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Spatial Non-Stationarity Effects of Unhealthy Food Environments and Green Spaces for Type-2 Diabetes in Toronto

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Abstract: Environmental factors may operate differently when relations are measured across different geographical locations, a phenomenon known as spatial non-stationarity. This study investigates the spatial non-stationarity effect of unhealthy food environments and green spaces on the T2DM prevalence rate at the neighborhood level in Toronto. This study also compares how the results vary between age groups, classified as all adults (20 and above), young adults (from 20 to 44), middle adulthood (from 45 to 64), and seniors (65 and above). The geographically weighted regression model is utilized to explore the impacts of spatial non-stationarity effects on the research results, which may lead to biased conclusions, which have often been ignored in past studies. The results from this study reveal that environmental variables dissimilarly affect T2DM prevalence rates among different age groups and neighborhoods in Toronto after controlling for socioeconomic factors. For example, the green space density yields positive associations with diabetes prevalence rates for elder generations but negative relationships for younger age groups in twenty-two and four neighborhoods, respectively, around Toronto East. The observed associations will provide beneficial suggestions to support government and public health authorities in designing education, prevention, and intervention programs targeting different neighborhoods to control the burden of diabetes.

Keywords: diabetes; spatial non-stationarity; environmental health; spatial autocorrelation; GIS

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1. Introduction

The rising number of diabetes cases worldwide is emerging as one of the fastest-growing global healthcare emergencies of the 21st century [1,2]. More than half a billion people are living with diabetes, which is predicted to increase by 46% by 2045 [1]. Type-2 diabetes mellitus (T2DM) accounts for more than 90% of diabetes cases [1,3]. It is characterized by excess blood sugar levels caused by insulin deficiency, whereby the pancreas cannot produce enough insulin, and insulin resistance, whereby target organs respond poorly to the insulin that is produced and take in less glucose from the blood [1,3]. Diabetes can cause severe damage to body systems such as the eyes, kidneys, heart, and vascular system [4]. Although T2DM is recognized to be more common in older adults, there has been a recent trend of increasing rates among young adults due to obesity, physical inactivity, and energy-dense diets [5]. Using Toronto, Ontario, Canada, as an example, more than one in ten adults aged 20 years and above have been diagnosed with T2DM, and the prevalence rate has doubled in the past two decades [6]. As a result, governments and public health organizations are working to limit and reduce the prevalence of T2DM by understanding the environmental factors that contribute to its development in the hope of designing effective intervention programs.

Public health and medical researchers have been studying the effects of various environmental factors, such as air pollution, food, greenness, noise, physical activity, and walkability, on diabetes for decades [4]. These factors can affect the risk of T2DM by altering behavioral, psychological, and physical stresses and influencing decision-making [4]. Numerous studies have been performed to further advanced our knowledge of how physical environmental factors [7–24] and social environmental factors [25–29] influence T2DM. It has been well established that physical inactivity and unhealthy food environments, which promote the consumption of energy-dense foods, are significant predictors of T2DM [5]. People are likely to exercise more in a well-designed environment. Recreational resources, green spaces, and walkways that encourage physical activity have been shown to reduce the risk of diabetes [7,8,14–16,19]. Having supermarkets with fresh food in the community can promote a healthy diet, while unhealthy food outlets can increase the risk of diabetes [11,12,22]. Age and social–economic status also play a critical role in T2DM prevalence. Evidence suggests that T2DM prevalence rates are positively associated with age and unemployment [1,26,30], while education and income are negatively associated with T2DM prevalence rates [26,30,31].

With the increased use of geographic information science (GIS) and spatial analytical techniques, there have been growing concerns regarding how the environment affects human health worldwide [32]. Many studies have discovered associations between environmental factors and T2DM. For instance, some studies have found significant positive associations between the food environment and T2DM [12,13,22,23], while others have found no significant associations [10,25,28]. These examples highlight the uncertain geographic context problem (UGCoP) [33] and the modifiable area unit problem (MAUP) [34], which refer to the fact that associations found at different geographical scales (e.g., neighborhood, city, province, and country levels) may differ. The results may also be impacted by the various methods used to determine the contextual location when measuring exposure effects, such as using road networks or buffers to measure neighborhood health outcomes. However, environmental factors can affect different geographic areas dissimilarly when relationships are measured across space, a phenomenon known as spatial non-stationarity [35,36]. For example, an unhealthy food environment may positively correlate with the T2DM prevalence rate in one city but negatively correlate in another. Nevertheless, research often assumes that the relationships between environmental factors and diabetes effects are stable or stationary over space. Such presumptions may lead to incorrect conclusions about how the environment affects health outcomes [35]. While very few studies have focused on the spatial non-stationarity effect of the environment on T2DM, most have only examined this effect at the county level [37–39]. To the best of our knowledge, little research has been performed on the spatial non-stationarity effects between the environment and T2DM at the citywide neighborhood level; thus, this is worthy of investigation. Understanding the geographic variation in T2DM rates at the city level can help when planning and determining where management and prevention resources should be allocated [37].

The goal of this paper is to address the research gap by (1) examining the spatial non-stationarity associations between T2DM and contextual variables (focusing on green space densities and unhealthy food environments) and (2) determining to what extent these associations differ between age groups at the neighborhood level in Toronto, Canada. It is worth noting that spatial autocorrelation may exist for the prevalence of T2DM. Spatial autocorrelation measures the extent to which geographic features and associated values are clustered together or dispersed in space. For example, a higher incidence of diabetes in the city center may indicate that some processes, such as clusters of fast food restaurants, contribute to the increased prevalence in that location. Therefore, this study will use global and local Moran's indexes to assess the existence of spatial autocorrelation and explore the spatial non-stationarity effect of the environment on T2DM through geographically weighted regression (GWR). The GWR model addresses the issue of spatial autocorrelation and reduces inaccurate spatial data estimations due to non-randomness errors. This research further intends to advance our understanding of how these relationships vary based on Toronto's geographical locations and age groups. The findings from this study could provide valuable evidence and suggestions to support the government and public health authorities in designing customized education, prevention, and intervention policies. The intervention policies will target different neighborhoods, age groups, and minority populations to control and reduce the increasing rate of diabetes in Toronto.

2. Materials and Methods

This study investigated the spatial non-stationarity relationships of T2DM prevalence rates with both green space and unhealthy food environments in the 158 neighborhoods in Toronto. The neighborhood-level geographic unit was used as a contextual area for all analyses. Four geographical weighted regression (GWR) models were employed to investigate the spatial non-stationarity associations between environmental factors and T2DM prevalence rates in different age groups. The four dependent variables are the T2DM prevalence rates for individuals aged (1) 20 and above (all adults), (2) between 20 and 44 (young adults), (3) from 45 to 64 (middle adulthood), and (4) 65 and above (elder generations). The independent variables included the green space density, unhealthy food outlet density, and social–economic status (as control variables), which were kept the same for all GWR models. Figure 1 illustrates the workflow of this study using the GWR models.

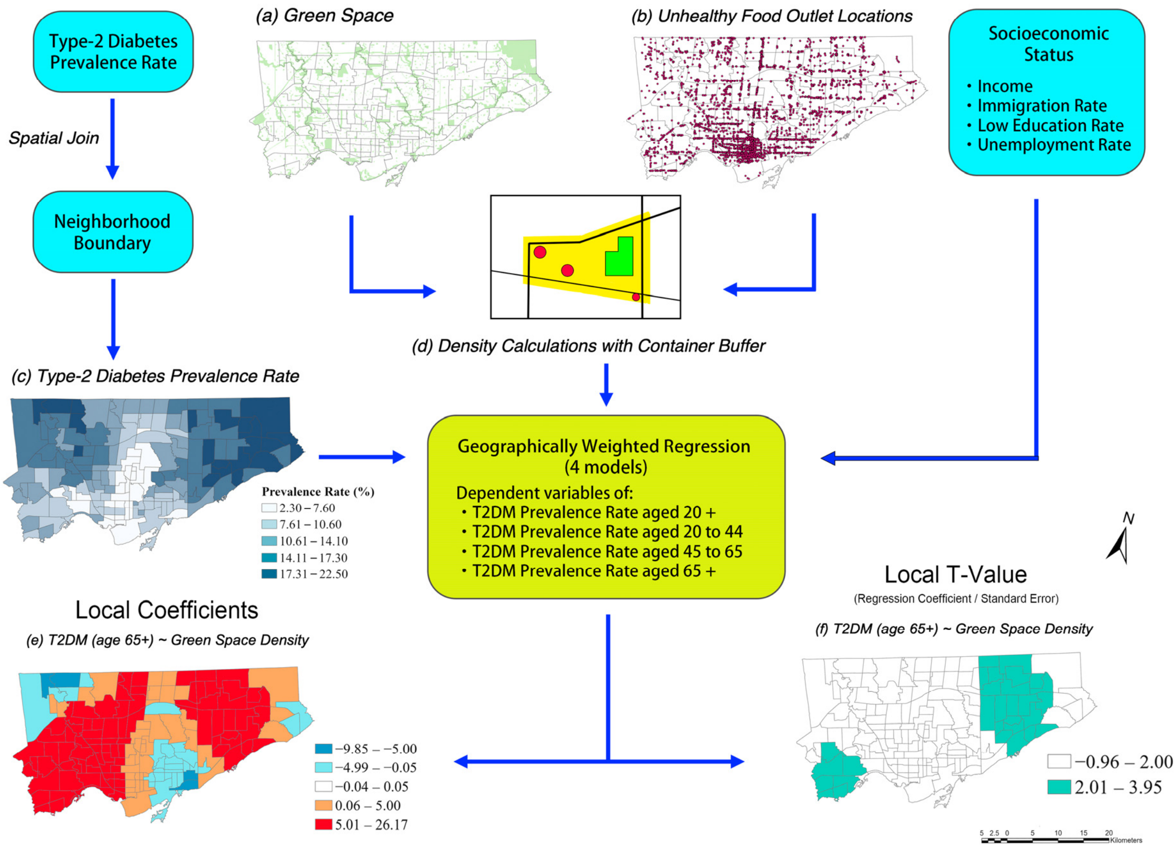

Figure 1. Using geographically weighted regression model to examine the spatial non-stationarity effects of green space density (**a**) and unhealthy food environment (**b**) with container buffer (**d**) for type-2 diabetes mellitus prevalence rates (**c**). With mappings of local coefficients (**e**) and *t*-value (**f**).

2.1. Study Area

Toronto, the capital city of Ontario, is located in southern Ontario and has a land area of 630.2 km^2. It is the most populated municipality in Canada, with an estimated three million culturally diverse inhabitants living at a density of 4720 persons per km^2 in 2019 [40]. According to the city of Toronto and the 2016 Canadian census, 47% of the population is made up of immigrants [41]. The city has 158 officially registered neighborhoods, which serve as a microcosm of the population. Unlike census tracts or dissemination areas, these social planning neighborhood boundaries change infrequently over time, making them suitable for statistical reporting [42]. Given the diverse environments and demographic characteristics of Toronto's neighborhoods, it is likely that spatial non-stationarity effects exist between environmental factors and T2DM. This research, therefore, conducts a large population-based study, covering all of Toronto's neighborhoods, to investigate whether environmental exposure is associated with the prevalence of T2DM. The 158 neighborhoods in Toronto have an average area of 4.07 km^2, with a median of 3.14 km^2 and a standard deviation of 3.87 km^2. The smallest neighborhood, North Toronto, has an area of 0.40 km^2, while the largest neighborhood, West Humber-Clairville, covers 30.16 km^2.

2.2. Data

2.2.1. Type-2 Diabetes Mellitus Prevalence Rates

The type-2 diabetes mellitus prevalence data for Toronto neighborhoods used in this study were obtained from the Ontario Community Health Profiles Partnership (OCHPP) under the Adult Health and Disease section [43]. The diabetes data were sourced from validated disease databases maintained by the Institute for Clinical Evaluative Sciences (ICES) [44]. The database includes records of all citizens and permanent residents aged 20 and above who interact with Canada's universal healthcare system, regardless of their social status. The population demographics for Toronto's 158 neighborhoods, classified by different age groups, are summarized in Table 1. These demographics were summarized according to the Ontario Ministry of Health and Long-Term Care Registered Persons Database (RPDB), including individuals who were alive and living in Toronto on 1 April 2019 [43]. If an individual filed an Ontario Health Insurance Plan (OHIP) claim, had two doctor claims, or was admitted to the hospital for diabetes within two years, they were recorded in the database as being diagnosed with diabetes. This study analyzed the most recently published 2018/2019 Adult Health and Disease dataset, focusing on diabetes prevalence rates for individuals aged 20 and above at the neighborhood level in Toronto.

The data were divided into age groups: 20 and above, 20 to 44, 45 to 64, and 65 and above. Each data record was matched and spatially joined with the boundary shapefile for the 158 neighborhoods in the City of Toronto to carry out spatial analyses. Figure 2 illustrates the spatial distribution of the T2DM prevalence rates across Toronto neighborhoods. Higher rates of T2DM were observed in the eastern and northwestern areas of Toronto, while lower rates were found in the central downtown region. For instance, neighborhoods around Humbermede and Scarborough had higher T2DM prevalence rates, while those in the Young-Bay corridor had lower rates.

Table 1. Toronto's 158 neighborhoods' population demographics by age group.

Population	Minimum	Maximum	Mean	Median	Standard Deviation	Total
All ages 20+	5360	29,457	15,167	14,392	5419	2,396,337
Age 20 to 44	2318	19,463	7241	6738	3064	1,144,070
Age 45 to 64	1845	9726	4966	4634	1837	784,704
Age 65 and above	679	7628	2959	2756	1340	467,563

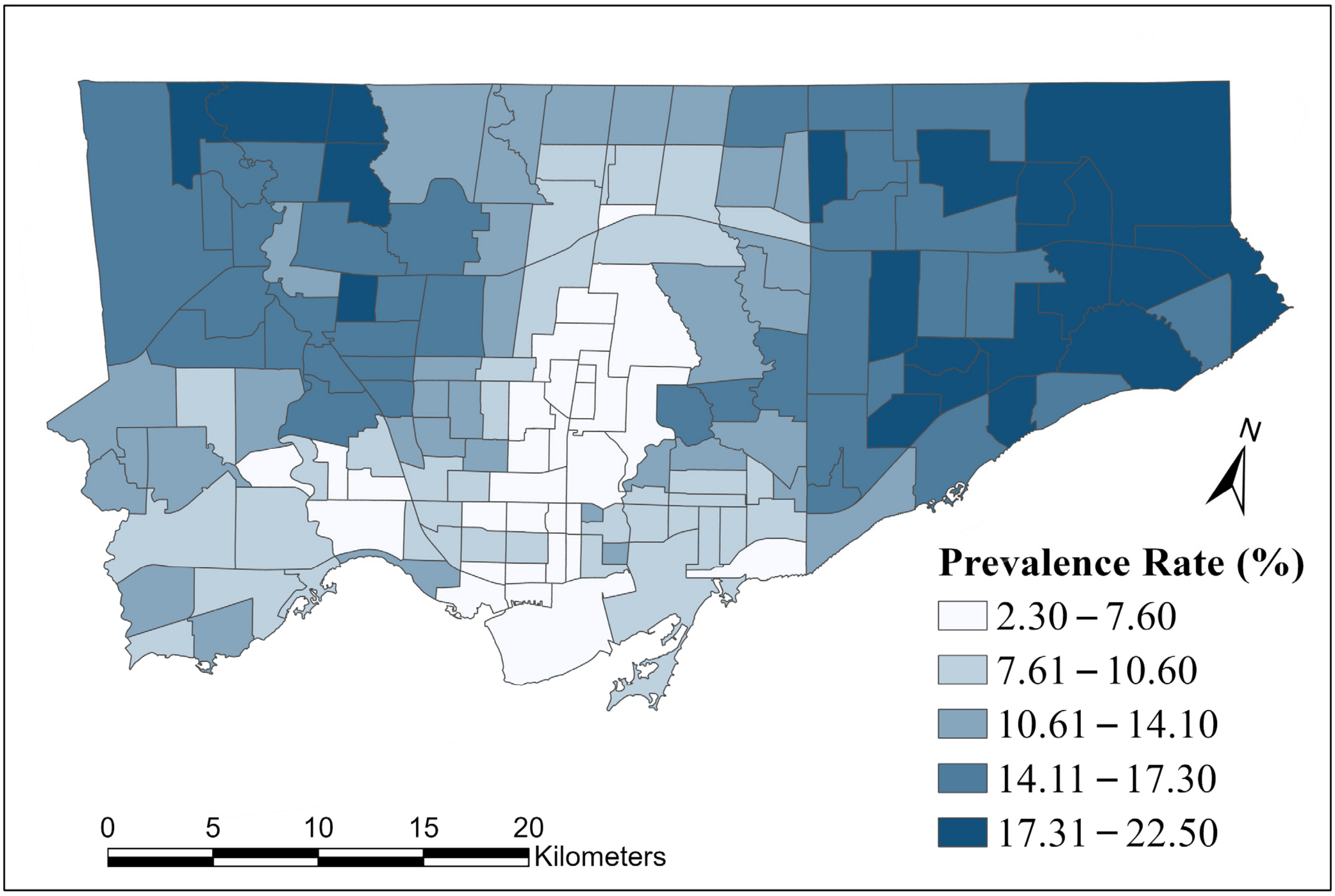

Figure 2. Neighborhood-level type-2 diabetes mellitus prevalence rates in Toronto, April 2019.

2.2.2. Unhealthy Food Outlets

Recent studies have shown that unhealthy food environments can impact T2DM [13,22,23]. For instance, fast food restaurants and convenience stores often provide energy-dense and high-carbohydrate food sources that can quickly raise blood sugar levels. In order to analyze the effects of unhealthy food environments on T2DM in Toronto, this study used data on the locations of food outlets in 2021 provided by SafeGraph [45]. SafeGraph is a company that offers points of interest (POI) data containing physical location information at the address level [46–48]. The data were classified using the North American Industry Classification System (NAICS). Food outlets were obtained from SafeGraph Core Places data and filtered using the NAICS code for unhealthy food outlets. Previous studies have commonly classified convenience stores, confectionery stores, and limited-outlet restaurants (fast food) as "unhealthy" retail food outlets [49–51]. Therefore, this study contextualized unhealthy food outlets using the following NAICS codes: 722513—Limited-Service Restaurants; 722515—Snack and Non-Alcoholic Beverage Bars; 445292—Confectionery Stores; 447110—Gasoline Stations with Convenience Stores; 445120—Convenience Stores; 311811—Retail Bakeries. The locations of unhealthy food outlets are shown in Figure 3. A total of 3964 of these outlets were located around Toronto.

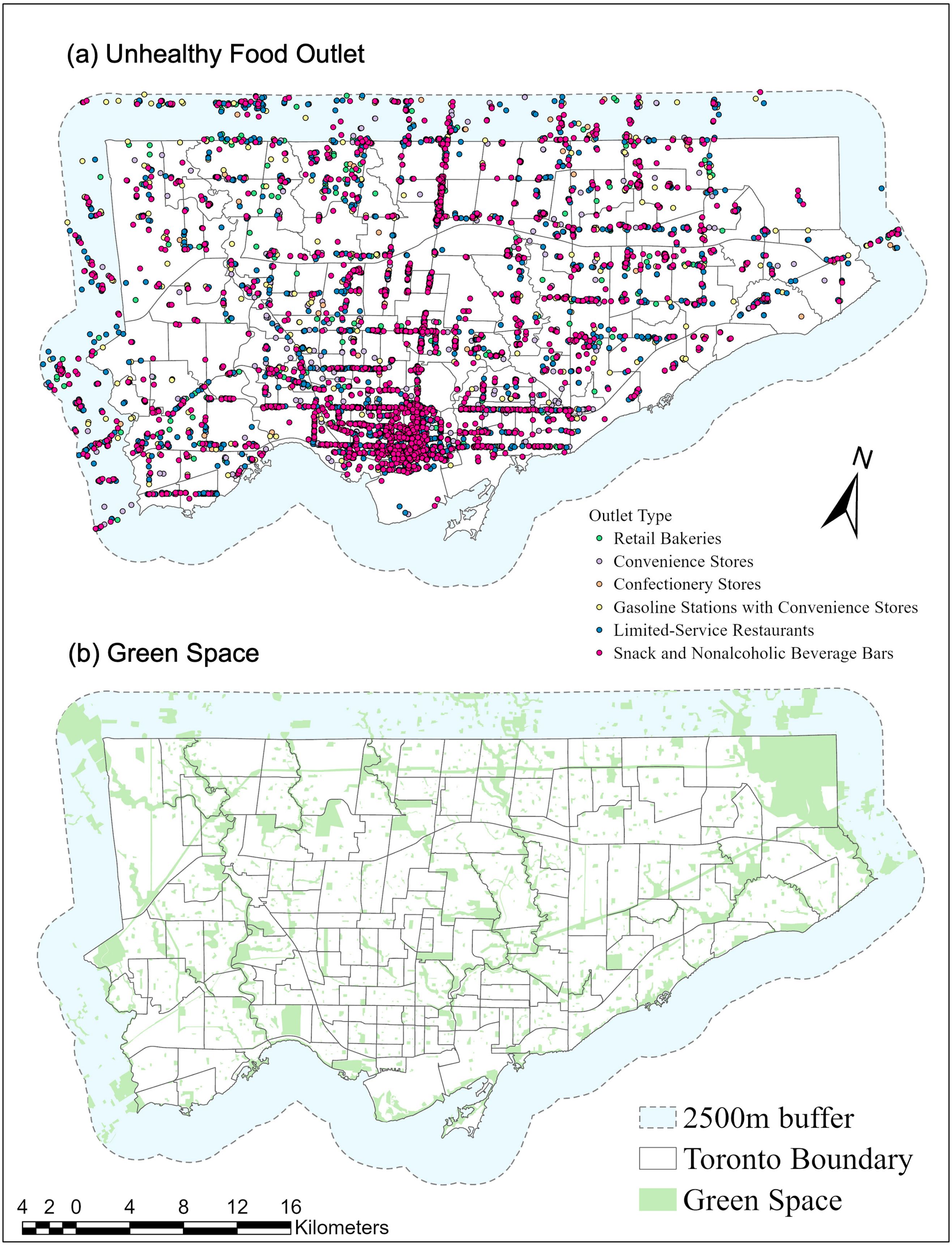

Figure 3. Distribution of (**a**) unhealthy food outlets and (**b**) green spaces around Toronto.

2.2.3. Green Spaces

Studies have found that neighborhood green spaces, such as parks, can reduce the risk of T2DM by promoting physical activity [4,7,8]. Exposure to green spaces and recreational facilities around residential neighborhoods can promote physical activity and benefit individuals' health [52–54]. When there is more green space in a community, residents will have easier access to these spaces for physical activity. The green space data were obtained from the Park Sports Field Region–2019 dataset published by DMTI Spatial, Inc., on Scholars GeoPortal [55]. The dataset includes polygon shapefiles of all parks and recreation areas in Canada, such as sports fields, open spaces, campgrounds, and golf courses. Toronto has a total green space area of 131.9 km^2, covering more than 20% of the city, as shown in Figure 3.

2.2.4. Socioeconomic Status

In addition to unhealthy food outlets and green spaces, socioeconomic status also significantly affects T2DM. Previous studies have shown that older adults and the unemployed have a higher risk of being diagnosed with T2DM [1,26,30]. Education and income are often negatively correlated with T2DM [26,30,31]. Regarding ethnicity, recent studies have found that the non-Hispanic white population has a lower prevalence rate of T2DM compared to other ethnic groups [56,57]. Certain immigrant groups were also found to have a higher risk of developing T2DM earlier in their life in Canada [26,58]. For example, South Asian and black immigrants are more likely to develop T2DM earlier than immigrants from the UK. Therefore, this study used socioeconomic characteristics to represent social environmental factors that impact T2DM. The socioeconomic factors used in this analysis included income, unemployment rate, low-education rate, and immigration rate. These variables were extracted from the 2016 Canadian Dissemination Area (DA) Level Census published by Statistics Canada [40]. The low-education rate was calculated by dividing the number of individuals without education certificates by the total population in each DA. The immigration rate was calculated similarly, by dividing the number of individuals identified as immigrants by the total population in each DA. The variables were then aggregated to the neighborhood level using ArcGIS Pro's (Version 3.0) Spatial Join function by calculating the average value of each variable for each neighborhood, as the boundaries of DA match the neighborhoods [59]. A summary of the variables used in this study is listed in Table 2.

Table 2. List of variables used in geographically weighted regression analyses.

Variable	Description	Year	Source
	Dependent Variable		
Type-2 Diabetes Mellitus Prevalence Rates	Total cases of diabetes by population in neighborhood	2019	Ontario Community Health Profiles Partnership
	Independent Variable		
Unhealthy Food Outlet Density (Count per km^2)	Number of locations of limited-service (fast food) restaurants, confectionery retailers, bakeries, and convenience stores by neighborhood area	2019	SafeGraph
Green Space Density (% km^2)	Area of parks and recreation spaces by neighborhood area	2019	DMTI Spatial Inc.
Medium Total Income	Median total income among recipients ($)	2015	2016 Canadian Census
Unemployment Rate	Percentage of residents who are unemployed	2016	
Low-Education Rate	Percentage of residents who have not obtained any certificates, diplomas, or degrees	2016	
Immigration Rate	Percentage of the residents who are, or who have ever been, landed immigrants and permanent residents	2016	

2.2.5. Derivation of Environmental Variables

The problem of an uncertain geographic context (UGCoP) arises from the use of arbitrary areal units while calculating area-based variables. Researchers do not have perfect knowledge of how different spatial and temporal configurations can affect health outcomes [33]. This study quantifies the effects of the environment on T2DM using a small spatial scale. However, it is not accurate to assume that residents in the arbitrary areal units (e.g., neighborhoods in this study) only have access to outlets and locations within their neighborhoods. People living near the borders of these units may have closer access to facilities in adjacent neighborhoods, which can influence the analysis results. This phenomenon is known as the "edge effect" [60]. This study used a container-based (buffer) measurement to address this issue. The analysis unit was given a buffered distance as a boundary to include locations outside each neighborhood as measurements of accessibility. However, there is a lack of agreement on the appropriate buffer threshold, as it depends on the areal units used in different studies [61]. The buffer distances in previous studies ranged from 500 m to 5 km. One study found that most buffers used to measure the density and proximity of retail food outlets varied between 2 and 3 km [62]. Therefore, this study created a buffer zone around the border of each neighborhood to include environmental variables (unhealthy food outlets and green space) up to 2.5 km away in the analysis, as shown in Figure 3.

This study calculates the density of unhealthy food outlets and green spaces within each neighborhood and their surrounding areas (buffer zones) to standardize the measurements of accessibility and environmental exposure. The density of unhealthy food outlets was calculated by dividing the number of locations within a 2.5 km buffer of each neighborhood by the area of the neighborhood with the container buffer. The density of green spaces was calculated in the same way, using the total area of the green spaces within a 2.5 km buffer of each neighborhood, and divided by the area of each neighborhood with the container buffer. A higher density indicates that citizens will have greater access to their surrounding environment. The variables included in the regression models are shown in Table 2.

2.3. Statistical Analysis

2.3.1. Spatial Autocorrelation

Spatial autocorrelation in the prevalence of T2DM in Toronto neighborhoods was examined using global Moran's index statistics in ArcGIS Pro [59]. Using a default setting with an inverse Euclidian distance, the calculation yielded a Moran's I of 0.7995, with a z-score of 18.05 ($p < 0.001$). This indicated that a strong positive spatial autocorrelation exists in Toronto neighborhoods, meaning that similar T2DM prevalence rates tend to be clustered spatially. This can also be seen in Figure 2. Anselin's local Moran's I was applied at the neighborhood level to further identify local clusters or spatial outliers in the T2DM prevalence rates. Figure 4 illustrates the results of this analysis, using ArcGIS Pro's Cluster and Outlier Analysis program with a default setting of an inverse Euclidean distance. Statistically significant (at the 95% confidence level) clusters of high T2DM prevalence rates (HH) were found in northeastern and eastern Toronto. In contrast, clusters of low (LL) prevalence rates were located in central Toronto. The Regent Park neighborhood was an outlier, as it had a high T2DM prevalence rate but was surrounded by neighborhoods with low rates (HL).

Both the global and local Moran's I analyses indicated that spatial autocorrelation exists for the T2DM prevalence rates in Toronto neighborhoods. However, many studies that examine the associations between T2DM prevalence and environmental factors frequently ignore how spatial autocorrelation may impact the research results. To address this, this study used a spatial regression model called geographically weighted regression to account for the effects brought on by spatial autocorrelation.

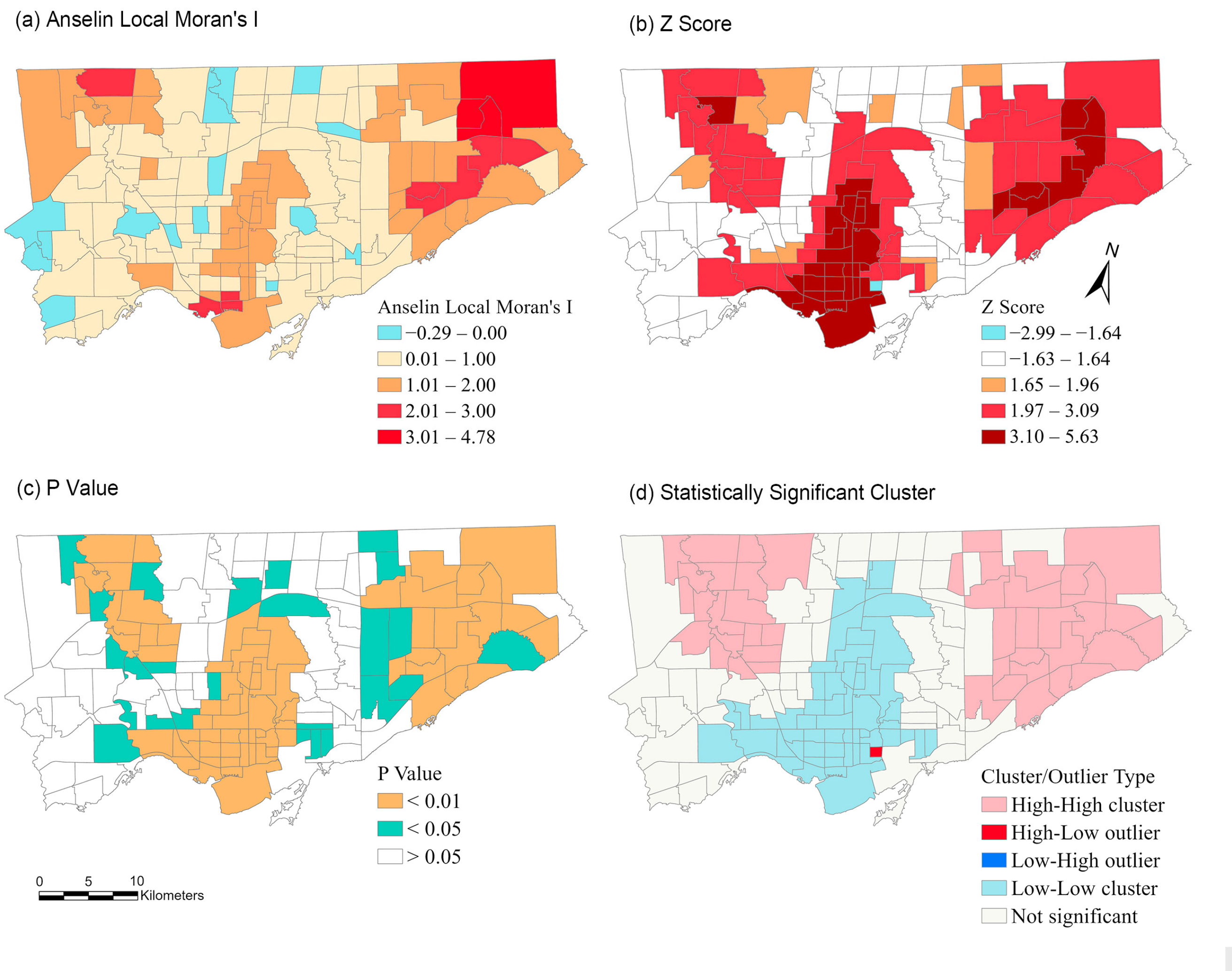

Figure 4. Analysis of Anselin's local Moran's index (**a**) for type-2 diabetes mellitus prevalence rates in Toronto neighborhoods with results of *z*-score (**b**), *p*-value (**c**), and statistically significant cluster (**d**).

2.3.2. Geographically Weighted Regression (GWR)

The geographic weighted regression (GWR) model is an extension of the traditional OLS regression model that generates local regression models for each spatial unit (e.g., each neighborhood in this study). The ordinary least squares (OLS) regression model is a widely used statistical model used to determine the relationships between variables [63,64]. The OLS approach models a continuous dependent variable as a linear function of one or more independent variables, allowing for us to understand how the independent variables contribute to the outcome. However, OLS regression models do not consider spatial variability, nor do they handle spatial autocorrelation in georeferenced data. GWR is a spatial regression model that controls the bias created using spatial autocorrelation and can be used to explore and address the issue of spatial non-stationarity [65]. The equation of the GWR model is shown below:

$$y_i = \beta_{i0} + \sum_{k=1}^{L} \beta_{ik} x_{ik} + \epsilon_i \qquad i = 1, 2, \ldots, n \tag{1}$$

The dependent variable y_i represents the neighborhoods, i, in this study. The local regression coefficients β_{ik} and values for the kth independent variable x_{ik} at each location i are used to predict y_i; β_{i0} is the intercept and ε_i is the random error, where $\varepsilon \sim N(0, \sigma^2)$ at location i. Unlike the "global" OLS model where the coefficients β_k are fixed, the regression coefficients β_{ik} in the GWR model vary by location. Four continuous (Gaussian) GWR models were created to examine the relationships between environmental factors and T2DM prevalence rates for ages 20 and above, from 20 to 44, from 45 to 64, and 65 and above. ArcGIS Pro (version 3.0) was used to run the GWR models for this study [59].

In ArcGIS Pro, a weighting procedure was applied for each location i. Bandwidths were calculated at each location to determine which other neighborhoods would be included in the estimation of each local model. The observations were weighted based on their proximity to location i [66]. The distance bandwidth was determined using the golden selection procedure, selecting the regression model with the lowest model Akaike information criterion (AIC) that best fits the data. A local *t*-value was also calculated to estimate the significance of the regression coefficients in this study. This was calculated by dividing the local regression coefficient by the local standard error for each observation (in this case, neighborhoods in Toronto). These *t*-values act as pseudo-*t*-statistics, testing the null hypothesis that the regression coefficients are equal to zero. Since GWR tends to overfit the model, the *t*-values can be used to identify the regional areas where relationships occur [67].

2.3.3. Multicollinearity

Multicollinearity can occur when two or more independent variables are highly correlated in a regression model. The existence of multicollinearity in a regression model inflates the standard errors of regression coefficients and hinders the interpretation of regression results. To ensure that multicollinearity did not exist between the independent variables, this study used the variable inflation factors (VIF) measured from the companion to applied regression (car) package in R [68,69]. A higher VIF value indicates severe multicollinearity. Independent variables included in the regression analyses should have VIFs that are less than four [70]. The selection of variables started with all variables included in the regression model. If any variables were found to have VIF values greater than four, indicating multicollinearity, the variable with the highest VIF value was removed from the model. This process was repeated until all the model variables had VIF values of less than four. There was no evidence of multicollinearity among the selected independent variables (all VIF values < 4); hence, all of them were included in the regression analyses, as shown in Table 2.

3. Results

3.1. Descriptive Statistics

The summary statistics of the T2DM prevalence rates, environment, and socioeconomic variables are shown in Table 3. The prevalence rates of T2DM among citizens aged 20 and above ranged from 2.3% to 22.5% in the neighborhoods of Toronto. The average prevalence rate of T2DM in Toronto neighborhoods was 12.2%, with a standard deviation of 4.4%. The average prevalence rate for the age group of 20–44 was 2.6%, while this increased to 14.6% for the age group of 45–64 and 31.6% for the age group of 65 and above. The standard deviation also increased from 1.14 for the 20–44 age group to 5.81 for the 45–64 age group and 7.8 for the 65 and above age group. On average, 19% of the Toronto neighborhoods were covered with green space. There were an average of 7.6 unhealthy food outlets per km^2 in Toronto neighborhoods. Toronto's neighborhoods also had diverse socioeconomic characteristics, as the percentages of immigrant populations varied from 20.73% and 70.23%, including neighborhoods with both local residences and immigrants. The percentages of residents without certificates, diplomas, or degrees varied from 2.47% to 30.46%. There were neighborhoods with annual incomes ranging from CAD 19,797 to CAD 65,639 and unemployment rates ranging from 5.43% to 12.28%. The variations in environment and socioeconomic status among Toronto's neighborhoods may contribute to spatial non-stationarity and environmental influences on T2DM prevalence rates.

Table 3. Descriptive statistics for T2DM, environmental, and socioeconomic variables.

Variables	Minimum	Maximum	Mean	Median	Standard Deviation
T2DM Prevalence Rate Age 20+ (%)	2.30	22.50	12.20	12.00	4.40
T2DM Prevalence Rate Age 20–44 (%)	0.90	5.50	2.60	2.30	1.14
T2DM Prevalence Rate Age 45–64 (%)	4.70	31.00	14.60	13.70	5.81
T2DM Prevalence Rate Age 65+ (%)	14.70	50.00	31.60	30.90	7.80
Green Space Density (% km^2)	7.70	64.00	19.00	20.30	8.60
Unhealthy Food Outlet Density (Count per km^2)	1.66	52.0	7.6	12.6	12.4
Immigration Rate (% Population)	20.7334	70.2330	44.9463	45.8499	12.4900
Low-Education Rate (% Population)	2.4690	30.4626	13.2855	13.1108	6.1950
Medium Annual Income ($)	19,797	65,639	34,701	32,387	10,360
Unemployment Rate (% Population)	4.5272	12.2839	7.9010	7.4982	1.5618

3.2. GWR Regression

This study created four geographically weighted regression models to examine spatial non-stationarity and environmental effects on the prevalence rates of T2DM in different age groups: “20 and above” (model 1), “20 to 44” (model 2), “45 to 64” (model 3), and “65 and above” (model 4). The results of these models are shown in Tables 4–7. The global R^2 values that measure the proportions of variation in the T2DM prevalence rates explained by the relationships with independent variables were 0.9173, 0.9018, 0.8769, and 0.9012 for the four models, respectively. The local R^2 values at the neighborhood level ranged from 0.74 to 0.90, 0.50 to 0.94, 0.67 to 0.93, and 0.76 to 0.95 for the four models, respectively, as shown in Figure 5. Most neighborhoods had local R^2 values of 0.80 or above (blue areas in Figure 5e–h), indicating that the GWR modes accurately predicted the T2DM prevalence rates in these neighborhoods. The residuals for the GWR models, shown in Figure 5a–d, were also examined. Positive residuals (mapped as green) represented underestimated T2DM prevalence rates, while negative residuals (mapped as purple) represented overestimated rates. No significant spatial autocorrelations existed in the residuals of any of the four GWR models, as indicated by the Moran’s I values of 0.1227, −0.0318, 0.047, and 0.0529 for the residuals in Figure 5a–d, respectively. The positive and negative coefficients, which estimate the percentages of the corresponding statistically significant coefficients (with $|t\text{-values}| \geq 2.0$), are presented in Tables 4–7.

Table 4. Summary of GWR model 1.

Variables	GWR Model 1 Response Variable: T2DM Prevalence Rate (Age 20 and Above) (R^2 = 0.9173; Adjusted R^2 = 0.8982; AIC = 581.1; Distance Band = 13.3870 km)							
	Positive Coefficient Estimates (%)	Significant Positive Coefficient Estimates (%) †	Negative Coefficient Estimates (%)	Significant Negative Coefficient Estimates (%) ††	Minimum Coefficient Estimate	Median Coefficient Estimate	Mean Coefficient Estimate	Maximum Coefficient Estimate
Green Space Density (β1)	72	18	28	3	−10.5258	2.4558	11.5205	11.5205
Unhealthy Food Outlet Density (β2)	0	0	100	87	−1.1155	−0.0547	−0.1761	−0.0251
Immigration Rate (β3)	89	70	11	3	−17.7147	8.3376	7.4683	30.153
Low-Education Rate (β4)	97	92	3	0	−24.3151	25.9015	26.9508	53.8229
Medium Annual Income (β5)	8	0	92	20	−0.000355	−0.000042	−0.000067	0.000029
Unemployment Rate (β6)	96	50	4	0	−0.0475	0.3733	0.3475	0.6921

	Mean	Median	Standard Deviation	Minimum	Maximum
Local R^2	0.8565	0.8648	0.03751	0.7408	0.9063
Residual	0.0425	0.0256	1.2647	−3.1460	2.830

† Number of positive significant (t-value ≥ 2.00) coefficient estimates/number of neighborhoods. †† Number of negative significant (t-value ≤ −2.00) coefficient estimates/number of neighborhoods. AIC: Akaike information criterion; sample size: n = 158.

Table 5. Summary of GWR model 2.

Variables	GWR Model 2 Response Variable: T2DM Prevalence Rate (Age 20 to 44) (R^2 = 0.9018; Adjusted R^2 = 0.8568; AIC = 223.89; Distance Band = 9.61 km)							
	Positive Coefficient Estimates (%)	Significant Positive Coefficient Estimates (%) †	Negative Coefficient Estimates (%)	Significant Negative Coefficient Estimates (%) ††	Minimum Coefficient Estimate	Median Coefficient Estimate	Mean Coefficient Estimate	Maximum Coefficient Estimate
Green Space Density (β1)	71	29	28	3	−2.8841	2.1885	1.7834	5.8218
Unhealthy Food Outlet Density (β2)	1	0	99	26	−0.4595	−0.0171	0.0588	0.1266
Immigration Rate (β3)	78	45	22	11	−13.0359	2.9434	1.6437	15.2293
Low-Education Rate (β4)	88	45	11	3	−15.7521	4.3253	3.9859	12.9259

Medium Annual Income (β5)	43	0	57	5	−0.0001	−0.000005	−0.00001	0.000059
Unemployment Rate (β6)	89	55	11	0	−0.1551	0.1621	0.1920	0.5348

	Mean	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
Local R^2	0.7894	0.7974	0.0920	0.4946	0.9362
Residual	0.0289	−0.0128	0.9730	−3.1591	2.3771

† Number of positive significant (t-value ≥ 2.00) coefficient estimates/number of neighborhoods. †† Number of negative significant (t-value ≤ −2.00) coefficient estimates/number of neighborhoods. AIC: Akaike information criterion; sample size: n = 152.

Table 6. Summary of GWR model 3.

Variables	**GWR Model 3 Response Variable: T2DM Prevalence Rate (Age 45 to 64) (R^2 = 0.8769; Adjusted R^2 = 0.8479; AIC = 705.04; Distance Band = 13.5573 km)**							
	Positive Coefficient Estimates (%)	**Significant Positive Coefficient Estimates (%) †**	**Negative Coefficient Estimates (%)**	**Significant Negative Coefficient Estimates (%) ††**	**Minimum Coefficient Estimate**	**Median Coefficient Estimate**	**Mean Coefficient Estimate**	**Maximum Coefficient Estimate**
Green Space Density (β1)	82	24	18	1	−10.2352	5.7940	6.0480	21.5513
Unhealthy Food Outlet Density (β2)	21	0	79	28	−2.389	−0.0204	−0.2308	0.2108
Immigration Rate (β3)	71	49	29	11	−59.2993	9.6930	6.3398	58.8553
Low-Education Rate (β4)	90	55	9	3	−75.4935	18.1957	15.5273	49.1686
Medium Annual Income (β5)	0	0	100	85	−0.001003	−0.000164	−0.000222	0.000067
Unemployment Rate (β6)	100	63	0	0	0.0134	0.8120	0.8313	1.8059

	Mean	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
Local R^2	0.8175	0.8219	0.0607	0.6686	0.9268
Residual	0.1286	−0.0097	2.0344	−8.1336	7.1685

† Number of positive significant (t-value ≥ 2.00) coefficient estimates/number of neighborhoods. †† Number of negative significant (t-value ≤ −2.00) coefficient estimates/number of neighborhoods. AIC: Akaike information criterion; sample size: n = 152.

Table 7. Summary of GWR model 4.

Variables	GWR Model 4 Response Variable: T2DM Prevalence Rate (Age 65 and above) (R^2 = 0.9012; Adjusted R^2 = 0.8813; AIC = 784.66; Distance Band = 14.55 km)							
	Positive Coefficient Estimates (%)	**Significant Positive Coefficient Estimates (%) †**	**Negative Coefficient Estimates (%)**	**Significant Negative Coefficient Estimates (%) ††**	**Minimum Coefficient Estimate**	**Median Coefficient Estimate**	**Mean Coefficient Estimate**	**Maximum Coefficient Estimate**
Green Space Density (β1)	81	18	19	0	−9.8495	5.6945	5.6301	26.1653
Unhealthy Food Outlet Density (β2)	62	3	38	17	−2.0939	0.0264	−0.1292	0.1017
Immigration Rate (β3)	67	30	33	11	−43.7693	5.5009	2.9680	57.6589
Low-Education Rate (β4)	94	92	6	3	−82.5982	48.9387	44.3856	72.6199
Medium Annual Income (β5)	0	0	100	99	−0.00125	−0.000373	−0.000419	−0.000261
Unemployment Rate (β6)	57	14	43	10	−1.1561	0.1496	0.1120	1.2070
	Mean	**Median**	**Standard Deviation**		**Minimum**		**Maximum**	
Local R^2	0.8759	0.8782	0.0428		0.7576		0.9514	
Residual	0.1220	0.0991	2.4626		−7.5515		7.2896	

† Number of positive significant (t-value ≥ 2.00) coefficient estimates/number of neighborhoods. †† Number of negative significant (t-value ≤ −2.00) coefficient estimates/number of neighborhoods. AIC: Akaike information criterion; sample size: n = 158.

Environmental effects on the T2DM prevalence rates existed after controlling for socioeconomic factors, since most coefficients differed from zero. However, some regression coefficients were not statistically significant (|t-values| ≤ 2.0). This may have been due to the small sample size or high degree of random variation in the regression variables. It is not recommended to interpret the non-significant t-values because we cannot be sure that the values of the associated parameters in the regression model have an effect. Therefore, the regression results were interpreted cautiously by only reporting the geographical areas with significant coefficients.

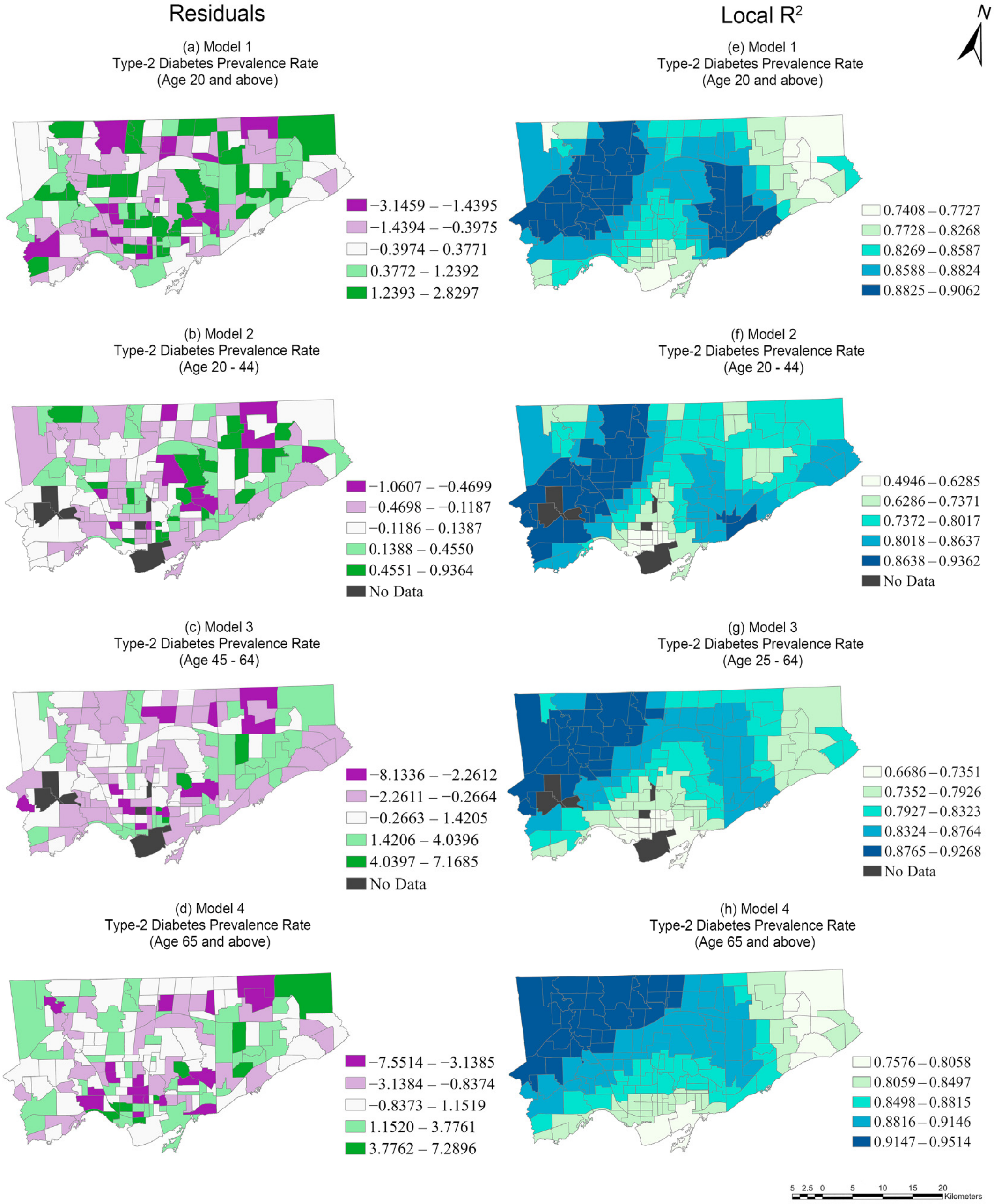

Figure 5. GWR model residuals (**a**–**d**) and R^2 values (**e**–**h**) by neighborhood.

According to the results of the GWR model 1 shown in Table 4, 18% of the neighborhoods in east and west Toronto showed significant positive associations between the green space density (β1) and the T2DM prevalence rate among those aged 20 and above. In contrast, 3% of the neighborhoods, such as those in the central north, had significant negative associations between the green space density (β1) and T2DM prevalence. A total of 87% of neighborhoods had significant negative associations between the unhealthy food outlet density (β2) and T2DM prevalence. Additionally, the immigration rate (β3), low-education rate (β4), and unemployment rate (β6) had statistically significant positive associations (70%, 92%, and 50%, respectively) with T2DM prevalence in neighborhoods in central Toronto. A total of 20% of the neighborhoods in the northwest or northeast of Toronto had negative relationships between the medium annual income (β5) and T2DM prevalence rates. Figure 6 shows the spatial variation in the local coefficients and *t*-values for GWR model 1. These results revealed that inconsistent associations existed between the green spaces and T2DM prevalence rates among those aged 20 and above across neighborhoods in Toronto.

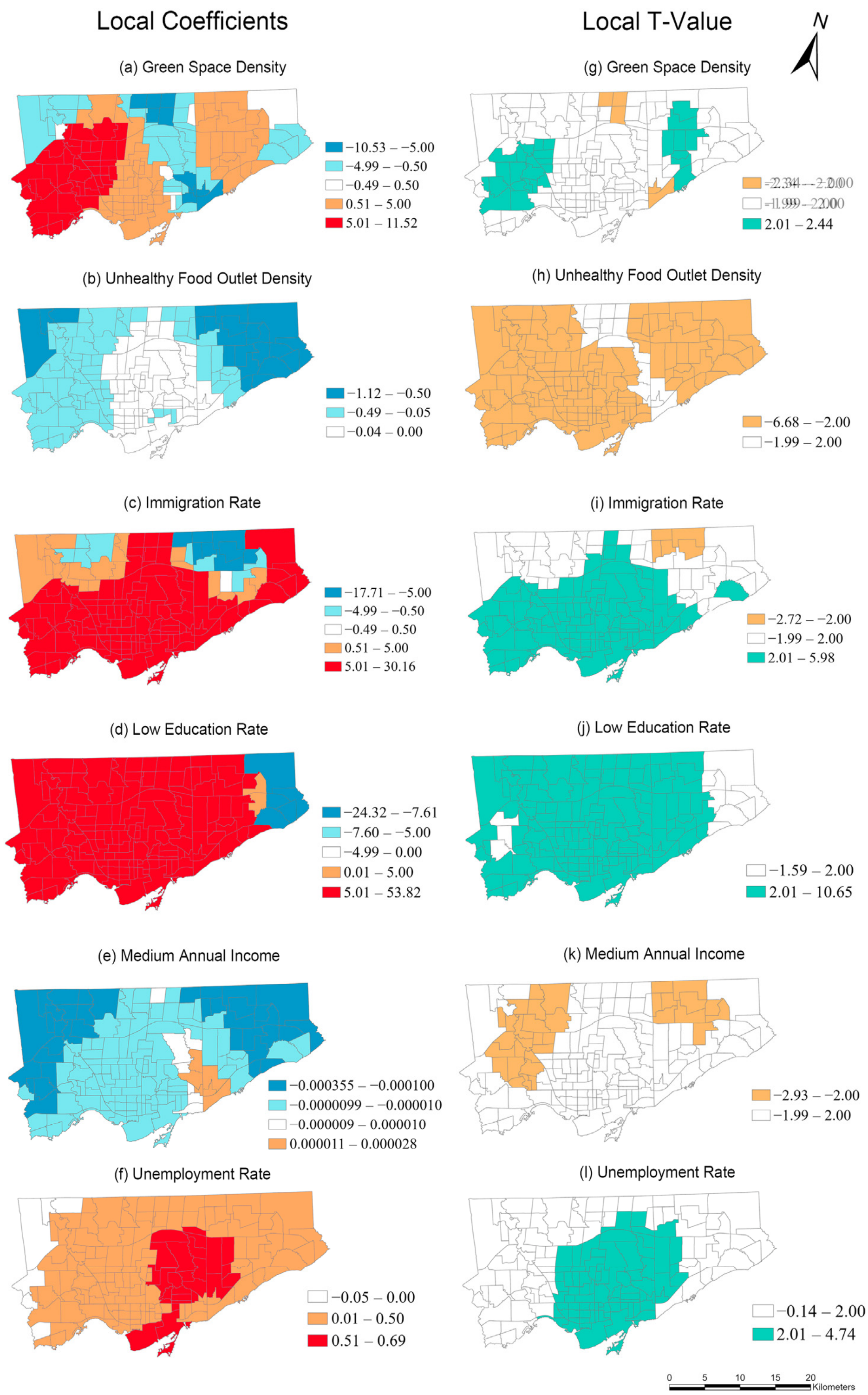

Figure 6. Spatial variation of local coefficients and t-values of GWR model 1 with T2DM prevalence rates in those aged 20 and above. (**a**–**f**) Local coefficients of the green space density (% km^2), unhealthy food outlet density (count per km^2), immigration rate (% population), low-education rate (% population), medium annual income ($), unemployment rate (% population), and (**g**–**l**) corresponding local t-values of all predictors.

The results also showed that spatial non-stationarity effects existed for environmental and socioeconomic factors on the prevalence of T2DM among those aged from 20 to 44 across Toronto neighborhoods. The results are reported in Table 5. A total of 29% of Toronto neighborhoods across the central–west area showed significant positive associations between the green space density (β1) and T2DM prevalence rate. However, 3% of the neighborhoods in the east of Toronto showed significant negative associations between the green space density (β1) and T2DM prevalence rate. Furthermore, an unhealthy food outlet density (β2) showed significant negative associations with T2DM prevalence in 26% of the neighborhoods, primarily in eastern Toronto. The immigration rate (β3), low-education rate (β4), and unemployment rate (β6) showed statistically significant positive associations (45%, 45%, and 55%, respectively) with T2DM prevalence rates in most of the Toronto neighborhoods. However, inconsistent associations also existed with the immigration rate (β3) and low-education rate (β4), where 10% and 5% of Toronto neighborhoods had significant negative associations with T2DM prevalence rates, respectively. The spatial non-stationarity effects can also be seen in Figure 7, where local coefficients change from blue (negative) to red (positive) across Toronto neighborhoods.

Similar to model 2, the green space density (β1) had a significant positive association with the prevalence of T2DM in 24% of the neighborhoods across Toronto for the age group from 45 to 64 years. An unhealthy food outlet density (β2) negatively correlated with T2DM prevalence in 28% of neighborhoods in this age group. Immigration (β3), low education (β4), and unemployment (β6) rates were positively correlated with T2DM prevalence rates in 49%, 55%, and 63% of neighborhoods, respectively, for the age group from 45 to 64 years. In contrast, the prevalence of T2DM negatively correlated with the immigration rate (β3), low-education rate (β4), and median annual income (β5) in 11%, 3%, and 85% of neighborhoods, respectively. The results for model 3 are shown in Table 6 and Figure 8.

Spatial non-stationarity effects were also discovered for both contextual and control variables on the T2DM prevalence rate with the fourth GWR model. The T2DM prevalence rate among those aged 65 and above was included as the dependent variable in GWR model 4. The spatial variations in the local coefficients and *t*-values of the fourth GWR model can be found in Table 7 and Figure 9. The green space density (β1) yielded significant positive associations with the T2DM prevalence rates among those aged 65 and above in 18% of the neighborhoods across Toronto. These neighborhoods were mainly located in the east and southwest of Toronto. However, unhealthy food outlet locations (β2) had positive associations with T2DM prevalence rates in 3% of neighborhoods (located southwest of Toronto), but negative associations in 17% of neighborhoods (in the east of Toronto). Among the socioeconomic factors, the medium annual income (β5) was negatively correlated with the T2DM prevalence rate among those aged 65 and above in 99% of the neighborhoods. The immigration rate (β3), low-education rate (β4), and unemployment rate (β6) had positive correlations with the T2DM prevalence rates among those aged 65 and above in 30%, 92%, and 14% of the neighborhoods, respectively. Nevertheless, the immigration rate (β3), low-education rate (β4), and unemployment rate (β6) had negative correlations with the T2DM prevalence rates among those aged 65 and above in 11%, 3%, and 10% of the neighborhoods, respectively.

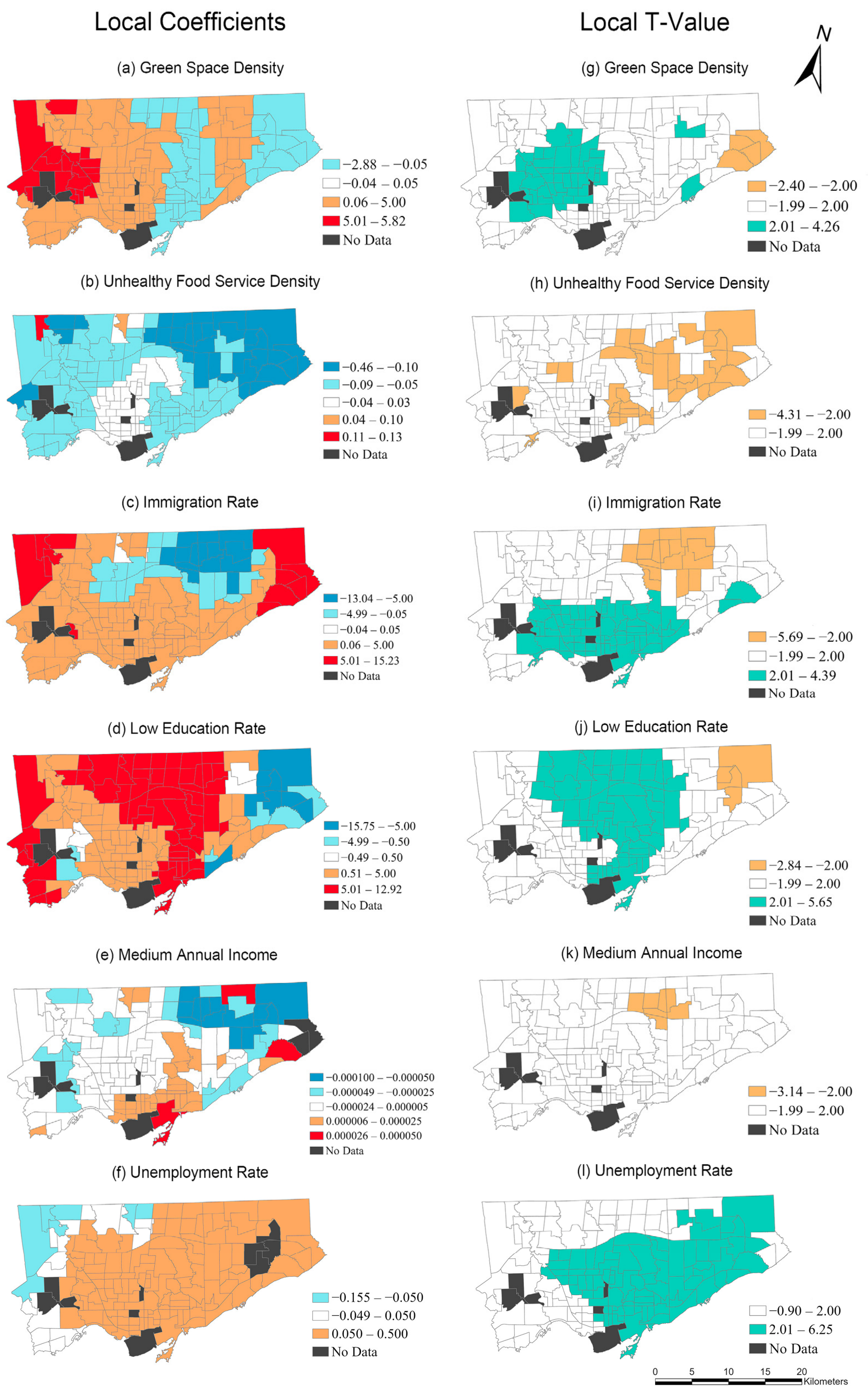

Figure 7. Spatial variation of local coefficients and t-values of GWR model 2 with T2DM prevalence rates in those aged 20 to 44. (**a**–**f**) Local coefficients of the green space density (% km^2), unhealthy food outlet density (count per km^2), immigration rate (% population), low-education rate (% population), medium annual income ($), unemployment rate (% population), and (**g**–**l**) corresponding local *t*-values of all predictors.

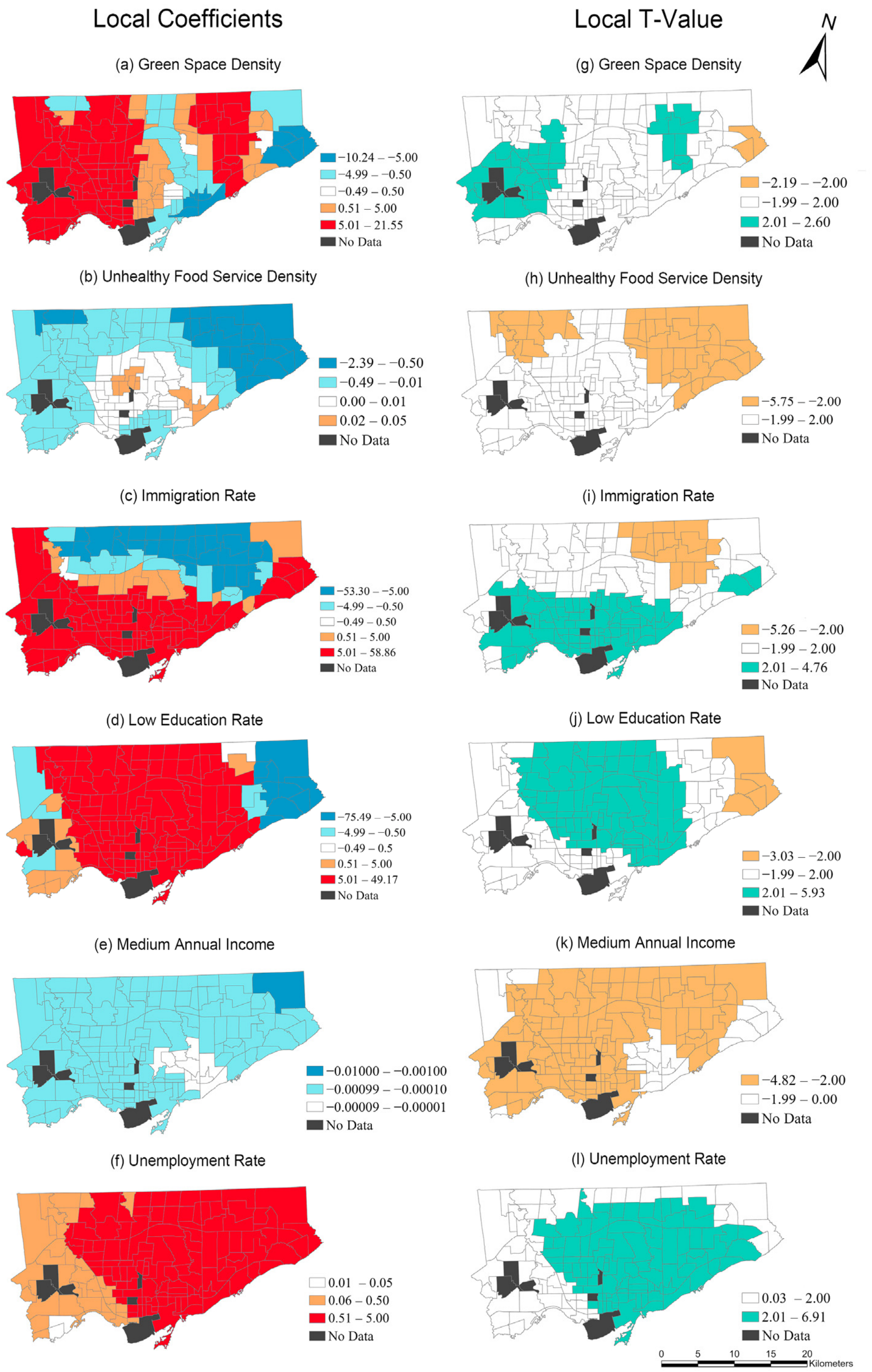

Figure 8. Spatial variation of local coefficients and t-values of GWR model 3 with T2DM prevalence rates in those aged 45 to 64. (**a**–**f**) Local coefficients of the green space density (% km^2), unhealthy food outlet density (count per km^2), immigration rate (% population), low-education rate (% population), medium annual income ($), unemployment rate (% population), and (**g**–**l**) corresponding local t-values of all predictors.

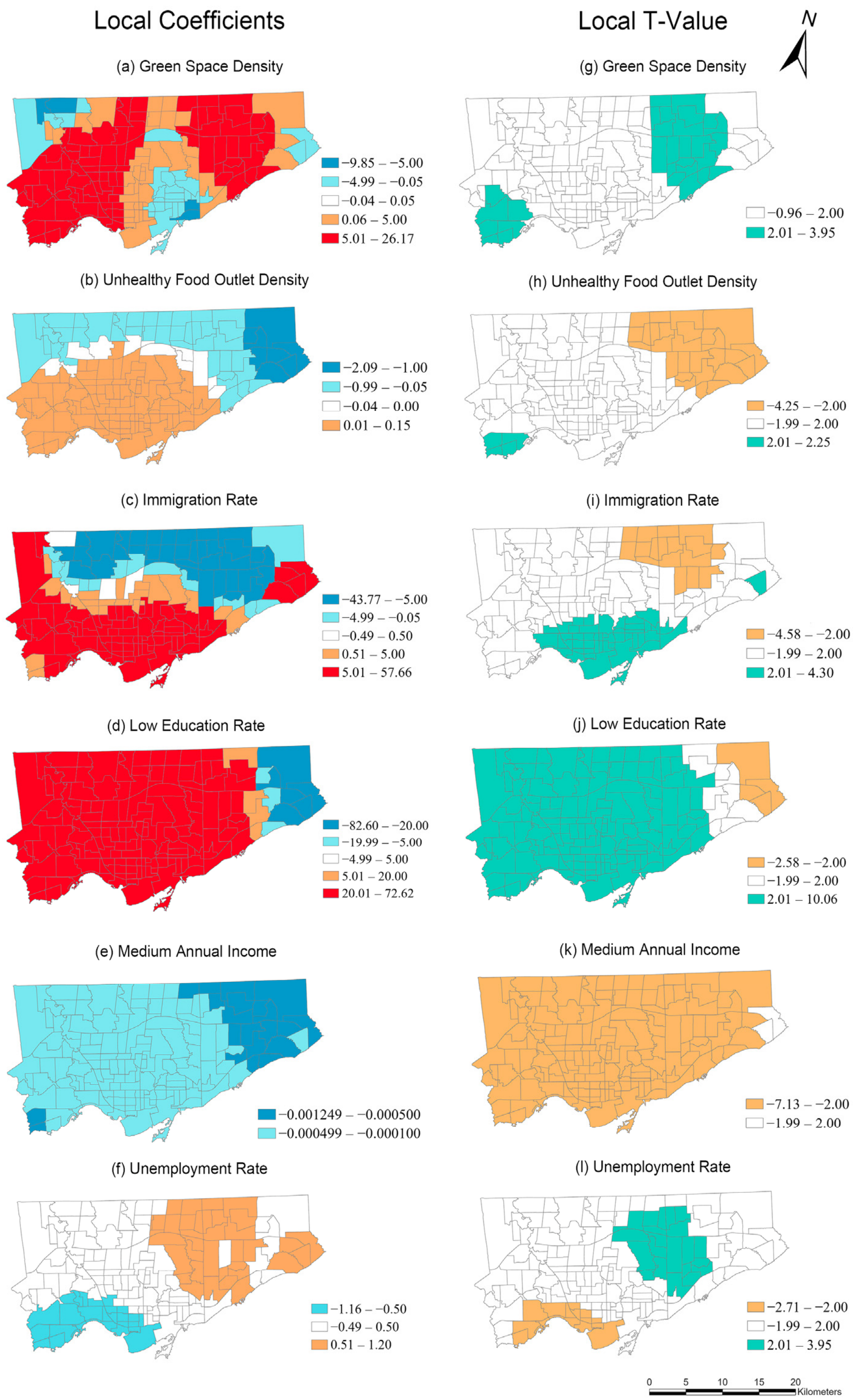

Figure 9. Spatial variation of local coefficients and t-values of GWR model 4 with T2DM prevalence rates in those aged 65 and above. (**a**–**f**) Local coefficients of the green space density (% km^2), unhealthy food outlet density (count per km^2), immigration rate (% population), low-education rate (% population), medium annual income ($), unemployment rate (% population), and (**g**–**l**) corresponding local *t*-values of all predictors.

4. Discussion

This study investigated the relationship between both unhealthy food and green space environments with the prevalence of T2DM at the neighborhood level in Toronto. The study used geographically weighted regression (GWR) models to analyze the associations between contextual factors and T2DM prevalence rates in four different age groups: 20 and above, from 20 to 44, from 45 to 64, and 65 and above. The results of all four models indicated that spatial non-stationarity effects existed between environmental characteristics and T2DM prevalence rates. The use of the GWR model successfully addressed the issue of spatial autocorrelations in the T2DM prevalence rate (Moran's *I* statistics of 0.7995) across Toronto and produced uncorrelated residuals. Previous studies have often ignored spatial non-stationarity and spatial autocorrelation, which can lead to biased results in environmental health research. Additionally, the inconsistent spatial relationships found between the prevalence rates of T2DM and environmental and socioeconomic factors create uncertainties in environmental health research, in addition to the modifiable areal unit problem (MAUP) and the uncertain geographic context problem (UGCoP). The conflicting findings from previous studies on the relationship between diabetes and the environment may be due to the spatial non-stationarity effects at different geographical locations. Hence, understanding these spatial non-stationarity associations can help inform the development of targeted education, prevention, and intervention policies for specific geographic areas.

The relationships between environmental factors and the prevalence rates of T2DM from four GWR models showed spatial non-stationarity across Toronto neighborhoods. The inconsistent coefficient of the estimates in the GWR models (shown in Tables 4–7) indicated spatial variation in the effects of the environment on the T2DM prevalence rates. Statistical tests were conducted on the estimates' coefficients to identify statistically significant ones with $|t\text{-values}| \geq 2.00$. These significant coefficients of the estimates, representing the results of local regression models, can help us understand the impacts of contextual variables on the T2DM prevalence rates at various geographic locations. For example, the green space density ($\beta 1$) was significantly positively associated with the prevalence rate of T2DM for 27% of the neighborhoods among young people aged from 20 to 44, but was negatively associated in 3% of the neighborhoods. Figure 6a shows that the associations between the green space density and T2DM prevalence rates varied from negative (blue polygons) to positive (red polygons) across neighborhoods in Toronto. The figure further illustrates that the significant positive coefficients were clustered around the central–west area of Toronto, but the significant negative coefficients were located in the east of Toronto. This showed that when the green space density increased in the central–west area of Toronto, the prevalence rates of T2DM also increased among citizens aged between 20 and 44; in contrast, when the green space density decreased around the east of Toronto, the prevalence rates of T2DM decreased among citizens aged between 20 and 44. On the other hand, when the green space density increased in the east and southwest of Toronto (green polygons in Figure 9g), the prevalence rates of T2DM also increased among the elder generation aged 65 and above. The positive correlation between green spaces and T2DM prevalence rates contradicts the previous research, which found that green spaces promote physical activity and reduce the risks of diabetes [7,8]. It is possible that the quality of green spaces and the presence of noise and unsafe environments in the central–west area of Toronto may have contributed to this contradiction. Poorly designed environments and unsafe neighborhoods may discourage physical activity and increase social isolation due to fear [71]. Elder generations could also have less access to green spaces as activity sites due to their limited mobility in the community compared to the youth.

Unhealthy food outlets ($\beta 2$) were found to have inconsistent effects on the prevalence rates of T2DM between younger and elder generations. The unhealthy food outlet density was negatively associated with T2DM prevalence among people aged from 20 to 64 in around 25% of the neighborhoods, primarily in eastern Toronto (shown in blue in Figures 7b and 8b). This meant that on average, as the number of unhealthy food outlets decreased, the T2DM prevalence rate for ages between 20 and 64 tended to increase. However, the unhealthy food outlet densities were found to have significant positive relationships with T2DM prevalence in four neighborhoods in southwest Toronto (labeled in green in Figure 9h) among the elder generation aged 65 and above. At the same time, some were negatively associated with T2DM prevalence in eastern Toronto for this age group. These results showed that unhealthy food outlets were associated with low diabetes prevalence rates in some neighborhoods when controlling for socioeconomic status. The results again contradict previous research showing that unhealthy food environments increase the risk of diabetes in neighborhoods [12,22,23,72]. This discrepancy may have been due to the complex interactions between T2DM and socioeconomic factors. For instance, the communities across Toronto were well-educated, where only 13% of the population held no diploma or certificate, as indicated in Table 3. The citizens recognized the adverse health outcomes of consuming unhealthy food and chose healthy food choices, such as cooking at home. On the other hand, the unhealthy fast food restaurants were mainly clustered around central–downtown Toronto due to the agglomeration effects around commercial districts, but were sparsely located around neighborhoods in which negative associations were discovered, as illustrated in Figure 3a. However, the citizens living around communities in downtown Toronto were usually wealthy and well-educated, with greater accessibility and more choices of various food sources. As a result, the socioeconomic and demographic characteristic variations among the neighborhoods may explain the inconsistent and contradictory results.

It is worth noting that the immigration rates (β3) were also found to have spatial non-stationarity effects on the T2DM prevalence rates across Toronto's neighborhoods. When the immigrant population increased in central–downtown Toronto, the T2DM prevalence rate also increased among all age groups. In contrast, the T2DM prevalence rate decreased when the immigrant population increased north of Toronto. The positive correlation between the immigrant population and T2DM may have been caused by the presence of unhealthy food outlets located around downtown Toronto, which could lead to changes in dietary structures and habits for immigrants, increasing their risk of being diagnosed with T2DM. Additionally, the low-education rate (β4), medium annual income (β5), and unemployment rate (β6) were found to increase, decrease, and increase the T2DM prevalence rates, respectively, across Toronto's neighborhoods.

This study's findings indicate the presence of spatial non-stationarity in environmental health studies of T2DM. This is consistent with the expectations but differs from the majority of the previous studies. As a result, it is possible and not surprising that research on the effects of environmental factors on T2DM conducted in different geographic locations would find inverse associations. This is a possible reason why the research findings on the impacts of environmental factors on diabetes health behaviors and outcomes are frequently inconsistent. Recognizing the spatial non-stationarity effects of the environment on T2DM across various geographical locations could help us to better understand the ignored spatial phenomenon of T2DM.

The findings of this study will help to inform the development of customized diabetes intervention and prevention policies. For instance, communities around central Toronto may consider improving the design and attractiveness of green spaces to promote physical activities. Intervention policies and education programs targeting specific social groups and communities with a higher risk of T2DM (such as immigrants and low-income populations) should be developed, as the negative impact of diabetes on health continue to increase. Other potential intervention policies that could be implemented include promoting active transportation (such as walking), providing diabetes education, and establishing clinics in areas with high rates of T2DM prevalence.

This study has several limitations that should be addressed in future research. Firstly, while six contextual variables were selected for the regression analyses, other factors may also influence T2DM. Hence, it would be useful to examine and investigate additional environmental characteristics in future studies, such as the density of sidewalks and the length of cycling trails. Furthermore, the quality of green spaces and neighborhood safety, which can impact physical activity, should also be considered as proxies for contextual variables. A safe neighborhood with attractive landscapes can promote physical activity and lower the risk of diabetes [9]. Secondly, this study did not consider environmental exposures outside the neighborhood, such as workplaces. Although residents spend most of their time in their communities (the most relevant areas that affect health behaviors and outcomes), people's exposure to social and physical environments is determined by the locations they visit and the time spent moving around for daily activities [73]. As a result, it would be useful to consider people's movement in space and time when estimating environmental exposures and their effects on health behaviors and outcomes. Thirdly, this cross-sectional study investigated the environmental associations with T2DM in 2019. Longitudinal data analyses using multiple years of data may provide additional insights into how the environment affects the T2DM prevalence rate. Lastly, this study explored the spatial non-stationarity associations between T2DM and environmental factors in various geographical locations at the city level, which has not been well-studied in previous research. However, further research is needed to investigate the causality, particularly the non-stationarity impacts of environmental factors on T2DM.

5. Conclusions

This study found that the relationship between T2DM and environmental factors varied depending on geography and age in Toronto. The results indicated that spatial non-stationarity effects of unhealthy food and green space environments on T2DM exist in Toronto neighborhoods. Future research should consider regional differences to accurately understand the relationships between T2DM and environmental factors and to fully understand the causes of spatial non-stationarity.

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Institutional Review Board Statement: Not applicable.

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Data Availability Statement: The dataset of Toronto's neighborhood boundary, diabetes prevalence, and population census, supporting this study's findings, are openly available at Toronto Open Data Portal [42], Ontario Community Health Profiles Partnership [43], and Statistics Canada [40], respectively. Restrictions applied to the availability of green space data and unhealthy food outlet data from DMTI Spatial Inc. [55] and SafeGraph [45], respectively, which were used under license for this study.

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Conflicts of Interest: The authors declare no conflict of interest.

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