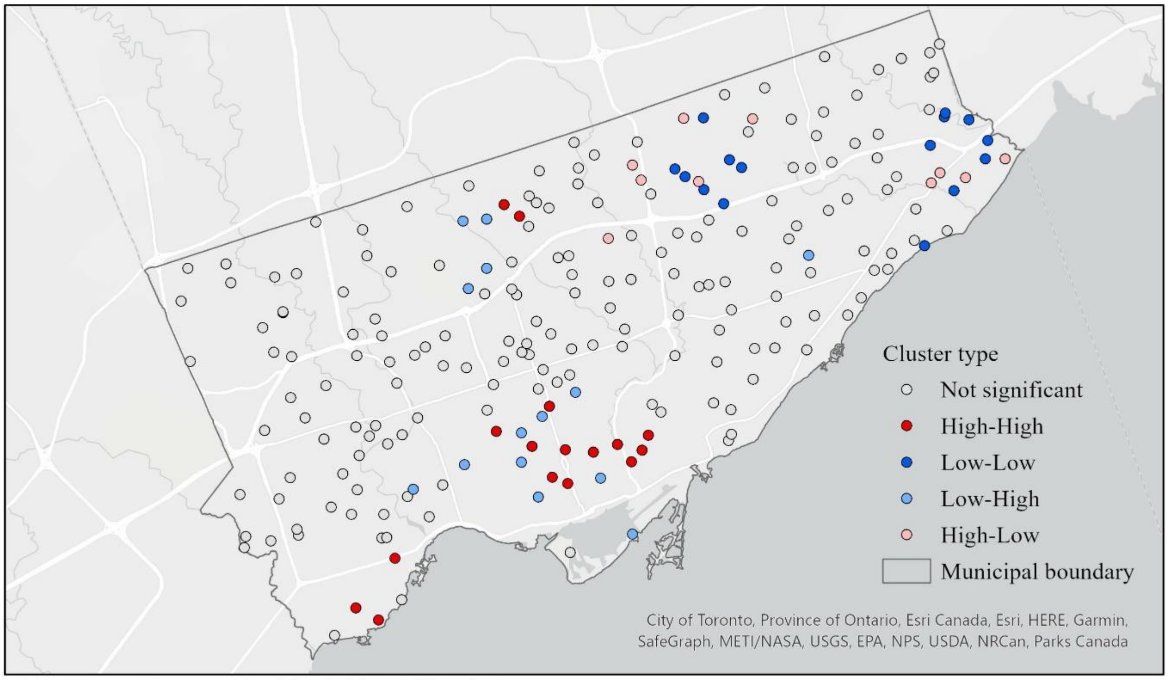
Appendices

Appendix A: Spatial structure of linear regression models

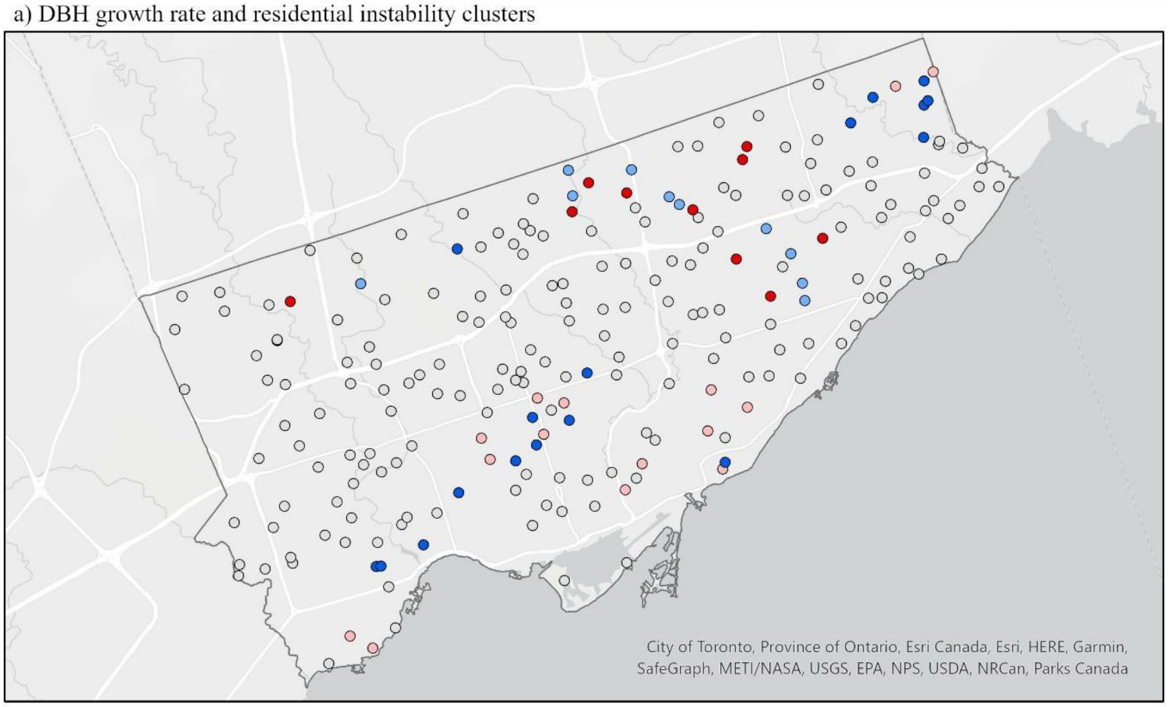
Table 9 Spatial structure diagnostics for multiple linear regression models for basal area per hectare and stems per hectare of Toronto's urban forest using the four indicators of marginalization as independent variables.

Variables	Moran's I		Lagrange Multiplier (lag)		Lagrange Multiplier (error)	
	Value	p-value	Value	p-value	Value	p-value
Basal area per hectare	0.28	0.779	0.04	0.845	0.01	0.924
Stems per hectare	0.33	0.741	0.17	0.678	0.02	0.888

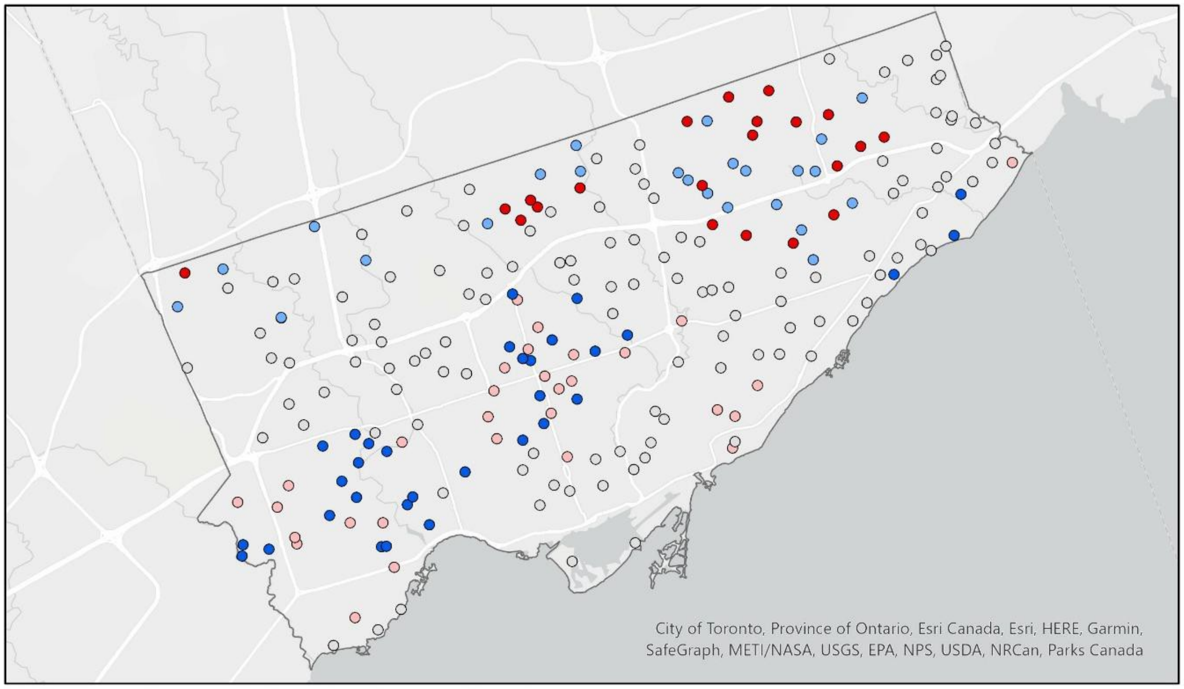
Appendix B: Maps



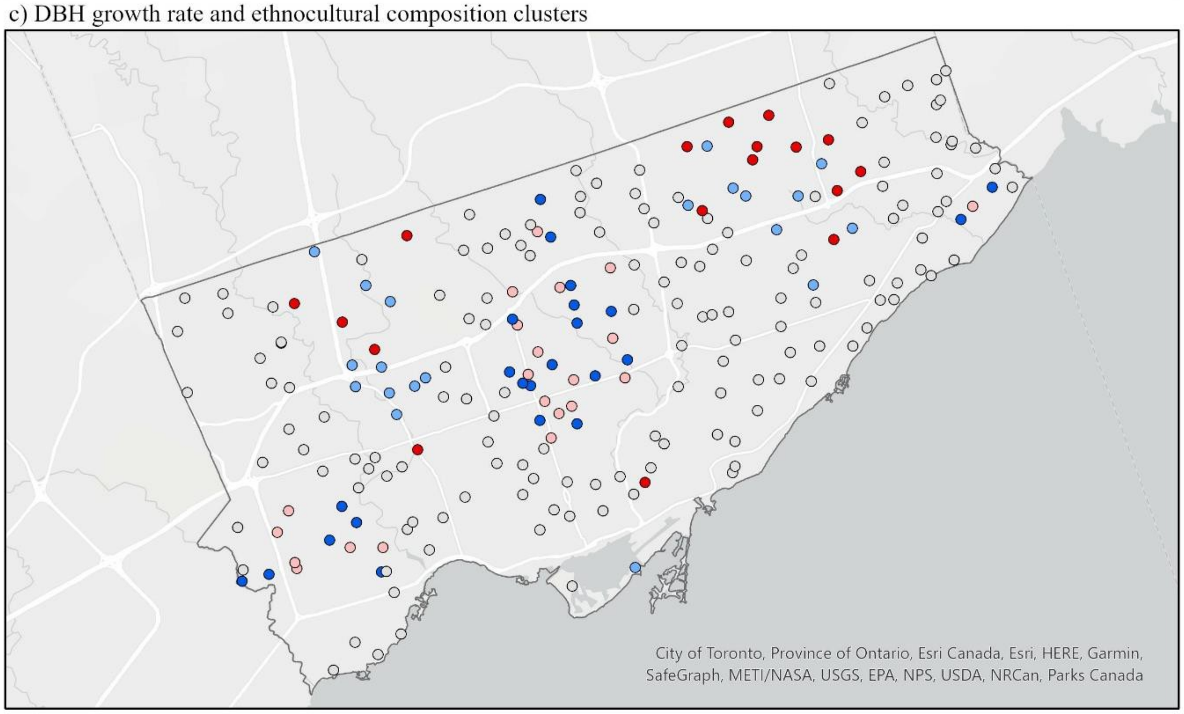
a) DBH growth rate and residential instability clusters



b) DBH growth rate and economic dependency clusters



c) DBH growth rate and ethnocultural composition clusters



d) DBH growth rate and situational vulnerability clusters

Data source: City of Toronto, 2008; City of Toronto, 2018;
City of Toronto, 2019; Statistics Canada, 2019
Spatial reference: NAD 1983 UTM Zone 17N

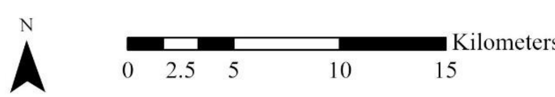
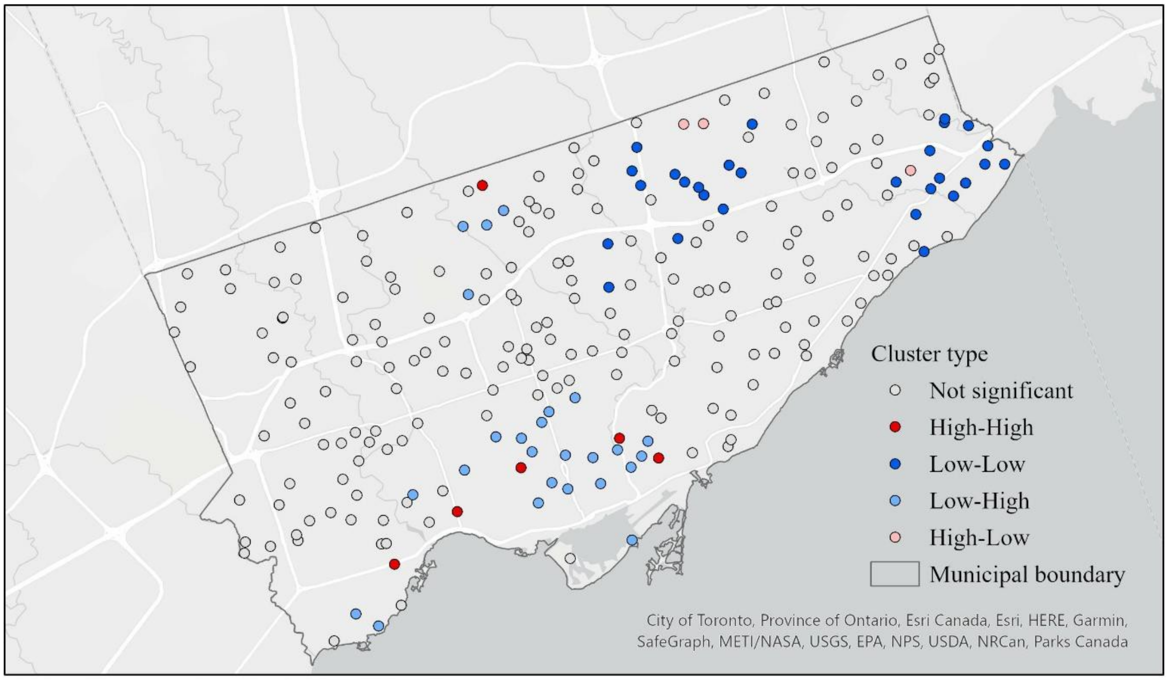
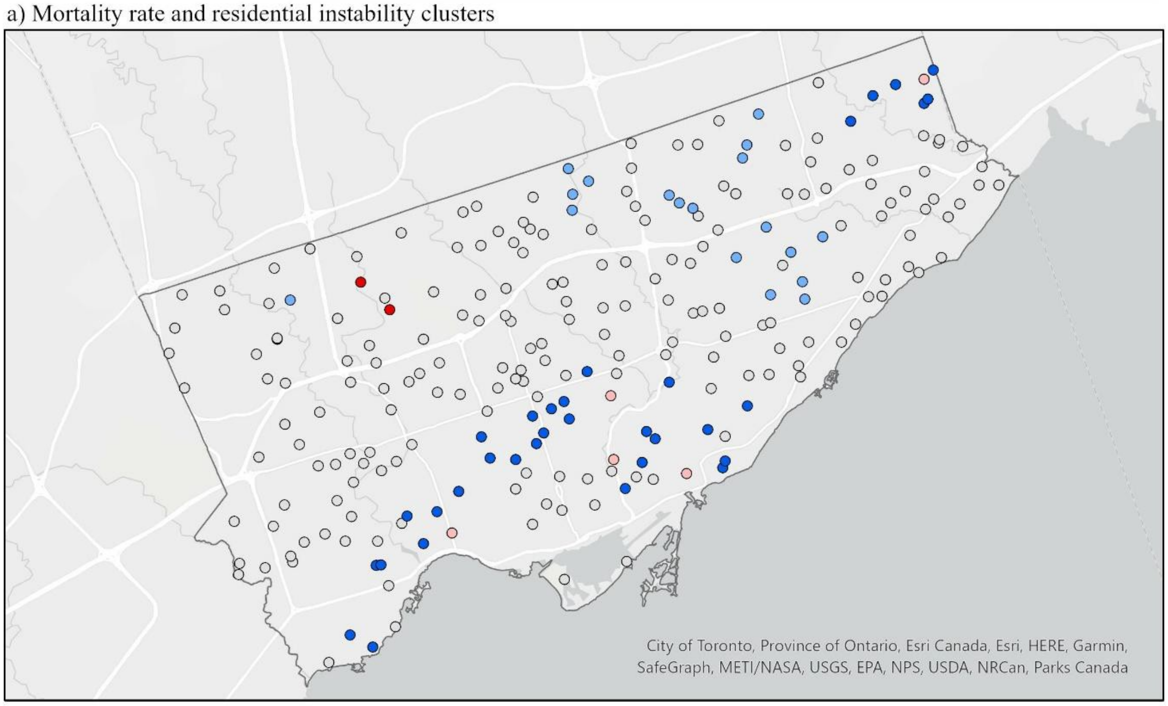


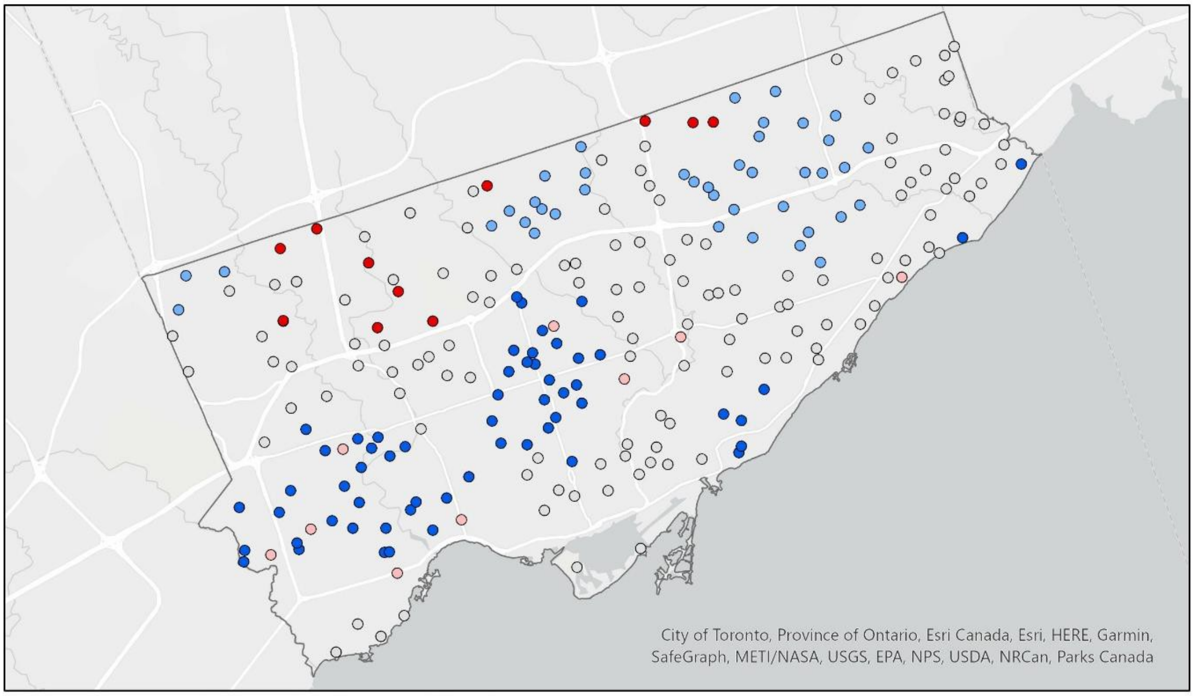
Figure 6 Local Bivariate Moran's I cluster analysis outputs for the diameter growth rate of plots across Toronto's urban forest and the corresponding indicators of marginalization, where low-high outputs are most indicative of inequity.



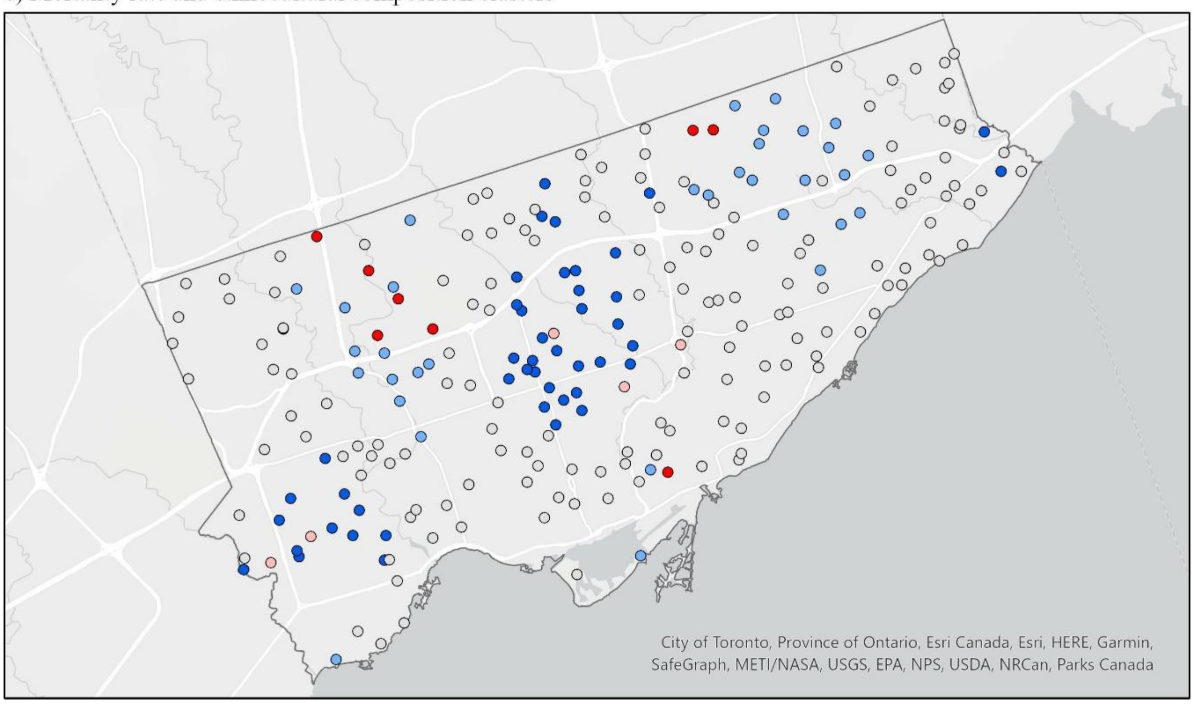
a) Mortality rate and residential instability clusters



b) Mortality rate and economic dependency clusters



c) Mortality rate and ethnocultural composition clusters



d) Mortality rate and situational vulnerability clusters

Data source: City of Toronto, 2008; City of Toronto, 2018;
City of Toronto, 2019; Statistics Canada, 2019
Spatial reference: NAD 1983 UTM Zone 17N

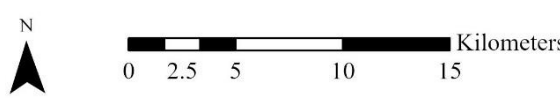
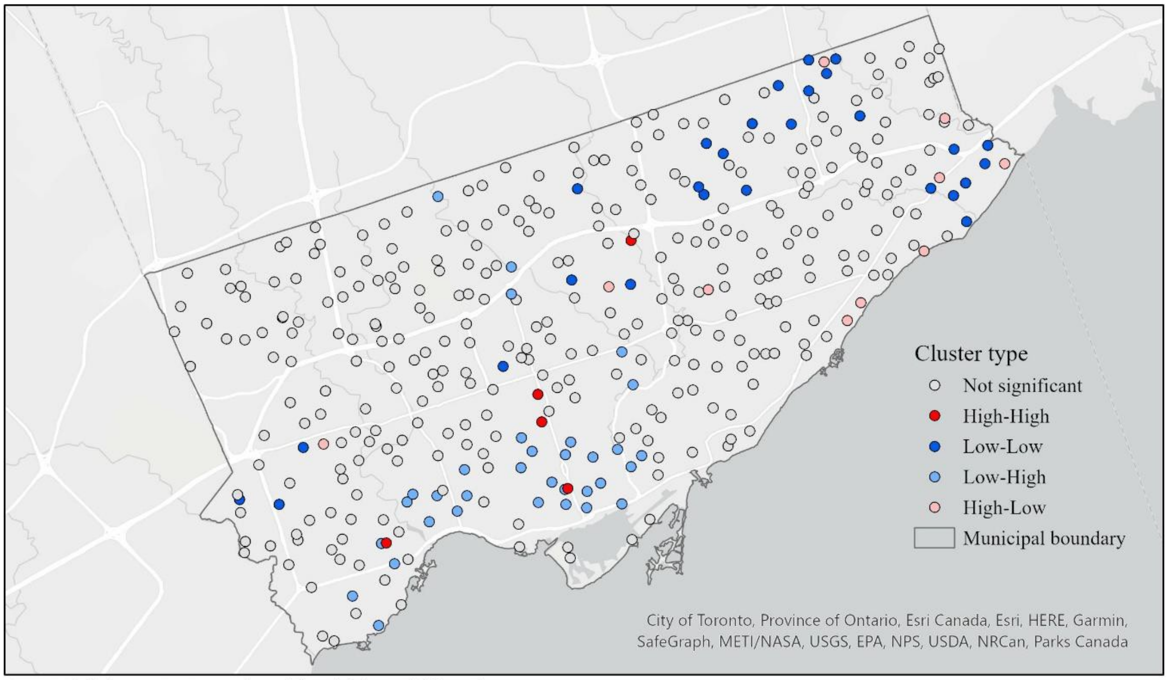
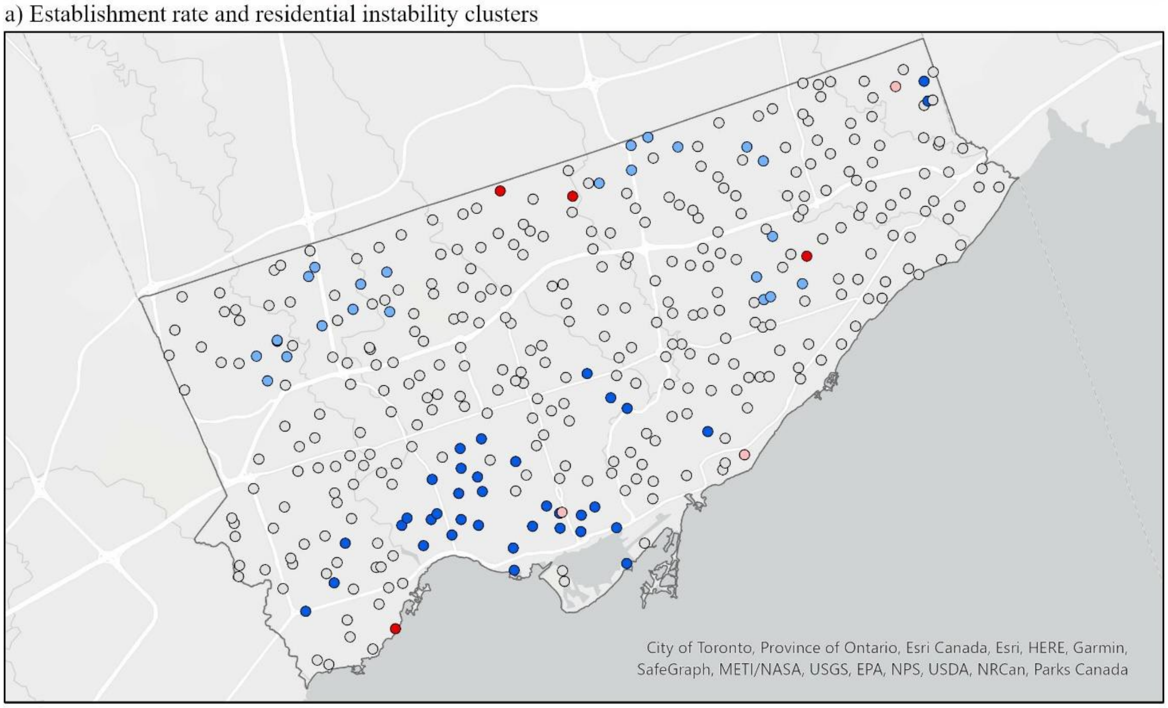


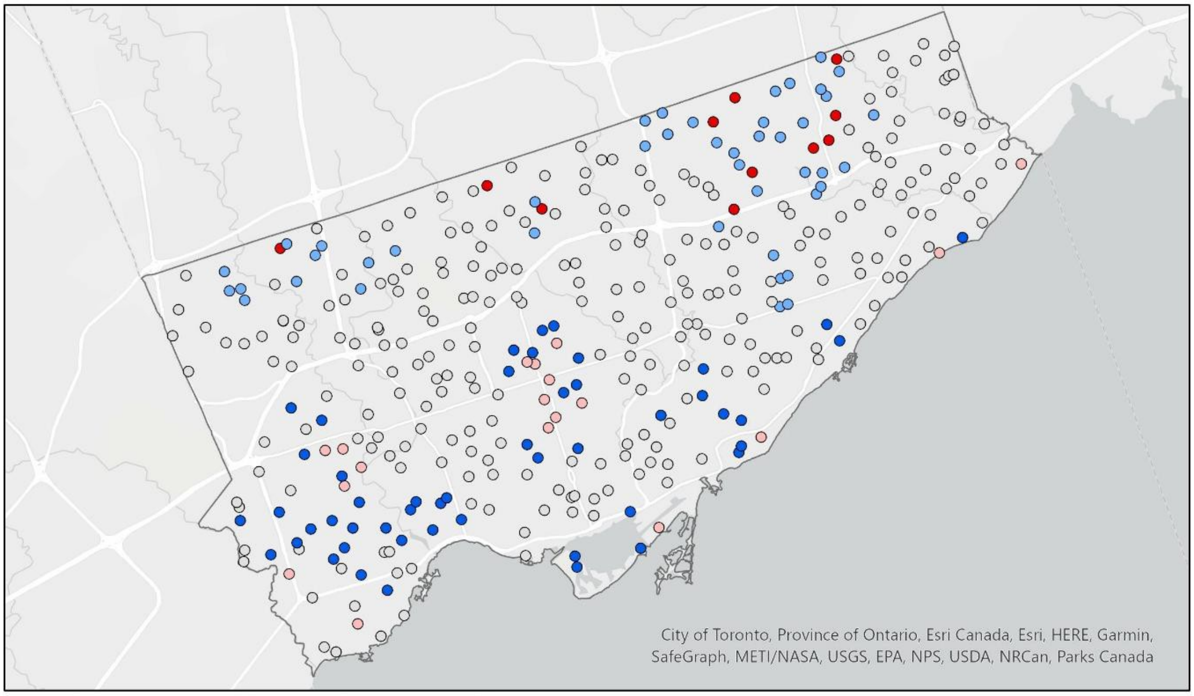
Figure 7 Local Bivariate Moran’s I cluster analysis outputs for the mortality rate of plots across Toronto’s urban forest and the corresponding indicators of marginalization, where high-high outputs are most indicative of inequity.



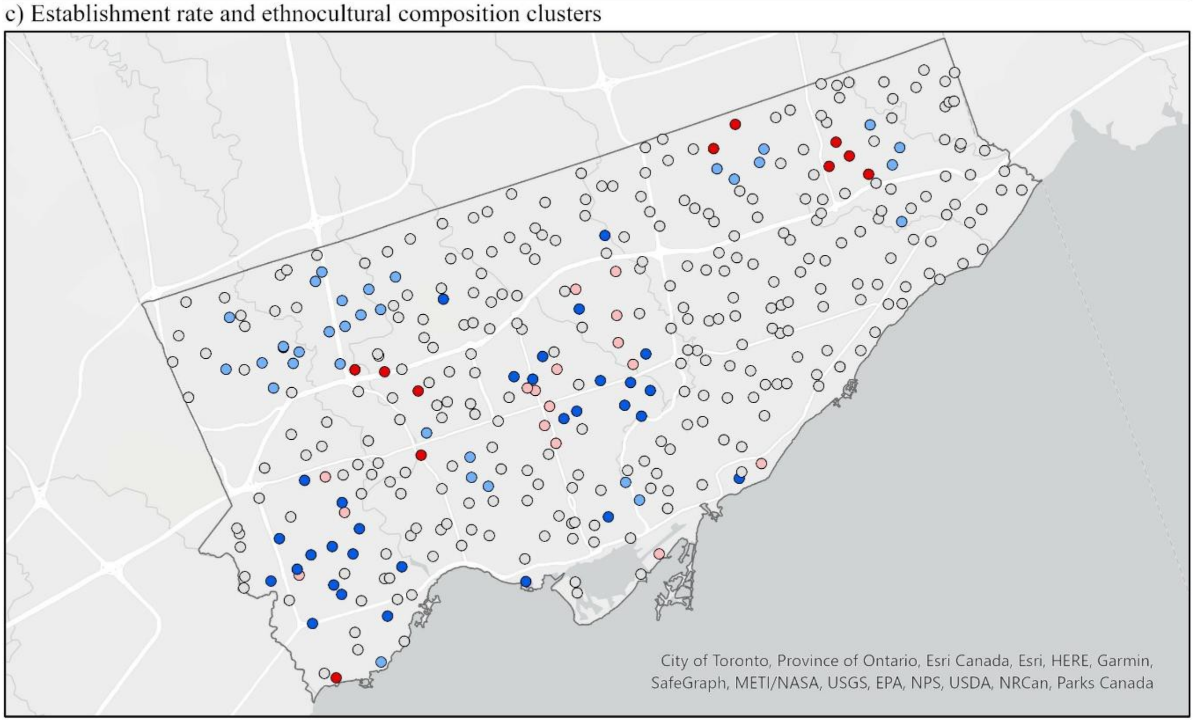
a) Establishment rate and residential instability clusters



b) Establishment rate and economic dependency clusters



c) Establishment rate and ethnocultural composition clusters



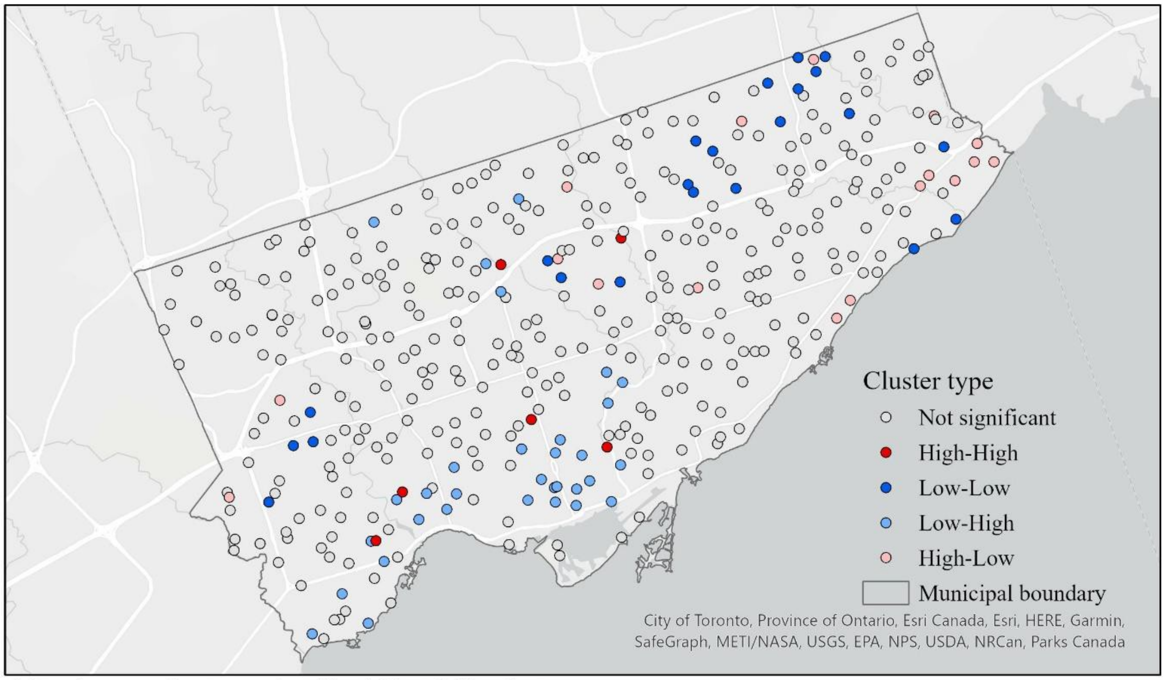
d) Establishment rate and situational vulnerability clusters

Data source: City of Toronto, 2008; City of Toronto, 2018; City of Toronto, 2019; Statistics Canada, 2019
Spatial reference: NAD 1983 UTM Zone 17N

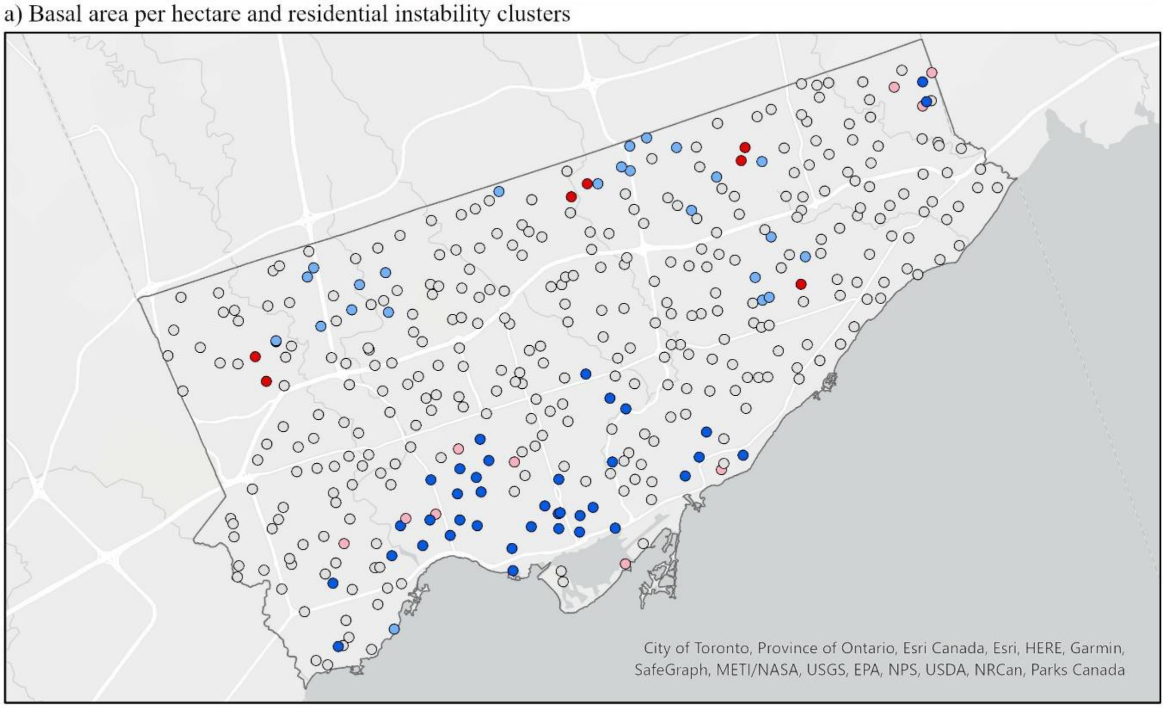
N

Kilometers
0 2.5 5 10 15

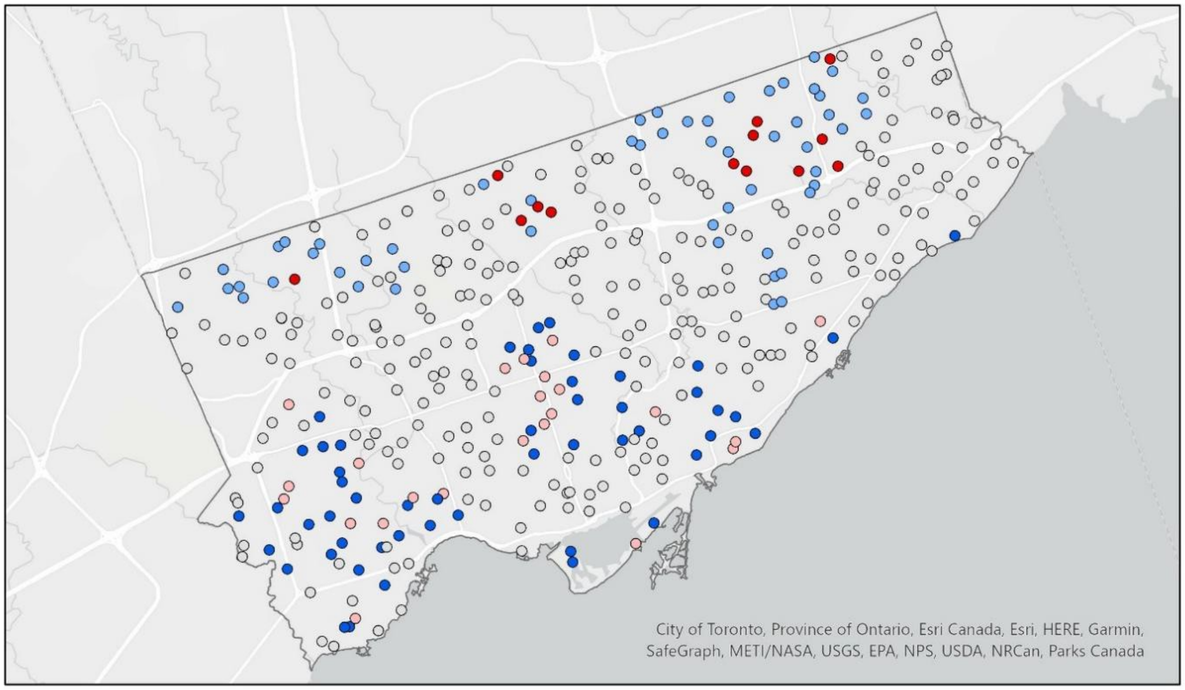
Figure 8 Local Bivariate Moran’s I cluster analysis outputs for the establishment rate of plots across Toronto’s urban forest and the corresponding indicators of marginalization, where low-high outputs are most indicative of marginalization.



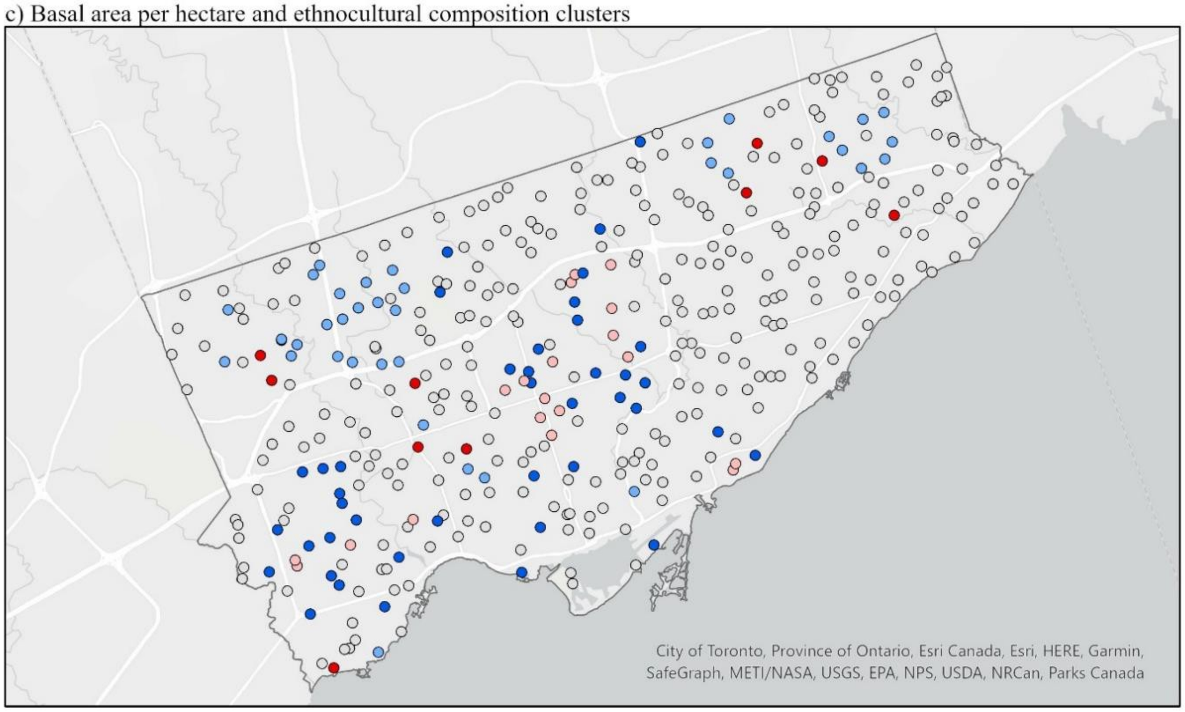
a) Basal area per hectare and residential instability clusters



b) Basal area per hectare and economic dependency clusters



c) Basal area per hectare and ethnocultural composition clusters



d) Basal area per hectare and situational vulnerability clusters

Data source: City of Toronto, 2018;
City of Toronto, 2019; Statistics Canada, 2019
Spatial reference: NAD 1983 UTM Zone 17N

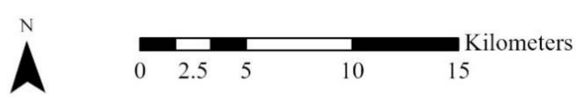
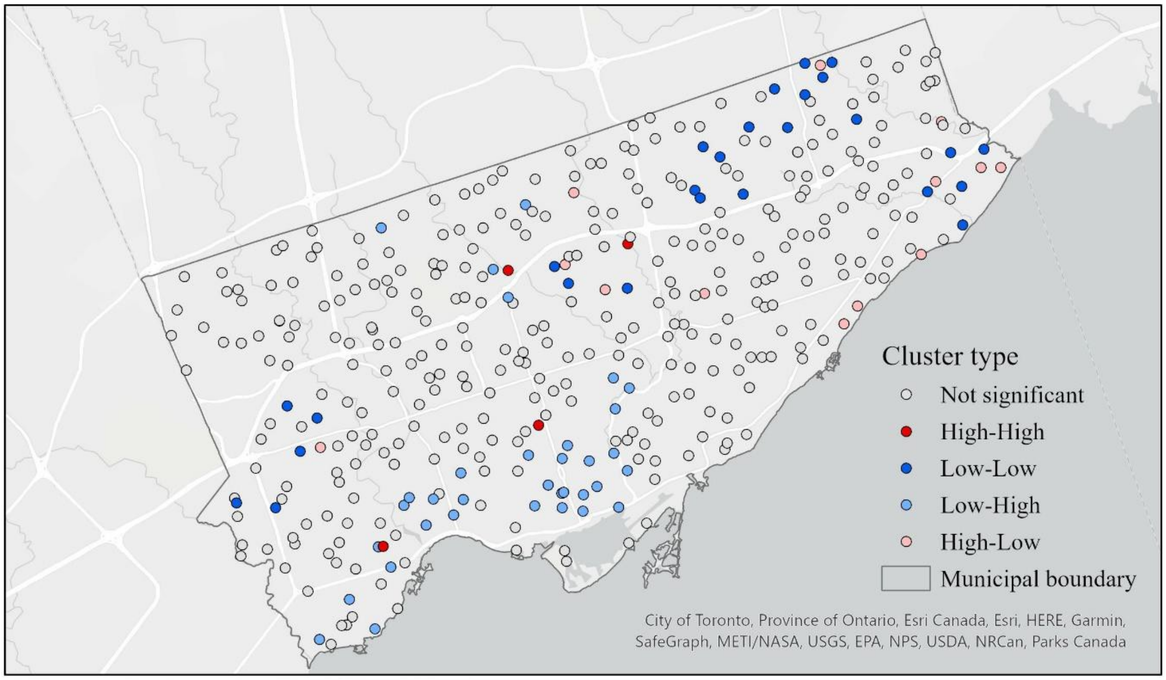
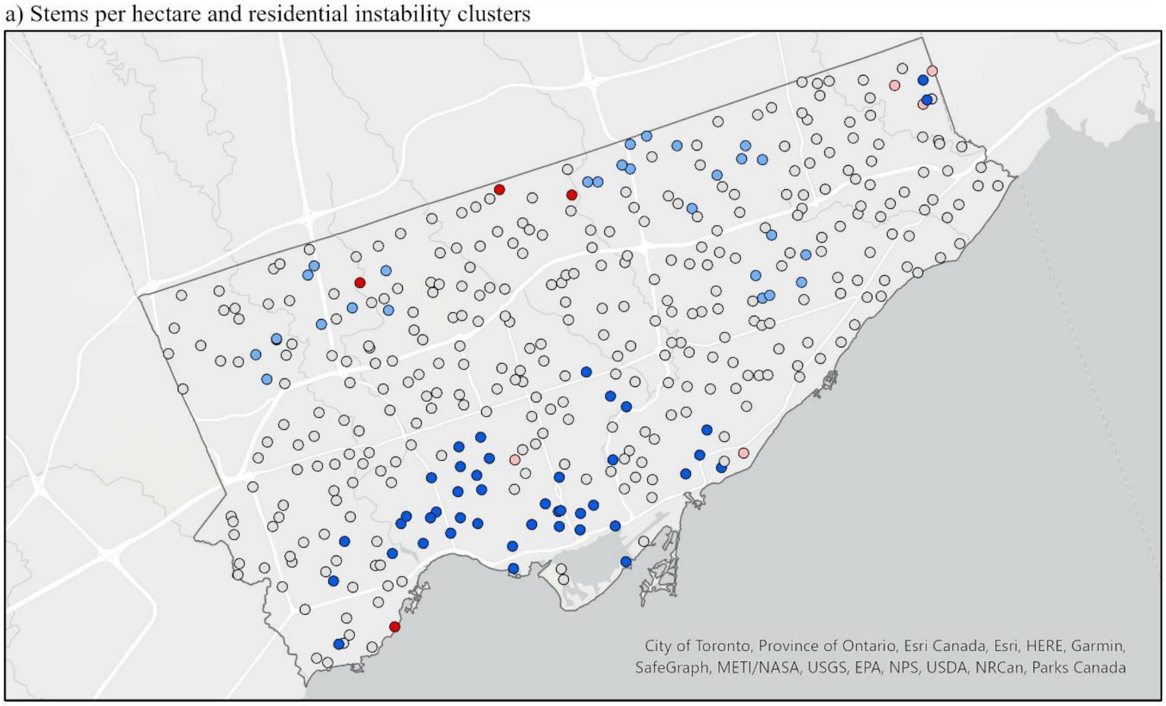


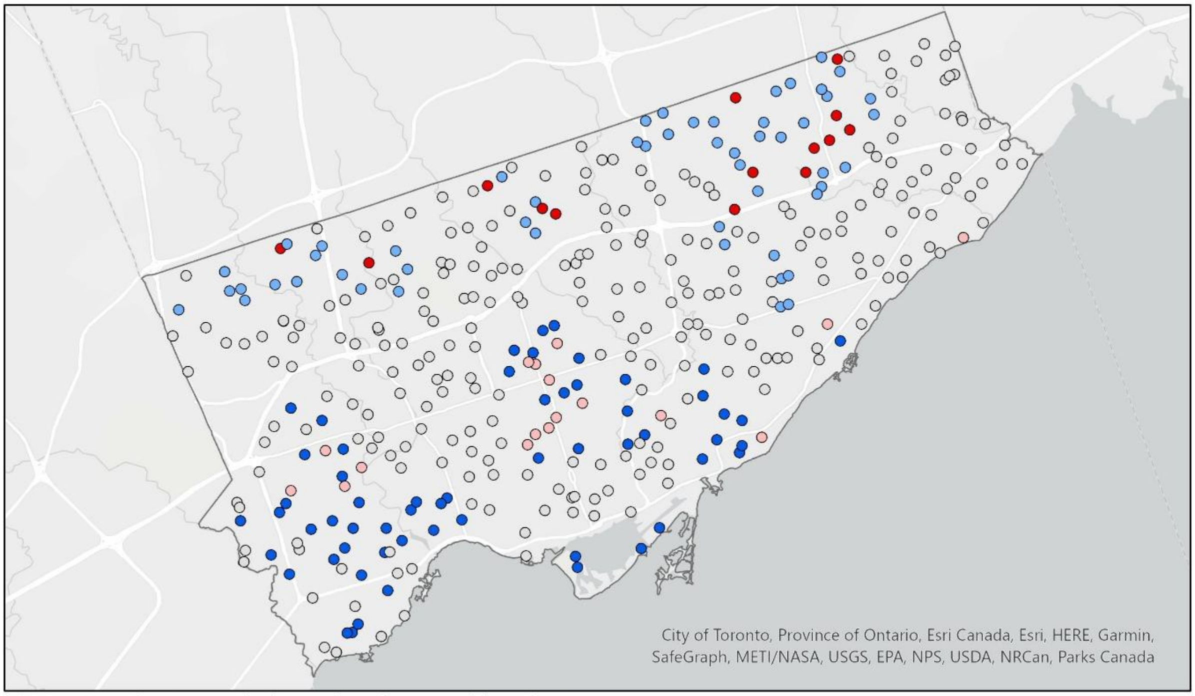
Figure 9 Local Bivariate Moran's I cluster analysis outputs for the basal area per hectare of plots across Toronto's urban forest and the corresponding indicators of marginalization, where low-high outputs are most indicative of marginalization.



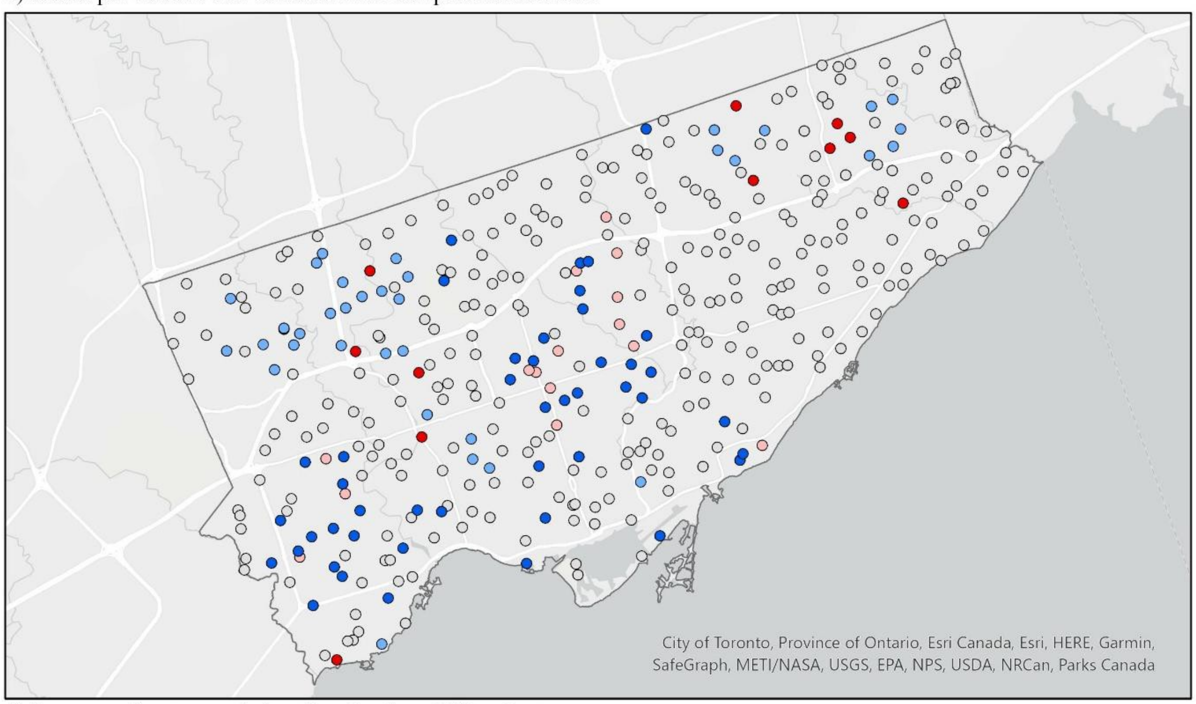
a) Stems per hectare and residential instability clusters



b) Stems per hectare and economic dependency clusters



c) Stems per hectare and ethnocultural composition clusters



d) Stems per hectare and situational vulnerability clusters

Data source: City of Toronto, 2018;
City of Toronto, 2019; Statistics Canada, 2019
Spatial reference: NAD 1983 UTM Zone 17N

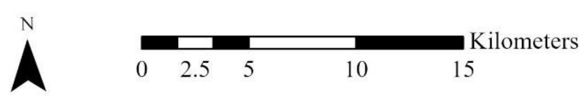


Figure 10 Local Bivariate Moran's I cluster analysis outputs for the stems per hectare of plots across Toronto's urban forest and the corresponding indicators of marginalization, where low-high values are most indicative of marginalization.

Appendix C: Statistical results of exploratory data analysis

Table 10 Spearman's rho and p-values for rates of urban forest change in residential land uses and indicators of marginalization in Toronto.

Independent variable	**Diameter growth rate**		**Mortality rate**		**Establishment rate**	
	Spearman's rho	p-value	Spearman's rho	p-value	Spearman's rho	p-value
Residential instability	0.15	0.063	0.03	0.701	-0.04	0.605
Economic dependency	0.07	0.431	-0.02	0.853	0.00	0.959
Ethnocultural composition	0.13	0.120	-0.12	0.143	-0.09	0.286
Situational vulnerability	-0.03	0.732	-0.02	0.780	-0.05	0.551

Table 11 Multiple linear regression analysis of diameter at breast height growth rate (DBH), mortality rate, and establishment rate of the urban forest in residential land uses by the four indicators of marginalization, in Toronto.

Independent variable	**Diameter growth rate**		**Mortality rate**		**Establishment rate**	
	ß	p-value	ß	p-value	ß	p-value
Residential instability	0.07	0.258	0.03	0.076	0.31	0.841
Economic dependency	0.02	0.852	0.01	0.625	1.55	0.446
Ethnocultural composition	0.08	0.203	-0.02	0.26	-1.05	0.521
Situational vulnerability	-0.12	0.220	0.02	0.514	-1.06	0.679
R^2	0.02	0.487	0.03	0.357	0.01	0.859

Table 12 Spearman's rho and p-values for rates of urban forest establishment rates and indicators of marginalization, in Toronto.

	Establishment rate	
	Spearman's rho	p-value
Residential instability	-0.93	0.393
Economic dependency	-0.56	0.634
Ethnocultural composition	0.95	0.445
Situational vulnerability	-0.98	0.576
Stems per hectare 2008	**0.03**	< 0.001
R^2	**0.14**	< 0.001