

# SOCIO-SPATIAL DISPARITIES IN URBAN GREEN SPACE ACCESSIBILITY: THE EXISTING CHALLENGE FOR TORONTO IN ITS ASPIRATION TO BE A LIVEABLE CITY

Ziyue 'Davia' Dong, Eric J. Miller

**Ziyue 'Davia' Dong**, MScEng (Corresponding author)  
Department of Civil and Mineral Engineering  
University of Toronto, Toronto, ON, Canada M5S 1A4  
[zy.dong@mail.utoronto.ca](mailto:zy.dong@mail.utoronto.ca)

**Eric J. Miller**, PhD  
Department of Civil and Mineral Engineering  
University of Toronto, Toronto, ON, Canada M5S 1A4  
[eric.miller@utoronto.ca](mailto:eric.miller@utoronto.ca)

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**Abstract:** Toronto, a thriving multicultural metropolis, aspires to create an inclusive and livable urban environment meeting diverse resident needs. However, challenges arise due to the uneven distribution of urban green spaces. This study employs a gravity model and Gaussian-based 2SFCA model to assess green space accessibility in Toronto's dissemination areas. A Gini index and local bivariate Moran's I illuminate socio-spatial disparities, while Geographically Weighted Regression unveils economic inequalities by correlating green space accessibility with housing prices and their five-year growth. Findings expose stark environmental inequity, with the bottom 20% accessing a mere 7% of spaces and the top 20% enjoying 40%. City center and low-income peri-central areas exhibit pronounced disparities, driven by limited green spaces and intense competition. In flourishing, dense areas, residents pay more for increased green space share, while less-dense areas with ample green spaces see higher housing prices where accessibility prevails. Neighborhoods with abundant green spaces and amenities, notably special school programs, attract families, correlating housing price growth with green space accessibility. Considering diverse district development phases and priorities and potential conflicts, tailored strategies for equitable green space systems are recommended citywide.

**Keywords:** Environmental justice; Urban green space accessibility; Socio-spatial disparities; Gaussian-based 2SFCA; Geographically weighted regression

## INTRODUCTION

Urban green spaces are critical infrastructure in cities given their essential role in promoting cities' livability and city dwellers' wellbeing (Parker and Simpson, 2018). They can encourage social interactions, foster social inclusion, stimulate innovation, and potentially alleviate depression and enhance self-awareness (Maurer et al., 2021; Wood et al., 2017; Tzoulas et al., 2007). The onset of COVID-19 in 2020 and subsequent social distancing regulations remarkably impacted outdoor activities, leading people to seek more recreation in open and green spaces instead of indoor leisure facilities such as cinemas and recreational centres (Yap et al., 2022; Ueno et al., 2022). The pandemic's lasting impact on people's recreation attitudes and behaviours remains uncertain (Kim et al., 2022; Senetra and Szczepańska, 2022). Nevertheless, what has been observed is that green spaces have been increasingly valued and people's demand for recreation in green spaces has been increasing (Pröbstl-Haider et al., 2023; Bristowe & Heckert, 2023; Ugolini et al., 2020).

Many cities, however, experience non-negligible gaps between green space demand and supply and socio-spatial disparities in green space accessibility (Buckland & Pojani, 2023; Pearsall & Eller, 2020; Chen et al., 2020). For example, Chen et al. (2020) found spatial inequality of green space access among communities in Shanghai. Wealthier communities in the central city have better access to green spaces compared to disadvantaged communities. Similarly, in Europe, Buckland & Pojani (2023) found that discrepancies in urban green space accessibility are related to income inequalities. However, whether high- or low-income communities have better accessibility varies based on the regional location of the cities.

Bridging the gap between green space provision and demand is complex, as solely adding more green spaces can trigger unintended consequences such as green gentrification. This phenomenon occurs when economically disadvantaged areas undergo transformations due to increased access to green spaces and improved living environment. The improvements make the areas more desirable and attract middle- or high-income residents whose influx lifts property values, leading to the transformation from once-affordable neighbourhoods into high-priced communities. Consequently, low-income urban dwellers are ineluctably excluded from these areas (Anguelovski et al., 2022; Jelks et al., 2021; Rigolon & Németh, 2020; Pearsall & Eller, 2020). Hence, the way to improve green space accessibility and enhance its equality is never straightforward. Without comprehensive assessments and proactive designs, a seemingly promising strategy may trigger a chain reaction of social and spatial impacts.

As North America's fourth largest city, Toronto is home to almost 3 million people with diverse ethnic and cultural backgrounds. Despite the fact that Toronto is attractive and leading in various domains, including business, technology, entertainment, and culture, residents' complaints of not having enough access to green spaces are also notable (City of Toronto, 2019a). The distribution of natural green spaces is not uniform within the city, with areas of highest population density having the least green spaces. The escalating demand for land for residential and commercial development is resulting in a severe scarcity of available land for green space development. The challenge Toronto is facing may be increasingly severe post-pandemic, as residents' demand for green spaces is likely to surpass the pre-pandemic level and may also require additional functionalities, which would all call for new strategies.

To facilitate evidence-based policy making on how to prioritize green space development given limited resources to promote city livability, this study investigates the existing social, spatial, and economic disparities in urban green space accessibility. The primary research goal is to identify environmental inequality in access to urban green space and then inform customized policy making. Specifically, the

study seeks to address the following questions: Do Toronto residents have equal access to urban green spaces? How does environmental inequality exist within the population across different neighbourhoods? What strategies could be implemented to reduce the inequality, e.g., prioritizing green space area or green space share? The analyses will aid in prioritizing neighbourhoods for green space redevelopment, customizing designs based on neighbourhood profiles, understanding the synergy between green space development and housing price, thereby facilitating intervention programs or providing complementary amenities. Ultimately, this study is expected to contribute to decision-making efforts for social inclusion, complete communities, and enhancement of urban livability.

The paper is organized as follows. Section 2 provides a literature review pertaining to environmental inequality in green space accessibility. Section 3 introduces the data and methods employed for the analysis. Section 4 presents research findings, with a particular focus on three key dimensions of environmental inequality: spatial, social, and economic disparities. Lastly, Section 5 concludes and discusses limitations and implications of the study and provides potential avenues for future research.

## LITERATURE REVIEW

Green space and urban forestry development have long been prescribed in land use designations and planning schemes, where the value of green space is not fully recognized or is sacrificed when competing with alternative land uses such as commercial and residential uses. This results in a mismatch between population growth, economic development and environmental development in the urbanization process. Environmental benefits are gathering increasing attention in recent decades and residents now place a higher value on greenspaces in the residential built environment. However, due to the limited natural green resources and scarce green space designated in the planning process, green space is available and accessible to only some but not to others. This creates inequality in urban green space accessibility which raises an issue of environmental justice. The concept of environmental justice, originating from anti-toxics and civil rights activism in the US in the last century, is defined based on the principle in contemporary environmentalism that "all people have a right to be protected from environmental pollution and to live in and enjoy a clean and healthful environment." The principle calls for proactive environment justice policies that ensure equitable distribution of environmental benefits socially and spatially, such as urban green spaces (Vaz et al., 2017; Walker, 2012; Agyeman & Evans, 2004).

The assessment of environmental justice in urban green space distribution and access often involves spatial analysis, examining where green spaces are located and the characteristics of the surrounding population (Walker, 2012). Accessibility is commonly measured through simple metrics (e.g., shortest distance, coverage), spatial interaction models (e.g., gravity-based model), and random utility-based models (Macfarlane et al., 2022; Wang et al., 2021; Geurs & van Wee, 2004; Miller, 2018; Ben-Akiva & Lerman, 1985). The general principle is that closer green spaces are more accessible and larger green spaces are more attractive. Approaches such as the Two-step Floating Catchment Area (2SFCA) also consider resource capacity and demand competition in measuring accessibility (Li et al., 2021; Wen et al., 2020; Ye et al., 2018; Dony et al., 2015; Dai, 2011; Delamater, 2013; Luo & Qi, 2009; Luo & Wang, 2003). Population characteristics studied in environmental justice research commonly include age, race, and income. Housing price, as another indicator of dwellers' economic status, is also included in some research (Chen et al., 2020; Park et al., 2017; Yasumoto et al., 2014). This represents the required affordability of inhabitants to acquire the desired green environment.

Environmental inequality in urban green space distribution and accessibility has been studied in many cities worldwide. The research foci and findings, however, have both commonalities and differences. Studies in a range of large cities such as Los Angeles, Melbourne, and Shanghai show that affluent neighbourhoods generally have better access to public green spaces compared to disadvantaged neighbourhoods (Chen et al., 2020; Astell-Burt et al., 2014; Wolch et al., 2005). However, this trend may not hold true in the UK, as studies from Sheffield and Birmingham indicate that low-income communities have better public green space accessibility, with the fact that affluent neighbourhoods own more private garden spaces (Buckland & Pojani, 2023; Barbosa et al., 2007). There are also studies suggesting that green space spatial distribution is uneven and social inequality is not systematic, as seen in New York and London, Ontario, Canada (Maroko et al., 2009; Gilliland et al., 2006). These variations in findings can be attributed to multiple factors, such as historical urban development patterns, urbanization status, social profiles, political and cultural backgrounds, emphasizing the need for localized environmental justice studies and policymaking that evolve with demographic changes and urbanization process.

Despite extensive research of green space accessibility, there remains a paucity of studies on comparing total green space area and green space share (green space area per capita) in accessibility disparity measures. In addition, this study also incorporates housing price and its increase rate over the latest two census years in evaluating the value of green space area and green space share to provide insights into the diverse needs or the priorities for green space resources in different neighbourhoods. Understanding housing price trends can shed light on economic pressures in pursuing environmental benefits and relate them to potential demographic changes. Besides, given the unique cultural diversity in Toronto, exploring socio-economic characteristics including migrants, generations, temporal residents, and housing stability, and their correlation to green space accessibility if of particular interest in the local context.

## DATA AND METHODS

### Study area

The study area is the City of Toronto. Green space data are obtained from the City of Toronto Open Data Portal. To inform urban green space strategies, green spaces in this research only include the green spaces in the Toronto's parkland system, which comprises over 3,600 hectares of City-owned and operated green parkland, and over 4,400 hectares of Toronto and Region Conservation Authority (TRCA) owned green parkland that is operated and maintained by the City. Other green spaces or open spaces such as cemeteries, hydro lines, civic squares and privately owned green spaces are excluded from the analysis.

Census data including socioeconomic and housing price statistics at the Dissemination Area (DA) level in 2021 are obtained from Censuumapper.ca, while the original data source is 2021 Census of Population file from Statistics Canada. This study chooses the DA as the primary unit of analysis as it is the smallest areal unit where socioeconomic statistics are available. There are 3743 dissemination areas in total which are occupied by a total population of 2,794,356 individuals.

### Green space accessibility measures

The study applies two spatial interaction-based methods to measure urban green space accessibility: a gravity model and Gaussian-based 2SFCA considering three factors (i.e., green space attractiveness, travel impedance, and demand competition).

Firstly, people do not always go to the nearest green space if a more distant green space can better meet their needs, such as a larger green space area. Secondly, green space accessibility decreases as travel impedance increases, which means that the longer the distance or travel time, the lower the accessibility. These two factors rule out approaches which measure shortest distance or isochrone-based cumulative opportunities. A spatial interaction model (i.e., gravity-based model) fulfills the first two requirements, which, as shown below calculates the total area accessible to each DA within its demand catchment area (Dai, 2011; Luo & Wang, 2003) such that:

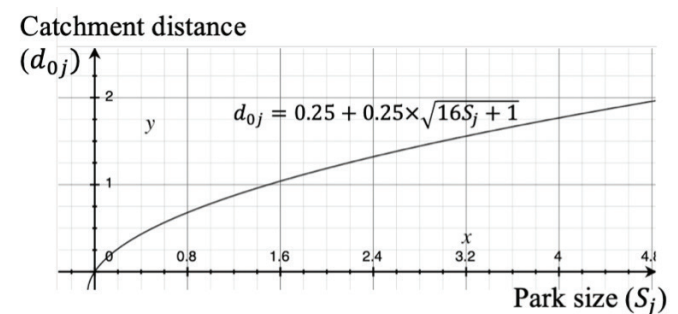
$$A_i = \sum_{j \in \{d_{ij} \leq d_{0j}\}} S_j \times G(d_{ij}, d_{0j}) \quad (1)$$

$$G(d_{ij}, d_{0j}) = \begin{cases} \frac{e^{-\left(\frac{1}{2}\right) \times \left(\frac{d_{ij}}{d_{0j}}\right)^2} - e^{-\left(\frac{1}{2}\right)}}{1 - e^{-\left(\frac{1}{2}\right)}}, & d_{ij} \leq d_{0j} \\ 0, & d_{ij} > d_{0j} \end{cases} \quad (2)$$

where  $A_i$  represents impedance-weighted green space supply for DA  $i$ ;  $S_j$  is the area of the urban green space  $j$  in square meters to represent its attractiveness and supply capability;  $G(d_{ij}, d_{0j})$  measures the travel impedance from DA  $i$  to green space  $j$  which depends on the network-based distance  $d_{ij}$ , and the catchment area of the urban green space  $d_{0j}$ . This study chooses Gaussian instead of negative square ( $d_{ij}^2$ ) as the relationship between travel impedance and travel distance, since when a green space is adjacent to a DA, the attractiveness should be as large as its area instead of infinite, and when a DA is out of the green space's catchment area, the attractiveness of the green space to the DA is zero. The Gaussian function perfectly fits these requirements by restricting the travel impedance within the range of 0 to 1 with the assumption that distance sensitivity is small on the two ends of the distance spectrum and increases towards the midpoint.

Green spaces' catchment areas vary depending on their size: a larger green space has a larger catchment area than a smaller one, i.e., individuals are willing to travel farther to a larger green space. The tradeoff between travel cost and green space attractiveness varies in different geospatial contexts. To be consistent with the Toronto Parkland Strategy, we determine green spaces' catchment areas based on the catchment-size table provided in the Parkland Strategy Final Report (City of Toronto, 2019b). For example, Queen's Park with greenspace of 5.4ha has a catchment distance of two kilometers, while High Park with a greenspace of 148.7ha has a catchment distance of twelve kilometers. We then convert the discrete datapoints into a continuous curve for the sake of accessibility calculation by curve fitting (FIGURE 1).

Figure 1. Catchment area versus green space size function





The gravity model measures total green space area accessible without considering the competition for resources. Given that the more crowded a green space gets, the less accessible it is for extra visitors, and the less probable that people will visit it, the third requirement of an ideal accessibility measure should be able to account for the demand competition in the face of limited supply. Note that this study deals with green space accessibility and demand for residents' daily needs. Special situations, such as people flocking to High Park during the cherry blossom season regardless of how crowded it is, are not considered herein.

Taking all conditions into account, one group of spatial interaction models, Enhanced-2SFCA models stand out. This study chooses Gaussian as the relationship between travel impedance and travel distance, so the resulting model used for accessibility measuring is the Gaussian-based 2SFCA (Wen et al., 2020; Ye et al., 2018; Delamater, 2013; Dai, 2011). This model measures accessibility as the impedance penalized supply versus impedance penalized demand, in short, impedance weighted green space areas per capita such that:

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \leq d_{0j}\}} P_k \times G(d_{kj}, d_{0j})}, \quad (3)$$

$$A_i = \sum_{j \in \{d_{ij} \leq d_{0j}\}} R_j \times G(d_{ij}, d_{0j}) \quad (4)$$

where  $R_j$  signifies demand-weighted supply of green space (i.e., green space areas per capita) by green space  $j$ ;  $P_k$  represents the population in DA  $k$ , indicating the potential total demand for green spaces from that area;  $A_i$  represents the impedance-weighted total green space share for each resident in DA  $i$ . Gaussian-based 2SFCA (Eq. 3, Eq. 4) extends an ordinary gravity model (Eq. 1, Eq. 2) by penalizing green space attractiveness,  $S_j$ , for considering potential demand competition,  $P_k$ , which is also distance inverted,  $G(d_{ij}, d_{0j})$ .

This study uses geographic centroids to represent DAs and green spaces and the cycling network to estimate travel time between DAs and green spaces using the R5py library (Fink et al., 2022). We choose geographic centroids instead of population weighted centroids of DA and green space access points (e.g., entrances) for the sake

of computation time, and also due to the lack of data at the time of the analysis. We choose the cycling network for evaluating green space accessibility for daily use within a moderate activity space. People are more likely to walk or bike to nearby green spaces for recreation in their daily lives, while auto modes are more commonly associated with longer distances and larger green spaces, which are often visited on weekends for different purposes and durations. Cycling rather than walking is chosen because cycling allows for a broader coverage and is also a popular choice for everyday recreation, while accessibility by walking may be more suitable for a specific walkability analysis.

### DA socio-economic profiles and principal factors

Eighteen variables are used to describe the social and economic profile of each DA (Table 1). All are measured by percentages except the median total income, which is measured by CAD dollars. DAs without complete data are excluded from analysis. As a result, 3268 dissemination areas are included in the disparity analysis.

In order to eliminate multicollinearity among explanatory variables and reduce the dimension for better profiling DAs, Principal Component Analysis (PCA) is conducted to extract factors from the eighteen variables. A varimax rotation is applied for the factor analysis to find a small number of important variables with high factor loadings (i.e., correlations between variables and factors) for each factor, while minimizing the factor loadings of the unimportant ones, which makes it easier to interpret the factors. In this study, four factors are selected based on the scree-plot, and they in total account for 63.5% of the total variance in the original data.

Based on the highlighted variables for each factor, the four factors could be labelled as "cultural assimilation", "socio-economic status", "housing stability", and "low child dependency" (Table 2). Factor 1 captures 20% of the original variation. For better interpretation, the sign of factor 1 is flipped and the factor is named "cultural assimilation" so that it is positively related to the length of residence in Canada and negatively associated with visible minorities. Factor 2 accounts for 19.1% of the original variation. The sign of factor 2 is flipped and the factor is named "socio-economic status", which has a higher value if income is high and lower value without bachelor and above degree. Factor 3 captures 15.9% of the total variance and is labelled

**Table 1.** Descriptive Analysis of Explanatory Variables

Dissemination Area (N= 3268)	Mean	STD	Min	Median	Max
More than one person per room (%)	0.05	0.07	0.00	0.02	0.61
First generation (%)	0.51	0.16	0.07	0.52	0.91
Immigrants 2011-2021 (%)	0.10	0.08	0.00	0.09	0.49
Third generation or more (%)	0.22	0.15	0.00	0.20	0.68
Spending 30% or more of income on shelter costs (%)	0.28	0.11	0.00	0.28	0.69
Age 0-14 (%)	0.14	0.05	0.01	0.14	0.35
Age 65 and over (%)	0.18	0.08	0.01	0.16	0.76
Main mode of commuting - Bicycle (%)	0.02	0.05	0.00	0.00	0.43
Main mode of commuting - Car, truck or van - as a driver (%)	0.55	0.16	0.00	0.56	0.95
Main mode of commuting - Public transit (%)	0.25	0.12	0.00	0.24	0.76
Main mode of commuting - Walking (%)	0.07	0.10	0.00	0.03	0.75
No high school diploma or equivalency certificate (%)	0.10	0.09	0.00	0.08	0.56
Employment insurance benefits recipients (%)	0.09	0.03	0.02	0.09	0.19
Income \$100k and over (%)	0.13	0.09	0.00	0.10	0.47
Renter (%)	0.40	0.28	0.00	0.34	1.00
Visible minority (%)	0.52	0.26	0.00	0.50	1.00
Median total income (\$)	41332.47	11237.34	22000.00	38000.00	90000.00
Income < \$20k (%)	0.22	0.05	0.08	0.21	0.44

Data Source: Statistics Canada. 2023. Census Profile. 2021 Census of Population.

**Table 2.** Factor Analysis Results

Input Variables	Factor 1	Factor 2	Factor 3	Factor 4
More than one person per room (%)	<b>0.543</b>	0.302	0.176	0.437
First generation (%)	<b>0.875</b>	0.397	0.026	-0.208
Immigrants 2011-2021 (%)	<b>0.758</b>	0.090	0.361	0.254
Third generation or more (%)	<b>-0.778</b>	-0.484	0.111	0.121
Spending 30% or more of income on shelter costs (%)	0.241	-0.026	<b>0.566</b>	-0.149
Age 0-14 (%)	-0.040	0.032	-0.331	<b>0.808</b>
Age 65 and over (%)	-0.003	-0.015	-0.288	<b>-0.516</b>
Main mode of commuting - Bicycle (%)	-0.350	-0.094	0.339	-0.076
Main mode of commuting - Car, truck or van - as a driver (%)	0.143	-0.004	<b>-0.911</b>	-0.037
Main mode of commuting - Public transit (%)	0.142	0.242	<b>0.550</b>	0.232
Main mode of commuting - Walking (%)	-0.172	-0.284	<b>0.585</b>	-0.165
No high school diploma or equivalency certificate (%)	0.148	<b>0.665</b>	-0.082	0.127
Employment insurance benefits recipients (%)	0.071	<b>0.581</b>	0.240	0.296
Income \$100k and over (%)	-0.441	<b>-0.854</b>	-0.054	0.038
Renter (%)	0.111	0.167	<b>0.717</b>	0.242
Visible minority (%)	<b>0.724</b>	0.475	-0.026	0.009
Median total income (\$)	-0.385	<b>-0.865</b>	-0.031	0.114
Income < \$20k (%)	0.452	<b>0.540</b>	-0.085	0.002
SS Loadings	3.602	3.444	2.869	1.519
Proportion Var	0.200	0.191	0.159	0.084
Cumulative Var	0.200	0.391	0.551	0.635

Note: Bolded are the variables mainly loaded into each factor.

"housing stability", after taking its opposite value. Housing stability increases when the proportion of house owners compared to renters increases and decreases if more people spend 30% or more of their income on dwelling costs. Commuting mode also significantly contributes to this factor. Given that commuting by public transit or walking have the same sign of loading as renter and shelter cost, while driving to commute has the opposite sign implies that people with housing stability tend to drive to work while people who walk or take public transit to work do not have enough housing stability. Factor 4 accounts for 8.4% of the total variance, and the major variable loaded to this factor is percentage of population under 15 years old. To align with the former three factors, we take the opposite sign of the factor and label it "low child dependency".

### Statistical methods for measuring disparities

Segregation and socio-spatial disparity are prevalent in large cities due to the inherent nature of urban development and economic activities. To facilitate interventions to balance social resources, various quantitative methods can be employed to assess the disparity first, such as statistical indices, bivariate correlation, and multivariate regression analysis.

#### Gini Index

To investigate green space accessibility disparity, we first use the Gini index to explore the degree of inequality in the distribution of green spaces within the population. The Gini index is a widely used statistical measure that quantifies the inequality of resource allocation (Guo et al., 2019; Lucas et al., 2016; Delbosc & Currie, 2011). A Gini coefficient of 0 reflects perfect equality, where all residents have the same access to urban green spaces, while a Gini coefficient of 1 reflects maximal inequality, i.e., a single individual having all the access to urban green spaces while all others have none. The higher the Gini index, the greater the gap between the green space accessibility of a city's green space-richest and green space-poorest DA.

The Gini index is mathematically derived from the Lorenz curve, which plots the cumulative accessibility for specified percentiles of the population. In a scenario of perfect equality, the Lorenz curve for-

ms a straight line connecting points (0,0) and (1,1). The Gini index is calculated as the ratio of the area between the Lorenz curve and the line of perfect equality to the area between the line of perfect equality and the line of perfect inequality, which is a horizontal line. The Lorenz curve reveals the proportion of social resources available to a specified percentage of population, while the Gini index indicates how the distribution deviates from complete equality (Gastwirth, 1972; Lorenz, 1905). The calculation of the Gini index in this study is based on the following formula:

$$Gini = 1 - \sum_{k=1}^n (X_k - X_{k-1})(Y_k + Y_{k-1}) \quad (5)$$

where  $Y_k$  is the cumulative percentage of rank-ordered green space accessibility for individual 1 to  $k$ ;  $X_k$  is the corresponding cumulative percentage of population of  $k$  individuals.

#### Bivariate Moran's I

To further explore green space accessibility disparity, we applied a local bivariate Moran's I statistics to examine the relationship between the population demographics of each DA and green space accessibility within its local neighbourhood. Bivariate correlation analysis such as Pearson correlation coefficients can assess global correlations between urban green space accessibility and socioeconomic characteristics, whereas local indicators of spatial association (LISA) such as local bivariate Moran's I index can examine spatially local correlations (Lee, 2001). These analyses enable the identification of disadvantaged population groups in terms of urban green space accessibility and investigate the spatial heterogeneity of correlations to identify regions with the most pronounced inequality. Local bivariate Moran's I statistics are given by:

$$I_{D,A} = Z_i^D \sum_{j=1}^N W_{ij} Z_j^A \quad (6)$$

where  $I_{D,A}$  refers to the Moran's I statistic measuring the correlation between a demographic factor (D) at DA ( $i$ ) and green space accessibility (A) at DA ( $i$ ) and its neighbourhoods ( $j$ );  $Z_i^D$  refers to the

standardized value of the demographic factor at DA ( $i$ );  $Z_j^A$  refers to the standardized value of green space accessibility at DA ( $j$ );  $W_{ij}$  refers to the row-standardized spatial weight matrix for evaluating the spatial correlation between DA ( $i$ ) and its neighbourhoods ( $j$ ). In this study, we apply a queen contiguity-based spatial weight matrix with its diagonal filled.

The resulting Moran's I statistic could identify four types of spatial correlations at the DA level: High-High refers to DAs with high demographic values situated in neighbourhoods with high green space accessibility; High-Low indicates DAs with high demographic values located in neighbourhoods with low green space accessibility; Low-High signifies DAs with low demographic value situated in neighbourhoods with high green space accessibility; and lastly, Low-Low represents DAs with low demographic value located in neighbourhoods with low green space accessibility. Permutations are set to calculate pseudo  $p$ -values in order to assess the statistical significance of the obtained statistic. In this study, a confidence level of 95% is set to determine the significance of the associations.

### Geographically weighted regression

In addition to socioeconomic characteristics, housing price represents another economic factor that could explain green space accessibility disparities (Park et al., 2017; Yasumoto et al., 2014). The relationship between green space accessibility and housing price could reflect the trade-offs individuals make when selecting residential locations, which may vary depending on individuals' socioeconomic characteristics. Given that housing price is usually impacted by numerous interconnected factors, multivariate regression models are more appropriate for estimating the effects of green space accessibility on housing price while controlling for other factors (Li et al., 2016). Ordinary Least Square (OLS) models are commonly used for estimating multivariate relationships when variables are normally distributed and the multivariate relationships are spatially homogeneous. Alternatively, spatial regression models, such as Geospatially Weighted Regression (GWR) models, are ideal for localized analysis in order to account for spatial heterogeneity in associations.

Taking housing price as the dependent variable, the study applies regression models to examine the effects of potential factors, including green space accessibility (i.e., accessible green space area and accessible green space area per capita), distance to Lake Ontario, population density, and four demographic factors on the housing price in 2021 and the increase rate from 2016 to 2021.

Unlike global regression models (e.g., ordinary least square), GWR is a spatial regression technique which handles spatial heterogeneity and analyzes spatially varying relationships by allowing regression coefficients to vary spatially. A general form of a basic GWR model is:

$$y_i = \beta_{i0} + \sum_{k=1}^m \beta_{ik} x_{ik} + \varepsilon_i \quad (7)$$

where  $y_i$  is the dependent variable (i.e., housing price) at DA  $i$ ;  $\beta_{i0}$  is the intercept for DA  $i$ ;  $x_{ik}$  is the  $k$ th independent variable for DA  $i$ ;  $m$  is the total number of independent variables;  $\beta_{ik}$  is the local regression coefficient of the  $k$ th independent variable for DA  $i$ ;  $\varepsilon_i$  is the random error at  $i$ .

Coefficients are location specific and are estimated based on the weight matrix, where nearby observations have more influence (i.e., weight) in estimating the local set of coefficients than observations farther away. The matrix expression of coefficient estimation by weighted least squares is as follows:

$$\hat{\beta}_i = (X^T W_i X)^{-1} W_i X^T y \quad (8)$$

The weight matrix is determined by the distance between the regression DA and its neighbours and the kernel bandwidth which specify the range of neighbours. The kernel function used to calculate the weight matrix in this study is Bisquare with the kernel bandwidth determined by searching for the optimal one based on AICc.

## RESULTS

### Green space accessibility

Figure 2 shows the spatial distribution of green space accessibility in Toronto measured by the Gaussian-based 2SFCA and depicts the imbalance of provision spatially. The values indicate how much green space area per capita can be reached by residents in each DA by bike. Being consistent with the color scheme used in the Parkland strategy (City of Toronto, 2019b), the study uses similar cutoff points for the bins to color label the accessibility. For reference, a 4-square-meter area is about a patio umbrella, a 12-square-meter is about a bus shelter, and a 28-square-meter area is about a mid-sized tree.

The results reveal a noticeable contrast in urban green space accessibility between the urban and the suburban area. The extensive red and orange areas, extending from downtown near the lake to midtown, signify areas facing significant shortage of green space resources. Conversely, the suburban areas and their surroundings, which are characterized by abundant natural green spaces and ra-

Figure 2. Green space accessibility in Toronto

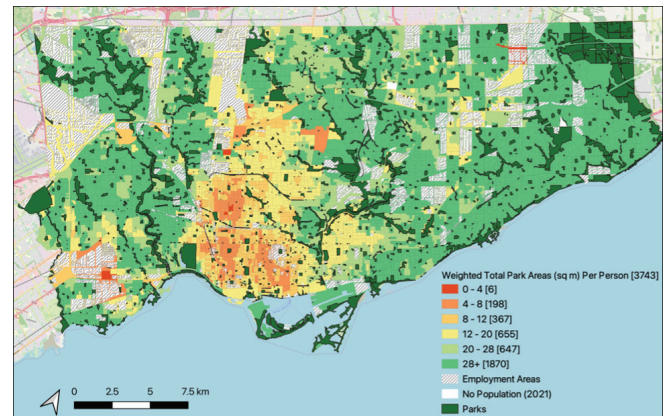
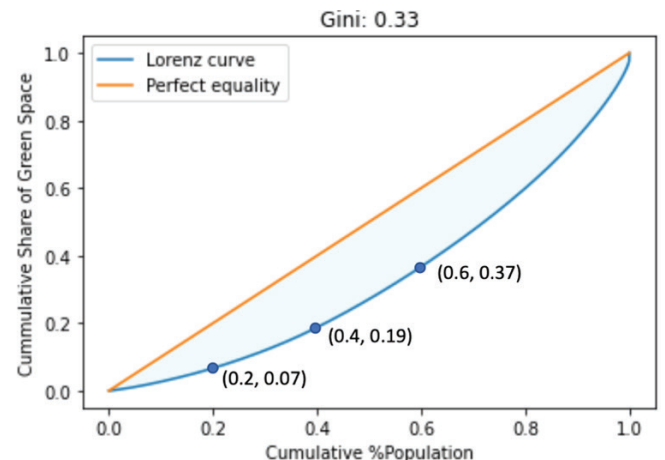


Figure 3. Gini index and Lorenz curve





vines, exhibit high levels of green space access. Additionally, it is important to note the presence of numerous small urban green spaces, both manmade and natural, in the central urban area. However, due to the high population density in proximity, the per capita allocation of green space area tends to be quite low.

### Green space accessibility disparity

To examine the unequal distribution of urban green spaces within the population, the study conducts an inequality analysis by plotting the Lorenz curve and computing the Gini index (Figure 3). The findings reveal that 60% of the population have access to only 37% of the available green space spaces. Furthermore, the top 20% of the population have access to 40% of the green space spaces, while the

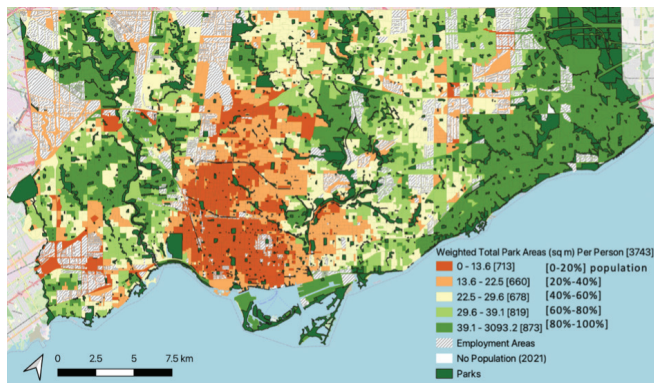
bottom 20% have access to only 7%. With a Gini index of 0.33, the results indicate an inequitable distribution of green space accessibility among residents of Toronto.

To visualize where the bottom 20% population and top 20% locate, the green space accessibility map is recolored by dividing the bins based on population quantiles. As shown in Figure 4, the bottom 20% population, which has the lowest share of urban green spaces, are concentrated in the central urban area and its surrounding regions extending to the west towards High Park and north through the midtown area. On the other hand, the top 20% population, with the highest share of urban green spaces, are predominantly located in the suburban areas, e.g., Scarborough and Etobicoke. The spatial pattern reflects the effect of two major factors that contribute to the level of green space accessibility: demand competition and accessible green space areas.

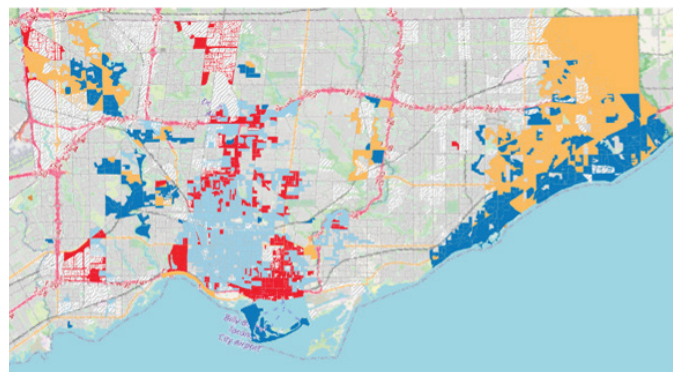
In addition to spatial disparities, social disparities of green space accessibility are also of interest to policymakers and urban planners. To analyze this, the study employs a spatial correlation statistic, a local bivariate Moran's I, to capture the association between green space accessibility and each of the four specified demographic factors.

Downtown Toronto stands out as a significant region with limited green space accessibility (Figure 5). The residents in this area exhibit the characteristics of a low rate of cultural assimilation (i.e., large proportion of newcomers), a low percentage of children (indicating a higher concentration of economically active individuals), a high level of education and income, and a low level of housing stability (characterized by a large number of renters and high living costs exceeding 30% of their income). In summary, the typical profile of the downtown population is new economically productive individuals with high levels of education but bearing excessively high living costs and inadequate access to urban green spaces.

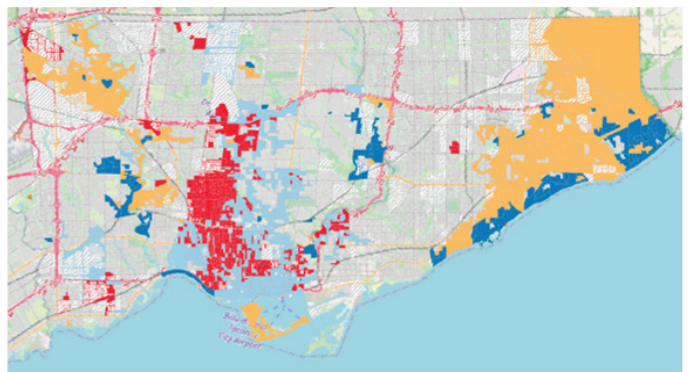
**Figure 4.** Green space accessibility (color classified by population quantile)



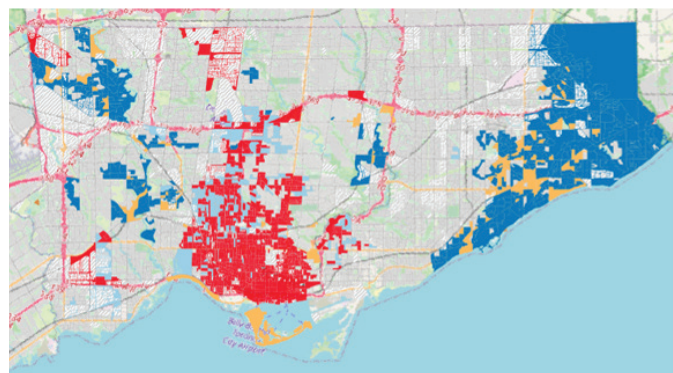
**Figure 5.** The association between principal demographic factors and green space accessibility



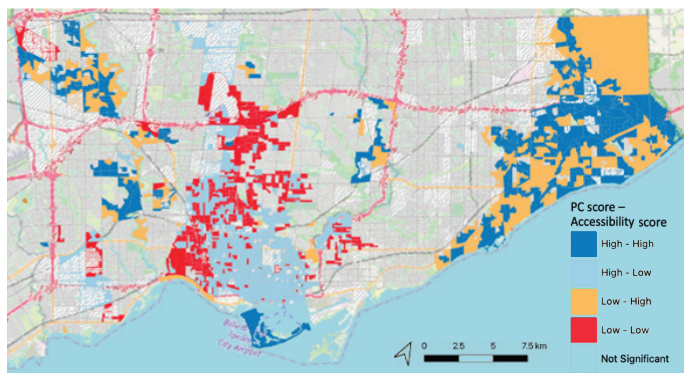
**A. Cultural Assimilation vs Park Accessibility (2SFCA)**



**B. Socioeconomic Status vs Park Accessibility (2SFCA)**



**C. Housing Stability vs Park Accessibility (2SFCA)**



**D. Low child dependency vs Park Accessibility (2SFCA)**

Another noteworthy area with limited urban green space area per capita is the region situated west of downtown and east of High Park. This area is primarily inhabited by people who were born or moved to Toronto decades ago and live with families with a high proportion of children. While they may also face the challenge of high housing prices in Toronto, many of them own their own homes. The education and income levels in this region vary across different communities. Despite the larger overall size of the green spaces in these areas, the share of green space spaces for residents remains low. This is attributed to the presence of large green spaces with larger catchment areas which elevate demand competition. For instance, a legacy park such as High Park attracts not only residents living nearby but also those from farther regions. Due to the high population density to the east of the green space, the demand for the green space is highly competitive, hence the individual share of green space areas goes down.

### Green space accessibility and housing price

Green space accessibility has been found to be significantly related to housing price in numerous cities worldwide. In order to gain insights into the situation in Toronto and establish a connection between green space accessibility disparity and land use planning as well as equitable economic development, we further explore the association between green space accessibility and housing price by applying Global Regression and Geographically Weighted Regression (GWR) models.

The global regression analysis examines the correlation between average housing price per room and various impact factors for the entire Toronto region. The modelling results (Table 3) indicate that, in general, areas with higher housing costs per room (which may imply dwellings with fewer rooms) tend to have lower green space accessibility and proximity to the lake. These areas are typically inhabited by a higher proportion of tenants or individuals who spend more than 30% of their income on housing, indicating a lower level of housing stability. Additionally, the model implies that areas with higher housing costs per room exhibit lower population density, and are occupied by residents with greater cultural assimilation, higher socioeconomic status, and a lower proportion of children.

Housing price per room is determined by both the overall housing price level in a particular area and the composition of dwellings with different sizes. A higher housing price per room could be attributed to either a higher overall housing price level in an affluent urban area or a greater proportion of small-sized dwellings, such as condominium units, compared to larger single-detached houses.

The City of Toronto encompasses various regions, including the downtown area, midtown, and suburban areas. Due to the varying characteristics of different regions, the nature and strength of correlations between housing prices and impact factors can significantly differ across the city. The global regression analysis, however, en-

compasses a broad range of scenarios and cannot identify the specific determinants of housing price per room. In contrast, localized analyses, such as GWR, can estimate the effects of factors at a local level, thereby unveiling the spatial heterogeneity of housing price factors and identify the determinants of housing prices per room based on the local characteristics.

Based on the GWR results (Figure 6), areas where accessibility to more green space areas increases housing prices per room (more likely due to higher overall housing market price) include neighbour-

**Table 3.** Statistical Modelling Results with Mean Housing Price per Room (2021) as the Dependent Variable

#### Estimated Global Regression coefficients

Variable	Est.	SE	t(Est/SE)	p-value
Constant	0.232	0.004	55.064	0.000
Park Accessibility (2SFCA)	-0.697	0.212	-3.292	0.001
Park Accessibility (Gravity)	-0.029	0.004	-7.311	0.000
Distance to Lake Ontario	0.068	0.037	1.812	0.070
Population Density	-1.291	0.127	-10.145	0.000
Cultural Assimilation	0.011	0.002	5.661	0.000
Socioeconomic Status	0.034	0.001	25.492	0.000
Housing Stability	-0.047	0.002	-28.830	0.000
Low child dependency	0.007	0.001	5.209	0.000

#### Estimated Geographically Weighted Regression (GWR) coefficients

Variable	Mean	STD	Min	Median	Max
Constant	0.214	0.197	-0.501	0.199	1.270
Park Accessibility (2SFCA)	-3.518	30.809	-238.785	0.826	107.414
Park Accessibility (Gravity)	0.168	0.693	-1.797	0.010	3.610
Distance to Lake Ontario	-0.511	2.359	-9.732	-0.285	19.726
Population Density	-1.473	2.231	-17.677	-1.117	7.104
Cultural Assimilation	-0.005	0.015	-0.085	-0.004	0.069
Socioeconomic Status	0.001	0.018	-0.075	0.002	0.073
Housing Stability	-0.018	0.018	-0.137	-0.014	0.043
Low child dependency	0.004	0.017	-0.039	0.000	0.099

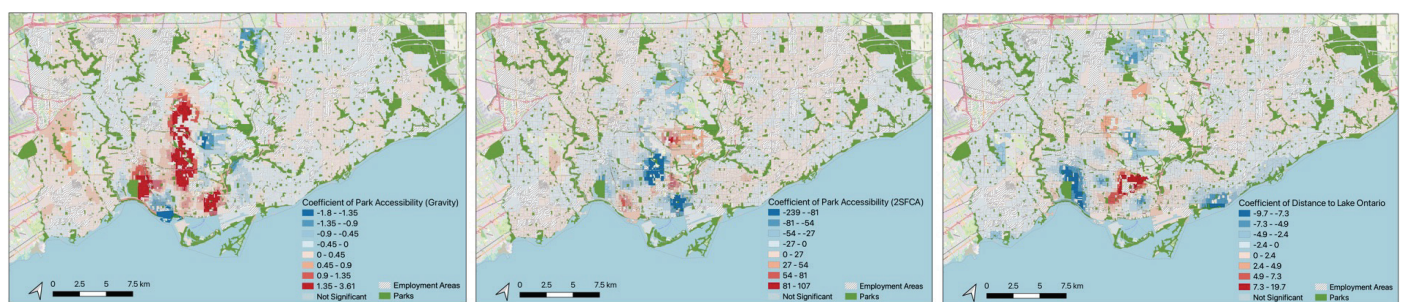
Adj. alpha (95%): 0.001; Adj. critical t value (95%): 3.340

#### Model Comparison

	AIC	AICc	RSS	R2	Adj. R2
Global Regression	-7980.818	-7978.747	13.909	0.437	0.436
Geographically Weighted Regression (GWR)	-9638.934	-9418.265	5.828	0.764	0.716

Note: 1) The unit of Mean Housing Price per Room is million; The unit of Distance to Lake Ontario is degree; The unit of Population Density is population per square meter; Park Accessibility (2SFCA) index is rescaled by dividing by 10<sup>4</sup>; Park Accessibility (Gravity) index is rescaled by dividing by 10<sup>7</sup>. 2) AIC, AICc, RSS, R2, Adj.R2 refer to the values of Akaike information criterion, Akaike's information criterion corrected, residual sum of squares, R-squared, and adjusted R-squared.

**Figure 6.** Spatial heterogeneity of GWR local coefficients with the dependent variable being the mean housing price per room in 2021





hoods with affluent and well-established households, such as the vicinity near High Park and neighbourhoods such as Annex, Casa Loma, Forest hill north, and Bedford Park-Nortown. Another area where green space accessibility leads to an increase in housing price per room (more likely due to smaller dwelling units) is the neighbourhood of Moss Park and Regent Park. These regions primarily consist of public housing and rental units and are predominantly inhabited by low-income families. In addition, the areas with higher

housing prices per room are densely populated areas within these neighbourhoods, which explains the negative sign of green space area per capita coefficients.

The trade-off between green space accessibility and population density varies in different regions. The aforementioned affluent regions with well-established households value green space areas more than living spaciousness. Hence the housing price in those regions is higher at areas with high accessibility to green spaces though with high population density. However, there are regions where residents value green space areas per capita more than green space areas. These regions include the trendy and culturally diverse Fort York - Liberty Village and West Queen West neighbourhood near the lake, as well as the flourishing Eglinton neighbourhood at the centre of mid-town Toronto. In these regions, areas with higher green space area per capita have higher housing price per room though with lower green space accessibility in terms of total green space areas. This implies residences with higher housing price per room locate at less dense areas but with higher green space accessibility per capita. A possible reason for the different patterns is that these trendy and flourishing neighbourhoods, compared to the High Park and Bedford Park affluent neighbourhood, are closer to central business areas and transit stations, but have less natural green space resources, so residents are willing to pay more for enjoying more green space area per capita and spaciousness.

In general, the closer the house to the lake the higher the housing price but, considering another determinant of housing price per room – dwelling size – houses close to the lake may have low housing price per room due to large dwelling size. For example, the houses near the lakeshore outside of downtown Toronto, such as in the Beaches neighbourhood located to the east of downtown, are mostly occupied with semi-detached and large-scale Victorian, Edwardian, and new-style houses. The neighbourhood is also characterized by a number of heritage buildings, and traditional, authentic specialty stores. Likewise, high housing price per room may be due to small dwelling size. For example, the areas near the Bloor-Yonge intersection and the areas to its south which are close to downtown and lakeshore have more condos than houses compared to the affluent Toronto neighbourhoods to its north, so the housing price per room increases as the distance to the lake decreases.

Table 4 presents the impacts of various factors on housing price increases from 2016 to 2021 globally and locally. The global regression analysis indicates that, on the whole, areas with significant influx of population and those situated near Lake Ontario tend to experience higher increases in housing prices. These areas are typically characterized by a higher proportion of newcomers, lower socioeconomic status population, and more renters or individuals facing a heavier burden of dwelling costs.

**Table 4.** Statistical Modelling Results with Mean Housing Price per Room Relative Change from 2016 to 2021 as the Dependent Variable

**Estimated Global Regression coefficients**

Variable	Est.	SE	t(Est/SE)	p-value
Constant	0.673	0.013	51.613	0.000
Park Accessibility (2SFCA)	-0.007	0.007	-1.015	0.310
Park Accessibility (Gravity)	-0.089	0.013	-6.690	0.000
Distance to Lake Ontario	-0.832	0.127	-6.573	0.000
Population Density Change	0.072	0.019	3.752	0.000
Cultural Assimilation	-0.034	0.006	-5.480	0.000
Socioeconomic Status	-0.046	0.004	-10.354	0.000
Housing Stability	-0.001	0.005	-0.122	0.903
Low child dependency	-0.034	0.005	-6.749	0.000

**Estimated Geographically Weighted Regression (GWR) coefficients**

Variable	Mean	STD	Min	Median	Max
Constant	0.647	0.137	0.327	0.639	1.051
Park Accessibility (2SFCA)	-0.166	0.233	-0.955	-0.146	0.390
Park Accessibility (Gravity)	0.089	0.325	-0.742	0.031	0.971
Distance to Lake Ontario	-0.919	1.397	-4.934	-0.978	3.362
Population Density Change	0.107	0.205	-0.316	0.077	0.729
Cultural Assimilation	-0.038	0.025	-0.126	-0.040	0.031
Socioeconomic Status	-0.033	0.026	-0.133	-0.031	0.048
Housing Stability	-0.016	0.025	-0.082	-0.015	0.053
Low child dependency	-0.014	0.026	-0.077	-0.016	0.048

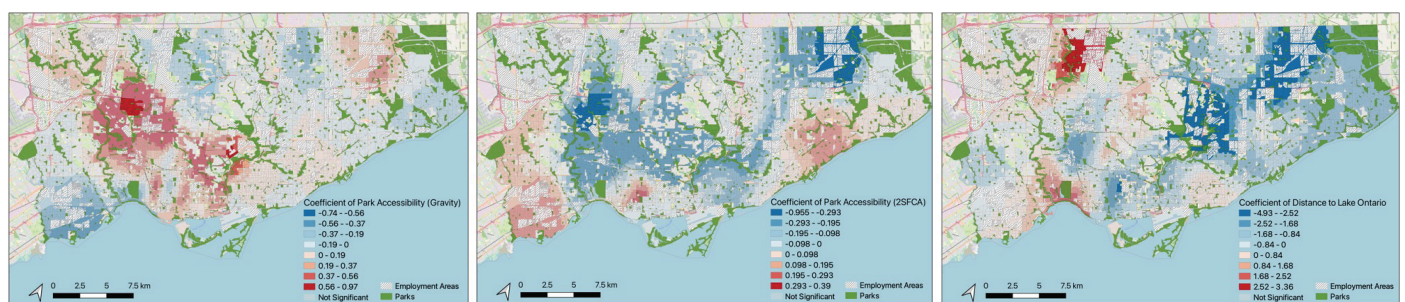
Adj. alpha (95%): 0.003; Adj. critical t value (95%): 2.955

**Model Comparison**

	AIC	AICc	RSS	R2	Adj. R2
Global Regression	-624.563	-622.487	136.393	0.071	0.068
Geographically Weighted Regression (GWR)	-821.958	-806.867	116.142	0.209	0.168

Note: 1) The unit of Distance to Lake Ontario is degree; The unit of Population Density is population per square kilometer; Park Accessibility (2SFCA) index is rescaled by dividing by 100; Park Accessibility (Gravity) index is rescaled by dividing by 10<sup>7</sup>. 2) AIC, AICc, RSS, R2, Adj. R2 refer to the values of Akaike information criterion, Akaike's information criterion corrected, residual sum of squares, R-squared, and adjusted R-squared.

**Figure 7.** Spatial heterogeneity of GWR local coefficients, with the dependent variable being the increase rate of mean housing prices-per room from 2016 to 2021



The GWR model evaluates the local variation in the impact of factors on housing price increases (Figure 7). The total green space area accessible to each dissemination area plays a pivotal role in driving housing price growth in areas predominately occupied by families with children. Notable examples include the Maple Leaf neighbourhood, which enjoys close proximity to multiple municipal parks including North Park, Rainbow Park, and Queen's Greenbelt, and the Leaside-Bennington neighbourhood, located besides the Don River. Despite their differing demographic characteristics – Maple Leaf having a larger population of first- or second-generation immigrants and a mix of residents from various socio-economic backgrounds, while Leaside being recognized for its higher education levels and upper-middle-income households – both areas boast abundant greenspaces and parklands, a fine selection of schools, and are especially sought-after by families with children who value the natural resources and community amenities, and therefore view them as ideal places to live and raise children.

Generally, the closer an area is to the lake, the greater the increase in housing prices per room. However, certain areas may deviate from this trend due to the influence of other factors which can also significantly influence housing prices per room, such as new condo establishment, public transportation accessibility, and the development of new commercial, cultural, and community centres. Furthermore, in areas where housing prices are already high, the potential for housing price increases is limited, as observed near High Park, for instance.

## DISCUSSION AND CONCLUSIONS

Environmental inequality in access to urban green spaces is evident in Toronto. The vicinities near large green spaces are occupied by established families who also enjoy spaciousness. Densely populated areas such as the urban centre and some flourishing TODs (Transit-Oriented Developments) are economically prosperous and attract newcomers who are economically productive with high levels of education. However, these residents face excessively high living cost and low green space accessibility. Low green space accessibility is also observed in inner-urban areas outside the city core, where socioeconomic levels are lower. Concerning the economic trade-off for enhanced green space access, residents in flourishing and densely populated areas with relatively scarce green spaces show a willingness to pay more for housing to enjoy greater green space area share and spaciousness. Conversely, in regions boasting ample green spaces where population density is lower, a larger total accessible green space area correlates with higher housing prices. The economic dimension of green space accessibility appears to be evolving. Neighbourhoods with abundant green spaces and community amenities, especially special school programs, attract families with children. In these areas, the growth in housing prices is notably correlated with the level of green space accessibility.

As underscored in prior research and policies, planning attention should be directed toward areas where the supply of green spaces does not align with the demand by sustaining, improving, expanding, and programming the green space system (TRCA, 2020; City of Toronto, 2019b). Additionally, this study posits that strategies aimed at rectifying disparities in green space accessibility must be tailored to the unique characteristics of local communities, encompassing their social and economic profiles. Decisions regarding prioritizing green space maintenance, improvement, or expansion, as well as navigating the trade-off between green space size and quantity, should be guided by the specific needs of neighborhoods, the provision of other essential amenities, and adherence to land use by-laws.

This study offers specific recommendations. Firstly, it suggests repurposing vacant office and non-residential spaces into green spaces or gardens as part of urban green space redevelopment plans, particularly in densely populated areas. Given the shift in work modalities post-pandemic, with remote and hybrid work becoming the new norm, office occupancy rates are expected not to fully recover to pre-pandemic levels. Capitalizing on this opportunity, planners and policymakers could initiate or proceed with innovative urban green space designs, considering the integration of indoor and rooftop gardens (City of Toronto, 2017). Secondly, enhancing the functionality of existing green spaces in densely populated areas where green space is limited. This may involve incorporating more natural elements within these green spaces, which may be a more feasible approach compared to constructing entirely new green spaces, which could be more suitable for less dense areas. Thirdly, conducting comprehensive system assessment in new developments and reserving reasonably adequate green spaces to ensure all developments contribute to the establishment of an equitable and sustainable living system. Synergistic effects with other essential amenities such as grocery stores, transit stations, and healthcare centres should also be systematically considered.

This study has certain limitations that should be acknowledged. Firstly, it does not consider the ecosystem within green spaces and other functions provided by the parks, which may play a crucial role in people's perception of green space provision especially in areas with limited available land for green spaces. Secondly, when measuring travel impedance, it might be more informative and accurate if taking access points, such as green space entrances, instead of geographic centroids as the destinations. However, it is worth noting that this adjustment may not significantly alter the results of the green space accessibility measurements. Thirdly, while the study examines the effect of current green space accessibility on current housing price and its increase rate over the past five years, a conclusive assessment of green gentrification cannot be fully established without considering the historical development and transformations of green spaces over an extended period of time.

As a global city, Toronto constantly attracts new residents and visitors from diverse cultural and economic backgrounds. The existing socio-economic and spatial disparities in green space accessibility may undergo changes as the population distribution and economic development evolves. In addition, the shift in commuting patterns following the pandemic could also alter the demand for green spaces to the new normality of daily needs. Therefore, further analysis would be needed for a more comprehensive understanding of the anticipated green space demand and enable relevant agencies to develop informed strategies for designing new green space initiatives.

## REFERENCES

- Agyeman, J. & Evans, B. (2004). 'Just Sustainability': The Emerging Discourse of Environmental Justice in Britain?, *The Geographical Journal*, 170(2): 155–164.
- Anguelovski, I., Connolly, J.J.T., Cole, H., Garcia-Lamarca, M., Triguero-Mas, M., Baró, F., Martin, N., Conesa, D., Shokry, G., Del Pulgar, C.P., Ramos, L.A., Matheney, A., Gallez, E., Oscilowicz, E., Máñez, J.L., Sarzo, B., Beltrán, M.A. & Minaya, J.M. (2022). Green Gentrification in European and North American Cities, *Nature Communications*, 13(1): 3816.
- Astell-Burt, T., Feng, X., Mavoa, S., Badland, H.M. & Giles-Corti, B. (2014). Do Low-Income Neighbourhoods Have the Least Green Space? A Cross-Sectional Study of Australia's Most Populous Cities, *BMC Public Health*, 14(1): 292.



- Barbosa, O., Tratalos, J.A., Armsworth, P.R., Davies, R.G., Fuller, R.A., Johnson, P. & Gaston, K.J. (2007). Who Benefits from Access to Green Space? A Case Study from Sheffield, UK. *Landscape and Urban Planning*, 83(2): 187–195.
- Ben-Akiva, M.E., & Lerman, S.R. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press.
- Bristowe, A., & Heckert, M. (2023). How the COVID-19 Pandemic Changed Patterns of Green Infrastructure Use: A Scoping Review. *Urban Forestry & Urban Greening*, 81: 127848.
- Buckland, M. & Pojani, D. (2023). Green Space Accessibility in Europe: A Comparative Study of Five Major Cities. *European Planning Studies*, 31(1): 146–167.
- Chen, Y., Yue, W. & La Rosa, D. (2020). Which Communities Have Better Accessibility to Green Space? An Investigation into Environmental Inequality Using Big Data. *Landscape and Urban Planning*, 204: 103919.
- City of Toronto. (2017) City of Toronto Green Roof Bylaw. <https://www.toronto.ca/city-government/planning-development/official-plan-guidelines/green-roofs/green-roof-bylaw/>
- City of Toronto. (2019a) Parkland Strategy Phase 2 What We Heard Report. <https://www.toronto.ca/wp-content/uploads/2019/09/8ef6-parkland-strategy-phase-2-survey-summary.pdf>
- City of Toronto. (2019b) Parkland Strategy Final Report. <https://www.toronto.ca/wp-content/uploads/2019/11/97fb-parkland-strategy-full-report-final.pdf>
- Dai, D. (2011). Racial/Ethnic and Socioeconomic Disparities in Urban Green Space Accessibility: Where to Intervene?, *Landscape and Urban Planning*, 102(4): 234–244.
- Delamater, P.L. (2013). Spatial Accessibility in Suboptimally Configured Health Care Systems: A Modified Two-Step Floating Catchment Area (M2SFCA) Metric. *Health & Place*, 24: 30–43.
- Delbosc, A. & Currie, G. (2011). Using Lorenz Curves to Assess Public Transport Equity. *Journal of Transport Geography*, 19(6): 1252–1259.
- Dony, C.C., Delmelle, E.M. & Delmelle, E.C. (2015). Re-Conceptualizing Accessibility to Parks in Multi-Modal Cities: A Variable-Width Floating Catchment Area (VFCA) Method. *Landscape and Urban Planning*, 143: 90–99.
- Gastwirth, J.L. (1972). The Estimation of the Lorenz Curve and Gini Index. *The Review of Economics and Statistics*, 54(3): 306–316.
- Geurs, K.T. & Van Wee, B. (2004). Accessibility Evaluation of Land-Use and Transport Strategies: Review and Research Directions. *Journal of Transport Geography*, 12(2): 127–140.
- Gilliland, J., Holmes, M., Irwin, J.D. & Tucker, P. (2006). Environmental Equity is Child's Play: Mapping Public Provision of Recreation Opportunities in Urban Neighbourhoods. *Vulnerable Children and Youth Studies*, 1(3): 256–268.
- Guo, S., Song, C., Pei, T., Liu, Y., Ma, T., Du, Y., Chen, J., Fan, Z., Tang, X., Peng, Y. & Wang, Y. (2019). Accessibility to Urban Parks for Elderly Residents: Perspectives from Mobile Phone Data. *Landscape and Urban Planning*, 191: 103642.
- Jelks, N.O., Jennings, V. & Rigolon, A. (2021). Green Gentrification and Health: A Scoping Review. *International Journal of Environmental Research and Public Health*, 18(3): 907.
- Kim, E.E.K., Seo, K. & Choi, Y. (2022). Compensatory Travel Post COVID-19: Cognitive and Emotional Effects of Risk Perception. *Journal of Travel Research*, 61(8): 1895–1909.
- Lee, S.-I. (2001). Developing a Bivariate Spatial Association Measure: An Integration of Pearson's R and Moran's I. *Journal of Geographical Systems*, 3(4): 369–385.
- Li, H., Wei, Y.D., Yu, Z. & Tian, G. (2016). Amenity, Accessibility and Housing Values in Metropolitan USA: A Study of Salt Lake County, Utah. *Cities*, 59: 113–125.
- Li, Z., Fan, Z., Song, Y. & Chai, Y. (2021). Assessing Equity in Park Accessibility Using a Travel Behavior-Based G2SFCA Method in Nanjing, China. *Journal of Transport Geography*, 96, 103179.
- Lorenz, M.O. (1905). Methods of Measuring the Concentration of Wealth. *Publications of The American Statistical Association*, 9(70): 209–219.
- Lucas, K., Van Wee, B. & Maat, K. (2016). A Method to Evaluate Equitable Accessibility: Combining Ethical Theories and Accessibility-Based Approaches. *Transportation*, 43(3), 473–490.
- Luo, W. & Qi, Y. (2009). An Enhanced Two-Step Floating Catchment Area (E2SFCA) Method for Measuring Spatial Accessibility to Primary Care Physicians. *Health & Place*, 15(4): 1100–1107.
- Luo, W. & Wang, F. (2003). Measures of Spatial Accessibility to Health Care in a GIS Environment: Synthesis and a Case Study in the Chicago Region. *Environment and Planning B: Planning and Design*, 30: 865–884.
- Maantay, J. & Maroko, A. (2009). Mapping Urban Risk: Flood Hazards, Race, & Environmental Justice in New York. *Applied Geography*, 29(1): 111–124.
- Macfarlane, G., Turley Voulgaris, C. & Tapia, T. (2022). City Parks and Slow Streets: A Utility-Based Access and Equity Analysis. *Journal of Transport and Land Use*, 15(1): 587–612.
- Maurer, M., Zaval, L., Orlove, B., Moraga, V. & Culligan, P. (2021). More Than Nature: Linkages Between Well-Being and Greenspace Influenced by a Combination of Elements of Nature and Non-Nature in a New York City Urban Park. *Urban Forestry & Urban Greening*, 61: 127081.
- Miller, E.J. (2018). Accessibility: Measurement and Application in Transportation Planning. *Transport Reviews*, 38(5): 551–555.
- Park, J.H., Lee, D.K., Park, C., Kim, H.G., Jung, T.Y. & Kim, S. (2017). Park Accessibility Impacts Housing Prices in Seoul. *Sustainability*, 9(2): 185.
- Parker, J. & Simpson, G.D. (2018). Public Green Infrastructure Contributes to City Livability: A Systematic Quantitative Review. *Land*, 7(4): 161.
- Pearsall, H. & Eller, J.K. (2020). Locating the Green Space Paradox: A Study of Gentrification and Public Green Space Accessibility in Philadelphia, Pennsylvania. *Landscape and Urban Planning*, 195: 103708.
- Pröbstl-Haider, U., Gugerell, K. & Maruthaveeran, S. (2023). Covid-19 and Outdoor Recreation – Lessons Learned? Introduction to the Special Issue on “Outdoor Recreation and Covid-19: Its Effects on People, Parks and Landscapes”. *Journal of Outdoor Recreation and Tourism*, 41: 100583.
- Rigolon, A. & Németh, J. (2020). Green Gentrification Or 'Just Green Enough': Do Park Location, Size and Function Affect Whether a Place Gentrifies or Not?. *Urban Studies*, 57(2): 402–420.
- Senetra, A. & Szczepańska, A. (2022). Has the COVID-19 Pandemic Led to Permanent Persistent Changes in Recreational Activity? A Case Study of a Municipal Beach. *Bulletin of Geography. Socio-Economic Series*.

Toronto and Region Conservation Authority (TRCA). (2020) Greenspace Acquisition Project 2021-2030. <https://pub-trca.escribemeetings.com/filestream.ashx?documentid=6897>

Tzoulas, K., Korpela, K., Venn, S., Yli-Pelkonen, V., Kaźmierczak, A., Niemela, J. & James, P. (2007). Promoting Ecosystem and Human Health in Urban Areas Using Green Infrastructure: A Literature Review, *Landscape and Urban Planning*, 81(3): 167-178.

Ueno, Y., Kato, S., Mase, T., Funamoto, Y. & Hasegawa, K. (2022). Changes in the Use of Green Spaces by Citizens Before and During the First COVID-19 Pandemic: A Big Data Analysis Using Mobile-Tracking GPS Data in Kanazawa, Japan. in F. Nakamura (Eds.), *Green Infrastructure and Climate Change Adaptation: Function, Implementation and Governance: 257-270*. Springer Nature.

Ugolini, F., Massetti, L., Calaza-Martínez, P., Cariñanos, P., Dobbs, C., Ostoić, S.K., Marin, A.M., Pearlmutter, D., Saaroni, H., Šaulienė, I., Simoneti, M., Verlič, A., Vuletić, D. & Sanesi, G. (2020). Effects Of the COVID-19 Pandemic on the Use And Perceptions of Urban Green Space: An International Exploratory Study, *Urban Forestry & Urban Greening*, 56: 126888.

Vaz, E., Anthony, A. & Mchenry, M. (2017). The Geography of Environmental Injustice, *Habitat International*, 59: 118-125.

Walker, G. (2012). *Environmental Justice: Concepts, Evidence and Politics*. Routledge.

Wang, S., Wang, M. & Liu, Y. (2021). Access to Urban Parks: Comparing Spatial Accessibility Measures Using Three GIS-Based Approaches, *Computers, Environment and Urban Systems*, 90: 101713.

Wen, C., Albert, C. & Von Haaren, C. (2020). Equality in Access to Urban Green Spaces: A Case Study in Hannover, Germany, With a Focus on the Elderly Population, *Urban Forestry & Urban Greening*, 55: 126820.

Wolch, J., Wilson, J.P. & Fehrenbach, J. (2005). Parks and Park Funding in Los Angeles: An Equity-Mapping Analysis, *Urban Geography*, 26(1): 4-35.

Wood, L., Hooper, P., Foster, S. & Bull, F. (2017). Public Green Spaces and Positive Mental Health – Investigating the Relationship Between Access, Quantity and Types of Parks and Mental Wellbeing, *Health & Place*, 48: 63-71.

Yap, K.K.L., Soh, M.C.K., Sia, A., Chin, W.J., Araib, S., Ang, W.P., Tan, P.Y. & Er, K.B.H. (2022). The Influence of the COVID-19 Pandemic on the Demand for Different Shades of Green, *People and Nature*, 4(2): 505-518.

Yasumoto, S., Jones, A. & Shimizu, C. (2014). Longitudinal Trends in Equity of Park Accessibility in Yokohama, Japan: An Investigation into the Role of Causal Mechanisms. *Environment and Planning A: Economy and Space*, 46(3): 682-699.

Ye, C., Hu, L. & Li, M. (2018). Urban Green Space Accessibility Changes in A High-Density City: A Case Study of Macau from 2010 to 2015, *Journal of Transport Geography*, 66: 106-115.

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